Bridging the innovation gap. AI and robotics as drivers of China's urban innovation

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Andrés Rodríguez-Pose* and **Zhuoying You°**

Abstract

Artificial intelligence (AI) and robotics are revolutionising production, yet their potential to stimulate innovation and change innovation patterns remains underexplored. This paper examines whether AI and robotics can spearhead technological innovation, with a particular focus on their capacity to deliver where other policies have mostly failed: less developed cities and regions. We resort to OLS and IV-2SLS methods to probe the direct and moderating influences of AI and robotics on technological innovation across 270 Chinese cities. We further employ quantile regression analysis to assess their impacts on innovation in more and less innovative cities. The findings reveal that AI and robotics significantly promote technological innovation, with a pronounced impact in cities at or below the technological frontier. Additionally, the use of AI and robotics improves the returns of investment in science and technology (S&T) on technological innovation. AI and robotics moderating effects are often more pronounced in less innovative cities, meaning that AI and robotics are not just powerful instruments for the promotion of innovation but also effective mechanisms to reduce the yawning gap in regional innovation between Chinese innovation hubs and the rest of the country.

Keywords: AI, robotics, China, technological innovation, territorial inequality.

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1. Introduction

The limited capacity of economic actors in many territories to increase their innovative capacity represents an important barrier for economic progress and well-being. Governments have implemented a variety of policies aimed at mitigating disparities in innovation between regions, yet these efforts have largely fallen short of making an impact on narrowing the widening innovation gap. Innovation is today more geographically concentrated than ever before and than any other economic indicator.

The geographical concentration of innovation in specific hubs is often the result of the geographical agglomeration of endowments, such as human and financial resources that drive the capacity of economic stakeholders to produce new products and processes (Audretsch & Feldman, 1996). Most less developed cities and regions are, in contrast, at or below the technological frontier (Aghion, 2019). The innovative capacity of the firms in these cities and regions is curtailed by either a dearth of adequate human or financial capital or by their incapacity to replicate the density of resources and talent at the base that most advanced innovation today (Rodríguez-Pose, 2001; Rodríguez-Pose et al., 2021). This dynamic suggests that simply increasing investment in science and technology (S&T) is no guarantee for driving innovation in less developed areas, nor does it facilitate bridging of the regional innovation divide. This is in spite of frequent past claims that investment in S&T can linearly improve technological innovation (Maclaurin, 1953; Pakes & Griliches, 1980) or through spillover effects (Audretsch & Feldman, 1996; Jaffe, 1993). Particularly, in the least developed cities and regions increases in S&T have often been regarded as a potential waste of resources. Often the results are limited, leading to a widening of the innovation divide (Li, 2009).

The growth in the geographical innovation gap has coincided with the rapid expansion of artificial intelligence (AI) and robotics. This expansion is revolutionising the world of production. It has been argued that AI and robotics can contribute to accelerate innovation in existing innovation hubs, further exacerbating the innovation gap (Lundvall & Rikap, 2022). Yet, the contribution of AI and robotics to innovation trends, especially in the less developed and less innovative regions, remains insufficiently explored.

This paper seeks to address this gap in existing knowledge by asking a series of questions. First, we enquire the extent to which AI and robotics serve as catalysts for technological innovation across cities and regions. More specifically, we explore whether the adoption of these technologies can enhance the innovation capacity of less innovative areas, there where investments in S&T and research and development (R&D) have often failed. We then consider the interaction between investment in S&T expenditure with AI and robotics, respectively. We ask whether AI and robotics moderate the returns of S&T spending on technological innovation, considering whether these effects vary along to the innovative spectrum of cities, from the most innovative hubs to the least innovative places.

The analysis is applied to China. We examine the innovation dynamics across 270 Chinese cities over the period 2009-2019. We use OLS and IV-2SLS estimators to assess the direct influence of the deployment of AI and the use of robotics on technological innovation and their potential moderating effects on enhancing the efficacy of S&T investment. We subsequently employ a quantile regression approach to identify whether AI and robotics contribute to the growing territorial innovation gap or, by contrast, are tools that can help combat it.

We find that the development of AI and robotics considerably increases regional innovation and that this impact is particularly relevant for the less innovative cities of China. Less innovative cities in China often extract similar or greater innovation gains from AI and robotics than the main innovation hubs. Additionally, the introduction of these new technologies augments the returns of S&T investment on local technological innovation, particularly in cities and regions in the lower echelons and the middle of the innovation distribution.

The paper makes several contributions to existing knowledge. First, we confirm the limits of S&T investment in the cities far away from the technological frontier. Second and more piercingly, we reveal that the development of AI and robotics are powerful tools for innovation, particularly in medium and less innovative areas. Hence, at least in the case of China, they are a viable approach to narrowing the innovation gap. Third, the paper sheds light on the direct and moderating roles of AI and robotics, offering fresh insights into how cutting-edge technological progress can interact with and boost innovation at the regional level. This exploration into the moderating roles of these relatively new technologies unveils diverse pathways through which technological innovation can be achieved, enriching existing underpinnings of innovation research. Lastly, our findings provide actionable policy recommendations for subnational governments, proposing effective strategies for improving technological innovation and addressing the regional gulf in innovation performance.

The paper is structured as follows: the second section lays out the theoretical framework and formulates hypotheses; the third section describes the methodology used; the fourth section presents the empirical findings; while the final section discusses these findings and draws conclusions and outlines the implications of our research.

2. Theory and hypotheses

2.1 The limitations of S&T investment for increasing technological innovation

In recent years and in many parts of the world, innovation has become a sort of holy grail. Countries around the world have scrambled to foment innovation mostly by channelling public and private investment to S&T. Innovation strategies with clear S&T or R&D investment targets have mushroomed in recent decades. The EU's *Europe 2020 Strategy* aimed to raise the EU's R&D spending to 3% of GDP (European Commission, 2020). The *US Global Leadership initiative* raised S&T spending to approximately 60 million dollars in 2019 (National Science and Technology Council, 2020). Similarly, China's *14th Five-Year Plan* included a commitment to boost R&D expenditure by 7% by 2025 (Asian Development Bank, 2021). Investment in S&T has thus garnered significant attention as a catalyst for technological innovation. The majority of existing scholarly literature on the topic underscores how S&T investment is of paramount importance for propelling technological innovation. R&D spending is often considered the key metric in this respect, with different researchers putting the emphasis on its relevance in different realms, including companies (e.g., Audretsch & Feldman, 1996; Baumann & Kritikos, 2016; Griliches, 1986), industries (e.g., Freeman & Soete, 2009; Pavitt, 1982), regions (e.g., Bilbao-Osorio & Rodríguez-Pose, 2004; Rodríguez-Pose & Crescenzi, 2008), and nations (e.g., Crescenzi et al., 2007; Furman et al., 2002).

Why is S&T expenditure regarded as so crucial for innovation? Theories of linear innovation and endogenous growth are at the root of this deep-seated belief in the capacity of S&T to spur innovation. The initial works on the linear model of innovation (e.g., Maclaurin, 1953) posited that investment in S&T would attract resources and talents, thereby enhancing innovation capacity. This assertion is supported by research indicating that the influx of resources and human capital associated with increased S&T investment drives technological innovation growth (Bilbao-Osorio & Rodríguez-Pose, 2004; Hervás-Oliver et al., 2021; Pakes & Griliches, 1980). The endogenous growth theory put the emphasis on the existence of a technological frontier (e.g., Grossman & Helpman, 1994; Romer, 1986) which determined the returns of investment in R&D. This technical frontier is connected to endowments in knowledge and human capital, two factors that are crucial for securing long-term returns on technological innovation.

However, the link between S&T expenditure and technological innovation is often highly imperfect, especially in developing countries (Crescenzi & Rodríguez-Pose, 2012; Rodríguez-Pose et al., 2021). Frequently, the more developed and innovative regions reap the lion's share of the benefits from the human capital and advanced knowledge connected with increased S&T expenditure. In contrast, less innovative regions —often those father away from the technological frontier— frequently extract minimal returns, if at all, from increases in S&T investment (Rodríguez-Pose et al., 2021). For instance, innovation hubs in developing nations, such as the cities within China's Pearl River Delta region, benefit significantly from investment in S&T and consistently lead in national technological innovation (Liu & Sun, 2009). By contrast, many interior regions in China have struggled to transform investment in R&D into tangible innovation. This creates a stark contrast in the returns on S&T investment between regions, further widening the innovation gap.

Hence, while S&T investment is an essential indicator reflecting technological innovation, its effectiveness as a driver of innovation is compromised by pervasive regional disparities, rendering it a mechanism that may contribute to a wider geographical innovation gap. In this respect, S&T investment represents an imperfect mechanism for innovation over the long term, with the returns of this type of investment mostly resulting in the concentration of innovation in a few hubs, entailing considerable economic, social and even political risks.

2.2 AI and robotics as drivers of technological innovation

2.2.1 *Defining AI and robotics*

Artificial intelligence (AI) can be seen as a conglomerate of technologies, enabling machines to independently learn and tackle cognitive tasks without human intervention (Davenport et al., 2018; Liu et al., 2020; Madan & Ashok, 2023). AI encompasses two primary facets: perceptual intelligence, which includes human-like sensory abilities such as touch, hearing, and vision, and computational intelligence, which involves processing data and executing algorithms (Liu et al., 2020). The predominant strength of AI lies in its capacity for decision-making within complex environments (Furman & Seamans, 2019; Parteka & Kordalska, 2023). Robotics, on the other hand, is central to the industrial revolution and digitalisation, distinguished by its multipurpose functionality, autonomous control, and programmability (Acemoglu & Restrepo, 2020; Wang et al., 2023). While robots primarily substitute low-skilled labour, their impact on high-skilled labour still remains comparatively minimal (Acemoglu & Restrepo, 2020).

Despite the differences between AI and robotics, a significant overlap exists between the two. AI encompasses a broad array of technologies including robotics, machine learning, and more. Robotics, when integrated with AI algorithms, pave innovative pathways for enhancing human life and work (Agrawal et al., 2018; Haenlein & Kaplan, 2019). The widespread adoption of AI and robotics has been acknowledged as a formidable catalyst for economic growth (Aghion et al., 2019; Furman & Seamans, 2019), productivity enhancement (Autor, 2015; Parteka & Kordalska, 2023), and the expansion of international trade (Brynjolfsson et al., 2019; Goldfarb & Trefler, 2019), though some research indicates that AI and robotics may contribute to increased unemployment rates by replacing labour (Acemoglu & Restrepo, 2020).

From a territorial perspective, the development of AI and robotics is paramount, touching on every aspect of infrastructure and garnering attention from both the private sector and public authorities (Mergel et al., 2023; Neumann et al., 2022; Wirtz & Müller, 2019). Notably, in developing countries, local governments often spearhead the development of AI and robotics, with the private sector acting under governmental guidance. In this paper, AI is conceptualised as encompassing government-proposed AI initiatives, including the utilisation of AI's perceptual and computational abilities to bolster local technological advancement. This encompasses not only AI-centric technologies like data mining and decision support systems but also applications in fields such as smart transportation and autonomous vehicles (Han & Mao, 2023; Yang & Huang, 2022). Robotics is defined as the deployment of industrial robots aimed at enhancing efficiency and productivity in urban settings, reflecting the technological adoption pursuant to AI strategies laid out by local governments (Acemoglu & Restrepo, 2020; Lee et al., 2022; Wang et al., 2023).

2.2.2 *AI, robotics, and technological innovation*

AI and robotics have the potential to significantly enhance technological innovation. So far, most of the focus of the scholarly literature has been on their contributions to knowledge creation and technology spillovers (Cicerone et al., 2023; Liu et al., 2020; Tian et al., 2023). AI, in particular, underpins data collection, offering new avenues for exploring existing knowledge, diversifying search methods for uncovering new knowledge, and presenting novel ways of integrating knowledge (Agrawal et al., 2018; Liu et al., 2020). Moreover, the proliferation of digital platforms through AI development transcends traditional knowledge boundaries, enhancing the flexibility of knowledge dissemination. Thus, AI is becoming a key tool for knowledge creation, thereby fostering technological innovation.

AI and robotics can also significantly reduce the costs associated with knowledge spillovers in the quest for technological innovation. The adoption of AI and robotics increases the potential for technological innovation. As some have argued, their deployment can also benefit less developed regions as a consequence of their lower application costs, information exchange, sharing and transfer capabilities, and potential to channel efficiency (Liu et al., 2020). Unlike in most cases of S&T investment, where geographical spillovers tend to remain limited, in the case of AI, geographical distance can become less of an obstacle for knowledge exchange. Its lower adoption costs and entry barriers can facilitate its implementation in more remote areas facing significant challenges to develop an S&T base. In this respect, AI and, to a lesser extent, robotics can compensate for the resource deficits encountered by less-innovative regions in accessing certain technologies (Liu et al., 2020). For instance, their application in remote manufacturing can, for example, mitigate the distance limitations and the problem of resource distribution disparities at the root of the widening gulf in technological innovation (Coccia, 2008). Consequently, AI and robotics can play an important role in the promotion of technological innovation in less developed and less innovative areas, with the benefits accruing not only to already technologically advanced cities but also to places with traditionally limited innovation capacity.

Research in regional economics has explored the impact of AI and robotics across various domains, including decision support systems and global positioning systems (Mikko et al., 2021; Openshaw, 1992). This research has demonstrated the positive effects of robotics on technological innovation in China (Han & Mao, 2023), while confirming that AI and robotics enhance knowledge creation and technology spillovers (Liu et al., 2020), inciting more R&D investment in local technological innovation and yielding significant returns. Nevertheless, research exploring the effectiveness of AI and robotics as indicators of technological innovation improvement, particularly in relation to spatial differences, remains in its infancy (Buarque et al., 2020).

Considering these arguments, we posit that the development of AI and robotics is likely to enhance technological innovation across cities. Compared to S&T expenditure, AI and robotics could present greater benefits for less developed and innovative regions due to their cost-effectiveness, high efficiency, and the elimination of geographical constraints. Therefore, we propose the following hypotheses:

Hypothesis 1a: *The development of AI and robotics positively influences technological innovation.*
Hypothesis 1b: *The beneficial impact of AI and robotics on technological innovation could yield greater returns —in relative terms— in less innovative cities and regions.*

2.2.3 *The moderating effect of AI and robotics on technological innovation*

Progress in AI and robotics is heralding the arrival of intelligent devices and an influx of high-skilled talents. It, however, can also lead to the displacement of less skilled and low-cost labour by machines, leading to enhanced productivity (Acemoglu & Restrepo, 2020) but also triggering social and economic problems. The savings accrued from the reduction in low-end labour costs are then channelled into increased R&D investments and further talent acquisition. Within this framework, AI and robotics can serve to optimise the allocation of S&T expenditure, driving innovation efficiency and ultimately increasing innovation (Cockburn et al., 2019; Liu et al., 2020). An illustrative example of this dynamic is the use of AI by governments to refine the precision in the distribution of S&T funds for R&D objectives (Mergel et al., 2023; Wirtz & Müller, 2019). In this respect, AI can intensify the returns of S&T expenditure on local innovation. This section explores the moderating roles of AI and robotics in enhancing the effectiveness of S&T expenditure for driving technological innovation.

As highlighted in Section 2.1, the advantages of S&T expenditure do not apply uniformly across regions. In both developed and, to a probably greater degree, developing countries the geographical inequality in innovation capacity is marked. In innovation hubs —like the Silicon Valley, where substantial investments in S&T are a norm— AI and robotics are employed in all sorts of projects, ensuring that the returns of S&T funding not only accrue to ventures with higher prospects of success but also that S&T is used in the most effective way to increase innovation (Mergel et al., 2023). In such scenarios, S&T becomes far more effective leading to considerable increases in innovation across a broad range of knowledge fields (Laursen & Salter, 2006). Moreover, in innovation hubs AI contributes to streamline the process of information search and knowledge recombination, while robots become essential tools for research and production, thereby increasing the potential for innovation.

Conversely, in less innovative regions, S&T expenditure alone frequently does not suffice to radically transform local innovation capacity. However, the integration of AI and robotics may contribute to do the trick, as it allows for a more accurate channelling of funds into niche technological sectors, fostering local technological advancements at relatively low levels of investment. In these areas, the primary aim of S&T expenditure is to deepen the exploration of knowledge and augment the depth of knowledge (Laursen & Salter, 2006). The deployment of AI and robotics for this task can facilitate knowledge breakthroughs, addressing technological bottlenecks as well as improving the absorption of externally generated knowledge, thus catalysing the generation of technological innovations (Buarque et al., 2020; Cockburn et al., 2019). Nevertheless, owing to the focused nature of knowledge and technology domains in these regions and the lower overall endowments in other innovation producing factors, such as human capital and innovative firms, it may also mean that the moderating influence of AI and robotics on S&T expenditure is less pronounced compared to more innovative regions, where the presence of stronger knowledge and technology fields can extract higher returns from investments in both AI and robotics, the one hand, and S&T, on the other.

Given the above discussion, we posit that the introduction of AI and robotics magnifies the positive influence of S&T expenditure on technological innovation across all types of regions. However, the mechanisms through which AI and robotics moderate the impact of S&T investment differ between more and less innovative regions. Compared to their less innovative counterparts, we expect that more innovative regions stand to benefit more from the moderating effects of AI and robotics, given that their conditions allow them to explore, with introduction of AI and robotics, a wider range of knowledge and technology fields than in less innovative ones. However, in the latter type, AI and robotics will also contribute to enhance the, so far, meagre returns of investment in S&T. Accordingly, we propose the following hypotheses:

Hypothesis 2a: *The development of AI and robotics strengthens the positive impact of S&T investment on technological innovation across all cities and regions.*
Hypothesis 2b: *The positive moderating influence of AI and robotics on S&T investment is bound to be more significant in more innovative regions.*

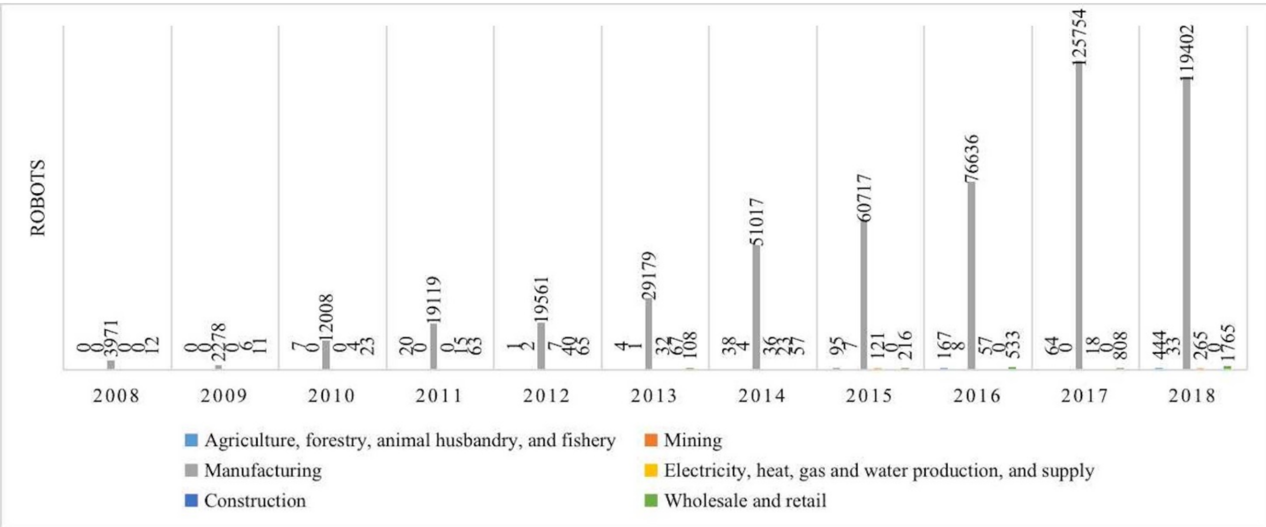
2.3 China as a case study

China has steadfastly aimed to transform itself into an innovation leader (Li, 2009; Zeng, 2021). To realise this ambition, China embarked on a national campaign to attract AI talent, notwithstanding the risks associated with failure (Zeng, 2021). Recent data reveal that, until 2017, Europe boasted over twice as many AI researchers as China. However, the penetration of AI skills in China from 2015 to 2020 was approximately 1.4 times the global average, positioning China behind only India and the United States in this regard (Lundvall & Rikap, 2022). Despite substantial investments in S&T, China's progress in local technological innovation has been relatively modest, with its less developed cities particularly lagging behind on this front (Li, 2009). In contrast to traditional S&T expenditure, the more recent increased focus on AI and robotics may offer a solution to this challenge. Hence, examining China's experience with AI and robotics in fostering local technological innovation could serve as a valuable reference for other developing countries.

China's swift progress is partly attributed to its decentralised approach —often described as "federalism, Chinese style". This approach empowers municipal governments to tailor AI development strategies based on local conditions to maximise technological dividends (Zeng, 2021). China's AI strategies should, therefore, be analysed through a policy lens. Since 2013, the Chinese government has underscored the importance of AI in various industries through national-level work reports. For instance, the "Internet +" action plan of 2015 promoted AI industries and advocated for increased investment in AI activities (Roberts et al., 2021). Concurrently, the "Made in China 2025" initiative was launched with the goal of positioning China as a global leader in high-tech manufacturing (McBride & Chatzky, 2019). This plan had, indirectly, a heavy influence on robotics. Following the central government's lead, many Chinese local governments have developed customised AI strategies. Shanghai, for example, implemented one with the aim of establishing itself as a national AI leader by 2030 through its own strategic initiatives (Shanghai, 2017).

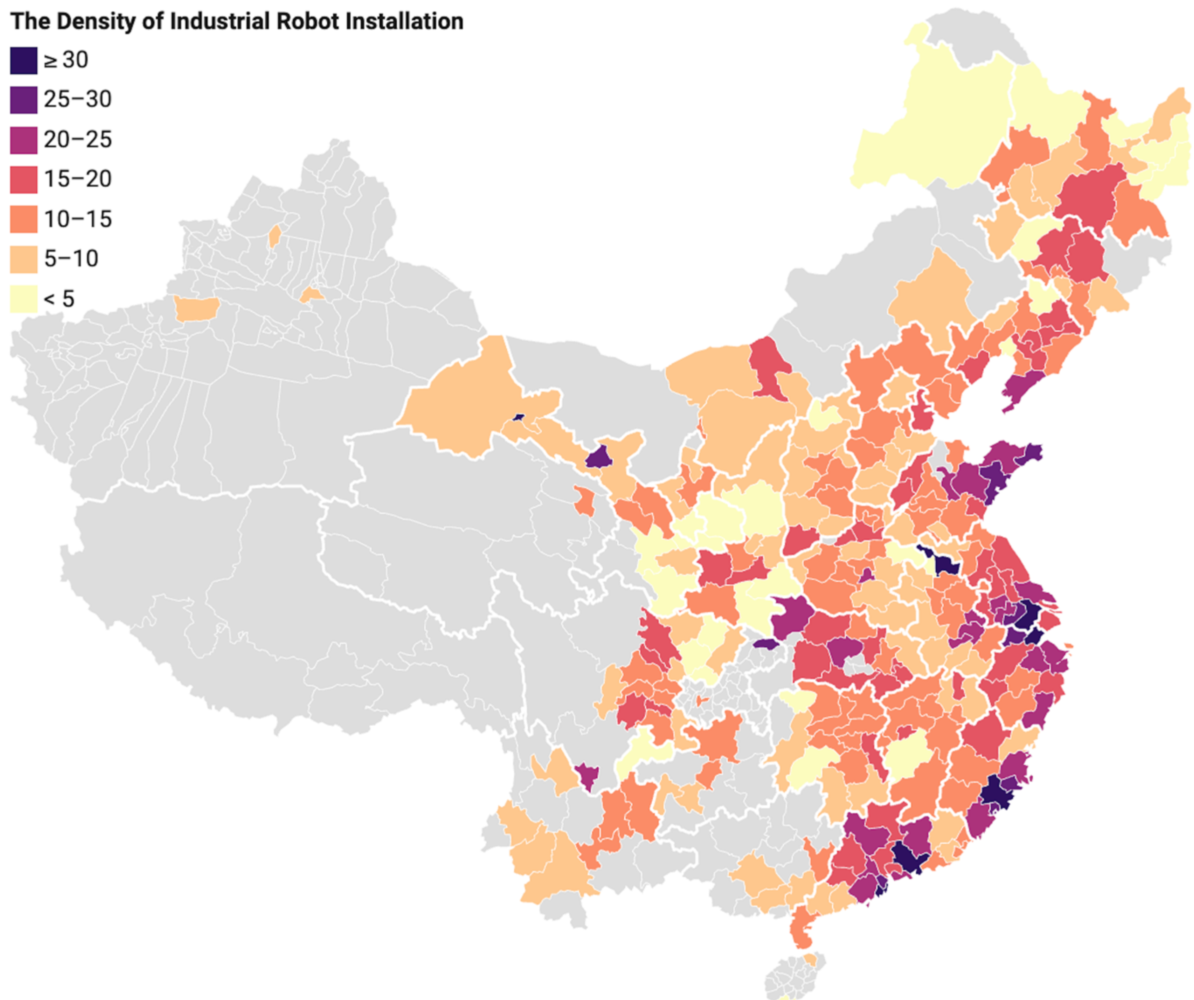
The rapid adoption of industrial robots further underscores the emphasis on innovation. Since 2013, the use of industrial robots across six major industries in China has seen consistent growth, with the manufacturing sector dominating their use. Since 2014, there has been a surge in the deployment of industrial robots across China, with the number of the units in manufacturing nearing 130,000 already from 2017, giving a positive response to the "Made in China 2025" initiative (Figure 1).

Figure 1. Annual trend of the number of industrial robots over six sectors (2008-2018)



Given the disparities in local-level innovation within China, the integration of new technologies such as AI and robotics could offer, according to some (e.g., Haenlein & Kaplan, 2019; Roberts et al., 2021; Zeng, 2021), less innovative places a pathway to enhance their innovation capacity, contributing to narrow the large innovation gap in the country. Figure 2 illustrates the geographical spread of industrial robot installations from 2008 to 2018, revealing a narrowing gap in the number of industrial robots per 10,000 employees across 270 Chinese cities. This suggests that the adoption of AI and robotics may be a more effective metric than traditional S&T investment (discussed in Section 2.1) for contributing to both increasing the overall level of technological innovation in the less developed regions of China and, as a consequence, leading to a more manageable gap between more and less developed innovation hubs in the country.

Figure 2. Geographical distribution of the average density of industrial robots (2008-2018) (mainland China)



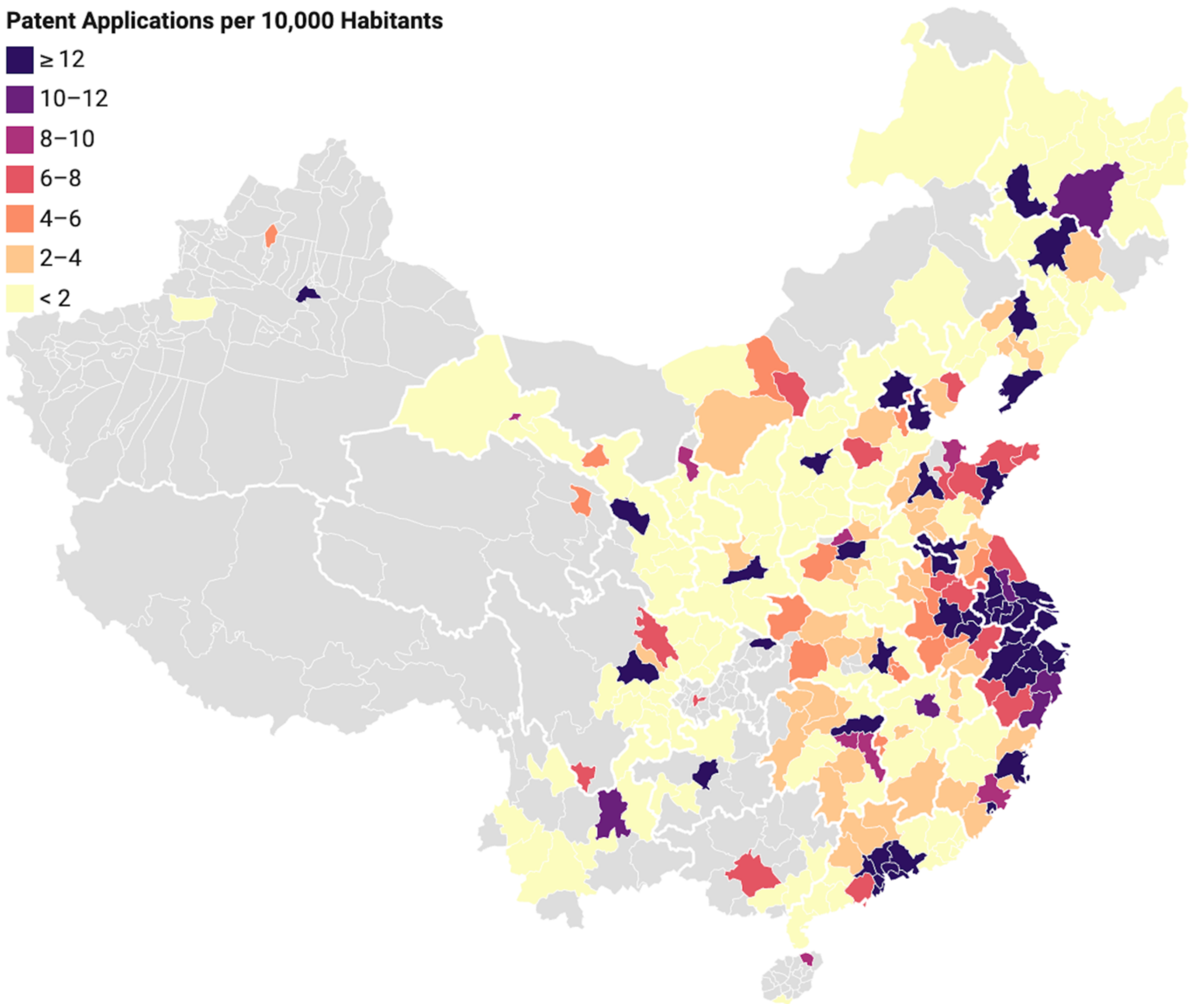
3. Methodology

3.1 Variables and Data

3.1.1 *Dependent variable: Technological innovation*

Our analysis of technological innovation in Chinese cities employs patent data obtained from the State Intellectual Property Office of the People's Republic of China (PRC SIPO). These data follow methodologies similar to those employed by Ács et al. (2002) and Pakes & Griliches (1980). While patent data are not without its limitations —for instance, many innovations never end as a patent (Pakes & Griliches, 1980) and the economic value of patents can vary significantly (Hall et al., 2001)— it offers advantages than make it a more viable proxy for technological innovation than any potential current alternatives. Specifically, patent records enable the tracking of the locations of inventors and the innovation process, as well as the commercialisation stages of innovation (Ács et al., 2002).

Figure 3. The spatial distribution of the intensity of patent applications in China in 2019 (mainland China)



We employ patent intensity as our metric in the analysis. It is calculated as the total number of domestic patent applications per 10,000 residents. Patent intensity gauges the technological innovation levels of Chinese cities from 2009 to 2019 (Rodríguez-Pose & Zhang, 2019). Figure 3 illustrates the geographical distribution of patent intensity across 270 Chinese cities in 2019, showcasing significant disparities in technological innovation, with most falling below 2. Higher concentrations of patent applications are in evidence in coastal cities, particularly in the Pearl River (e.g., Guangdong Province) and Yangtze River deltas (e.g., Zhejiang and Jiangsu Provinces) (Rodríguez-Pose & Wilkie, 2016). These areas benefit from advanced information infrastructure, greater talent inflow, and a more open environment (Liu & Sun, 2009; Rodríguez-Pose & Wilkie, 2016). They also boast a plethora of high-tech firms and innovation parks. Given the pronounced gap in innovation performance across regions, we assess whether the introduction of AI and robotics can enhance technological innovation in Chinese cities. This comparison will be made between more and less innovative cities distanced from technological hubs.

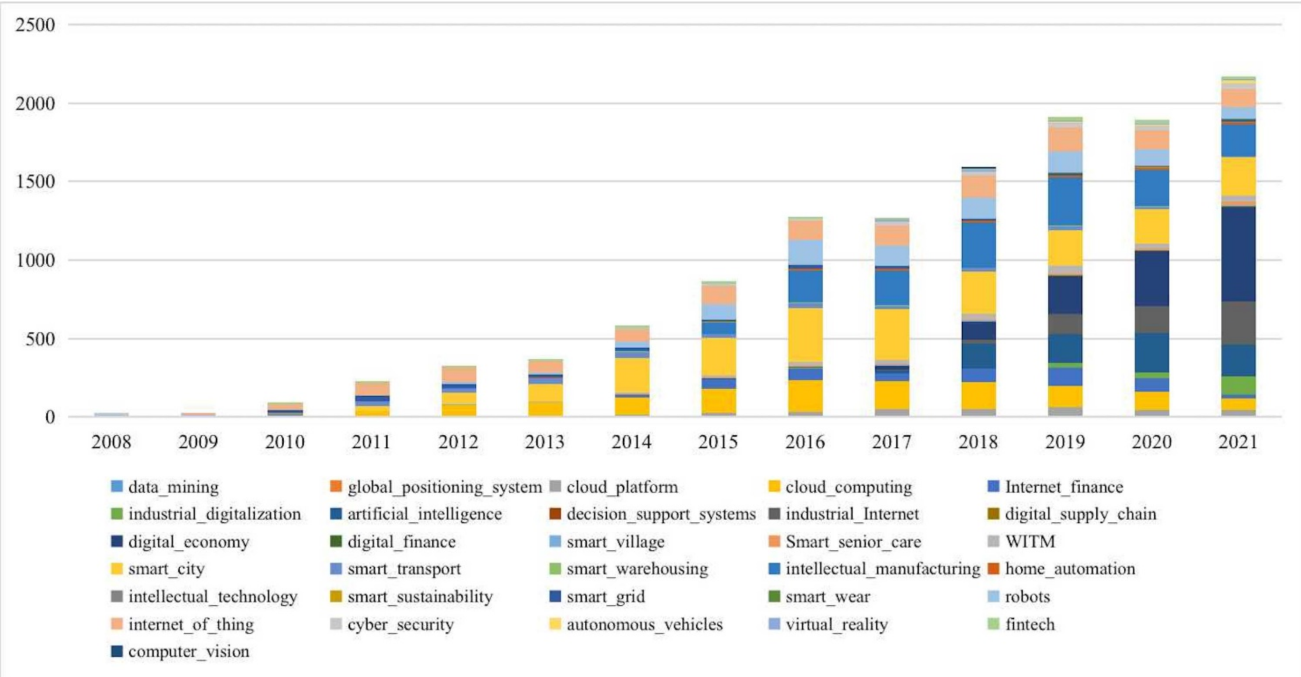
3.1.2 Independent variable: AI

To evaluate the varying degrees of local government engagement and perspectives on AI, we calculated the ratio of AI-related keyword frequencies to the total word count (per 1,000 words) in each city's annual work report (Cao et al., 2020). These reports, issued by city-level governments, encapsulate urban strategies and visions to promote economic, social, and technological transformations at the local level. They are fundamental to set and communicate local policy objectives, including those related to innovation (Roberts et al., 2021). They signal key development directions and enable the tracking of upcoming policy focus on technology (Roberts et al., 2021; Yang & Huang, 2022). Recognising that a "one size fits all" approach is unsuitable for the diverse Chinese context (Rodríguez-Pose & Wilkie, 2016), this method effectively captures the spatial diversity of AI initiatives across Chinese local governments.

The methodology for data collection involves several steps. Initially, we compiled annual work reports from the official websites of local governments, covering 270 cities across China. An example is provided in Figure A1 (Appendix A) from the Shanghai Municipal Government's 2023 work report, which mentions "artificial intelligence" on two occasions. Next, we identified a list of AI-related keywords, incorporating the 108 AI-related keywords listed by Yang & Huang (2022) and adding 19 more terms frequently used such as "cloud computing" and "digital economy" (Madan & Ashok, 2023). After eliminating keywords not found in reports from 2008 to 2021, 31 keywords remained (Appendix A). We then calculated the frequency of these 31 keywords relative to the total word count (per 1,000 words) in each report.

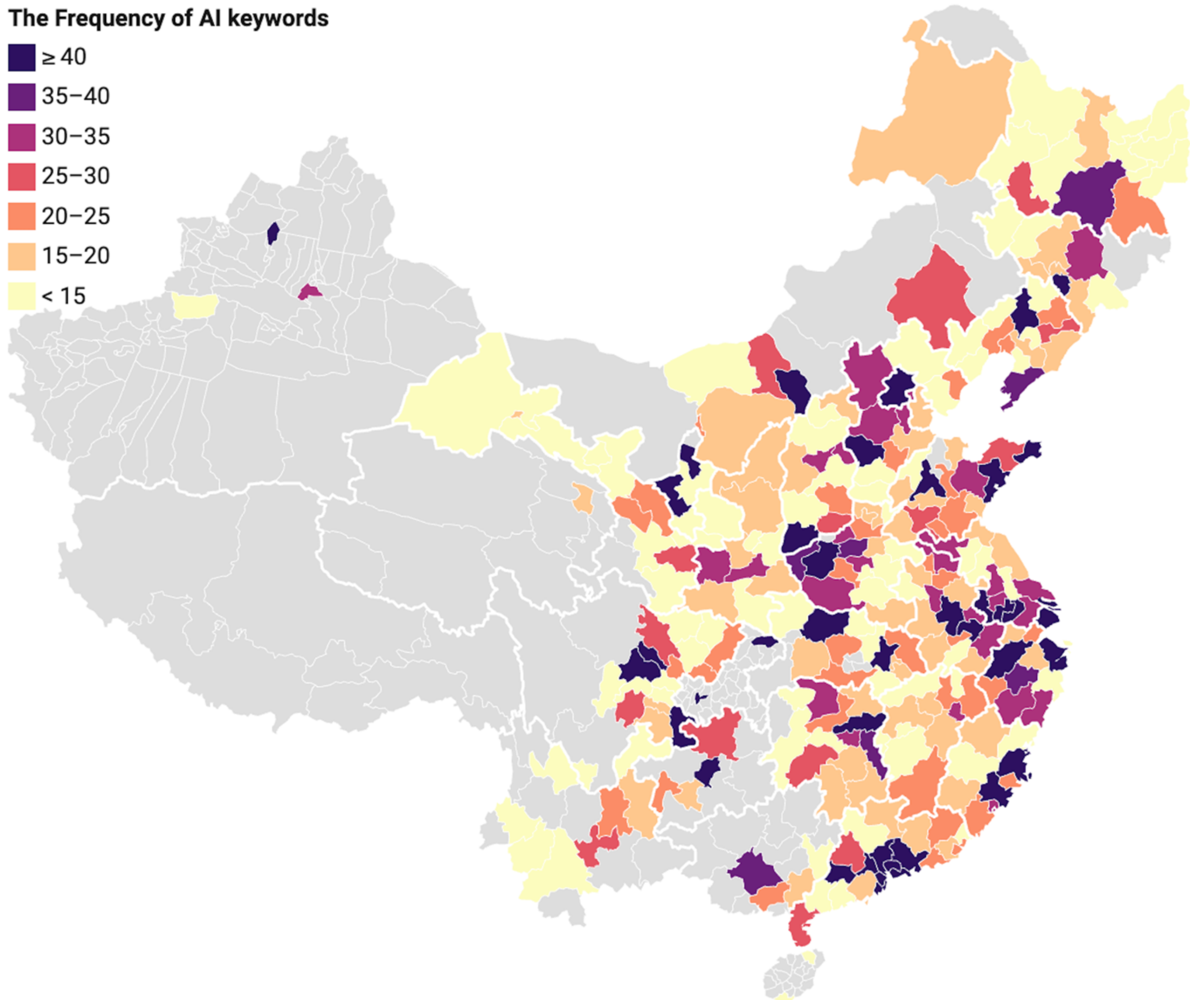
Figure 4 reveals a rapid increase in attention to AI by Chinese local governments, with the frequency of AI-related keywords surpassing 1,000 from 2016 onwards. Since then, concepts like cloud computing, smart city, and intelligent manufacturing have consistently gained prominence. From 2018 onwards, terms such as artificial intelligence and the internet of thing have been increasingly incorporated into government AI strategies. Figure 5 maps the volume of AI-related keywords from 2008 to 2018. In contrast with patent intensity, the distribution differences among 270 cities are smaller. Interestingly, as indicated in Figure A2, it is frequently the second-tier cities (e.g., Wuxi and Shenyang), rather than the more developed cities (e.g., Beijing and Shanghai), that have shown greater focus on AI development from 2008 to 2018, according to their work reports (further details on the AI plans measure are available in Appendix A).

Figure 4. Annual trends of AI keywords in work report of local governments (2008-2021)



This approach, however, is not without its challenges. First and for a uniform text analysis, work reports were translated from Chinese to English. While some government reports (e.g., Shanghai) are available in English on official websites, most others (e.g., Shangrao) required manual extraction and translation. This translation process inevitably introduces biases affecting both the total word count and the frequency of AI-related keywords. Second, while relying on AI-related keywords identified by Yang & Huang (2022) and Madan & Ashok (2023), we noted variations in keywords that convey similar meanings, leading to inconsistencies in keyword frequency, possibly compounded by translation. Third, although keyword analysis can highlight the focus on various AI technologies, unlike machine learning techniques, it cannot fully capture the nuanced essence of entire work reports concerning specific AI strategies.

Figure 5. The total frequency of AI keywords in 270 cities in China (2008-2018) (mainland China)



3.1.3 Independent variable: Robotics

Robot installations in Chinese production plants and elsewhere in the economy have soared in recent times. Although they are often associated with a progressive replacement of labour, they have contributed to increased productivity and innovation across the world (e.g., Felten et al., 2021; Lee et al., 2022). In China in particular, industrial robot adoption has surged from 550 units in 1999 to an estimated 650,000 units by 2018, according to the International Federation of Robotics (https://ifr.org/). To quantify the adoption of robots, we follow the approach of Acemoglu & Restrepo (2018), focusing on the density of industrial robot installations.

While the International Federation of Robotics (IFR) offers industry-specific data on robot installations, we apply the Bartik IV methodology, as adapted by Acemoglu & Restrepo (2020), to estimate robot installation density at the city level. The initial phase involves correlating the IFR's industry classification with the Industrial Statistics Classification of China (GB/T 4754-2011). We compile robot data across six distinct industries in China: 1. Agriculture, forestry, fishing; 2. Mining and quarrying; 3. Manufacturing; 4. Electricity, gas, water supply; 5. Construction; 6. Education, research, and development.

Second, for the analysis, we select 2008 as the base year to calculate the density of industrial robot installations. As shown in equation (1), *c* represents the city, j is the industry, *t* is the year. Emp_{jc2008} denotes the labour force (unit: 10,000) of industry j in city c in 2008. $Robot_{jt}$ represents the number of industrial robots (installation) in each industry j in year *t*. Emp_{c2008} indicates the number of employees (unit: 10,000) aged between 16 and 64 in city *c* in 2008. The data for this research was sourced from the Chinese Census Database and the International Federation of Robotics (IFR) (Liu et al., 2020). For the four cities in our sample where data are missing (Puer, Xiangyang, Huainan, Huaian), we use the average value of all other cities in the same province at the same year to fill in these missing data (Appendix B shows the details of this measurement).

The formula for calculating the density of industrial robots in each city *c* at time *t* integrates the proportion of industry-specific employment in the total city employment with the ratio of robot installations to employment within each industry. It is expressed as:

$$Robots_{ct} = \sum_j \frac{Emp_{jc2008}}{Emp_{c2008}} * \frac{Robot_{jt}}{Emp_{j2008}} \quad (1)$$

3.1.4 Control variables

We incorporate a set of control variables that, according to scholarly research, influence technological innovation at the local level, including S&T expenditure, foreign direct investment (FDI), population density, economic performance (GDP per capita), and unemployment rate, with data sourced from the China City Statistical Yearbook. The specifics are outlined as follows:

(1) **S&T Expenditure:** This metric supports various scientific activities, including R&D investment[1] and the facilitation of knowledge exchange and collaboration between academia and industry (Motohashi & Yun, 2007). Increases in S&T are bound to stimulate local technological innovation. We use the ratio of S&T expenditure to GDP to indicate this, as reported in the China City Statistical Yearbook. However, accurately measuring the actual investment in S&T is challenging due to the inclusion of expenses beyond equipment and personnel, and the tendency of S&T investment to favour high-tech sectors and more developed areas (Freeman & Soete, 2009; Cao & Suttmeier, 2017). Despite these limitations, the S&T metric offers insights into the objectives of China's S&T system reform, aiming at enhancing technological innovation.

(2) **FDI:** FDI introduces additional resources that support the R&D efforts of the host country. The technology introduced through FDI can generate a spillover effect on the domestic market, enhancing domestic technological innovation (Ning et al., 2016). We measure FDI in Chinese cities as the ratio of the realised value of FDI to GDP.

(3) **Population Density:** According to urban economics research, high population density is at the centre of the generation of new ideas, increasing the likelihood of technological innovation (Glaeser, 2011; Wang et al., 2019). We use the number of inhabitants per square kilometre as a proxy for population density.

(4) **GDP per Capita:** The economic performance of cities is closely linked to local innovation activities and technology development. We use GDP per capita as a measure of the local economic level to account for this economic factor (Wang et al., 2019).

[1] We opt for S&T expenditure over R&D expenditure as an indicator of investment in scientific activities, primarily due to the significant amount of missing data regarding R&D expenditure in Chinese cities; only about 20% of the required data are available. This decision warrants a more comprehensive and reliable analysis by using a metric with broader coverage across the dataset.

(5) **Unemployment Rate:** A higher unemployment rate can lead to a depreciation of the skills in the labour force (Stiglitz, 2014), negatively impacting individuals engaged in R&D activities. This could lead to a reduction in technological innovation. We represent the city-level unemployment rate as the ratio of unemployed individuals to the total labour force.

3.2 Models

To assess the extent to which AI and robotics influence technological innovation in Chinese cities, we use a panel data analysis. We initially assess the innovation impacts of AI and robotics as depicted in Equation (2), incorporating all control variables, with *c* representing the city and *t* the year. To account for city-specific heterogeneity and time-invariant characteristics, μ_c and ε_t are included. δ_{ct} denotes the error term. To reduce endogeneity concerns, we incorporate a one-year lagged dependent variable in the analysis.

$$Technological\ innovation_{ct} = \alpha_1 * AI_{ct-1} + \alpha_2 * Robotics_{ct-1} + \alpha_3 * Controls_{ct-1} + \mu_c + \varepsilon_t + \delta_{ct} \quad (2)$$

Additionally, we investigate the potential moderating roles of AI and robotics in amplifying the impact of S&T investment on technological innovation, as shown in model (3). This model includes interaction terms between lagged S&T expenditure, on the one hand, and both AI and robotics ($S\&T\ expenditure_{ct-1} * AI_{ct-1}\ and\ S\&T\ expenditure_{ct-1} * Robotics_{ct-1}$), on the other.

$$Technological\ innovation_{ct} = \beta_1 * AI_{ct-1} + \beta_2 * Robotics_{ct-1} + \beta_3 * S\&T\ expenditure_{ct-1} * AI_{ct-1} + \beta_4 * S\&T\ expenditure_{ct-1} * Robotics_{ct-1} + \beta_5 * Controls_{ct-1} + \mu_c + \varepsilon_t + \delta_{ct} \quad (3)$$

3.3 Econometric methods

To test our hypotheses, we employ various econometric strategies. Initially, we apply and Ordinary Least Squares (OLS) estimator with robust standard errors, incorporating year and city dummies to capture within-group effects and mitigate heteroskedasticity-induced bias (Cameron & Trivedi, 2005). We acknowledge several potential sources of endogeneity. First, AI initiatives and robotics applications may result from high levels of technological innovation.

Consequently, cities with advanced technological innovation will use more extensive AI planning and robotics adoption. Second, omitted variables not accounted for in our model — such as education levels and digitalisation degrees— could correlate with our independent variables (AI and robotics), potentially skewing our findings. To address these concerns, we resort to a two-stage least squares (2SLS) approach with instrumental variables (IV) for further robustness checks. We use the number of telephones (per million individuals) in 1984[2] as our instrumental variable (IV). The rationale for the use of this IV is the potential of telecommunications to facilitate knowledge exchange and the introduction of new technologies and, thus, facilitate innovation. In 1984. the availability and use of the telephone in China was not widespread —and, certainly, far less prevalent than in western countries— and it not always reflected density or economic reasons. Yet, telephones were key to transmit information and knowledge and facilitate transactions. Hence, a higher the telephone penetration at city level provided a considerable advantage for technological development (Liu et al., 2023). A denser telephone network has always contributed to the development of new technologies, including AI and robotics today. To underline exogeneity and avoid multicollinearity, we employ the interaction term between the number of telephones in 1984 and annual revenue of telecommunications business in each city (2008-2018) to measure this IV.

Moreover, to examine the diverse impacts of AI and robotics across the whole spectrum of Chinese cities classified by their innovation capacity, we resort to a quantile regression approach. This method allows us to discern the differential innovation impacts of AI and robotics across various deciles (in our case) of the distribution of innovative cities, as well as to assess whether AI and robotics can enhance the positive effect of S&T expenditure in cities at different distances from the technological frontier (Hervás-Oliver et al., 2021). Quantile regressions enable an investigation into how AI and robotics may bolster technological innovation, considering the variation in innovation levels among Chinese cities.

3.4 Descriptive statistics

Table 1 presents the descriptive statistics for all variables included in the study. With respect to technological innovation, there is a noticeable disparity among the 270 Chinese cities

[2] 1984 is the first year for which the government started recording telephone data. The data is only available at provincial level.

considered in the analysis. Overall, per capita patent applications across China remain modest, averaging about 5 patents per 10,000 inhabitants. The data also reveals that the maximum emphasis on AI by the Chinese government is approximately 5.38%, indicating that AI development remained a relatively minor focus during the period from 2008 to 2018. The low average presence of robotics, with about 13 industrial robots per 10,000 employees, underscores the nascent stage of robotic integration in Chinese cities. Notably, the average S&T expenditure stands at 0.25%, pointing to a relatively modest investment in science and technology, despite certain cities achieving higher investments of up to 6.31%. The analysis of other control variables underscores the continued attractiveness of the Chinese market for foreign investment, while also highlighting the importance of addressing the high unemployment rate.

Table 1. Descriptive Statistics

Variable	Measurements	Data Source	Obs	Mean	Std. Dev.	Min	Max
Technological innovation	Domestic patent applications (invention) per 10,000 habitants (2009-2019)	SIPO (State Intellectual Property Office of the P.R.C); China City Statistical Yearbook	2,970	4.97	12.40	0.00	167.73
AI (%)	The ratio of the frequencies of AI keywords (per 1,000 words) to the number of all keywords in the work report (2008-2018)	Work Reports from Chinese Municipal Government	2,970	0.38	0.56	0.00	5.38
Robotics	The density of industrial robot installation (the number of robots per 10,000 employees) (2008-2018)	The Chinese Census Database; The International Federation of Robotics	2,970	12.86	15.34	0.05	108.39
S&T expenditure (%)	The share of science and technology expenditure to GDP (2008-2018)	China City Statistical Yearbook	2,970	0.25	0.26	0.00	6.31
FDI	The ratio of realized value of Foreign Direct Investment to GDP (2008-2018)	China City Statistical Yearbook	2,970	0.02	0.02	0.00	0.20
Population density	The number of inhabitants per square kilometre (2008-2018)	China City Statistical Yearbook	2,970	456.01	355.90	4.94	5,030.06
GDPPC	Gross Domestic Products per capita (RMB) at the city level (2008-2018)	China City Statistical Yearbook	2,970	46,224.52	31,783.08	3,602.00	224,502.00
Unemployment rate	The ratio of unemployed individuals to the sum of unemployed individuals and employees (2008-2018)	China City Statistical Yearbook	2,970	0.05	0.03	0.00	0.56
The penetration level of telephones	The number of telephones of each city in 1984 * the annual revenue (10,000 yuan) of telecommunications business of each city (2008-2018)	China City Statistical Yearbook	2,849	554,977.1	2,479,210	2,213.81	57,000,000

Notes: We take the measures for all variables: the natural logarithm of (Variables +1) to avoid the bias caused by outliers. The telephone data is missing in 11 cities including Meishan, Shanwei, Jiuquan, Zhangjiajie, Jinzhong, Baishan, Guangan, Ankang, Shuozhou, Qingyuan, Panzhihua.

Figure 6. Correlations between the determinants of technological innovation and innovation

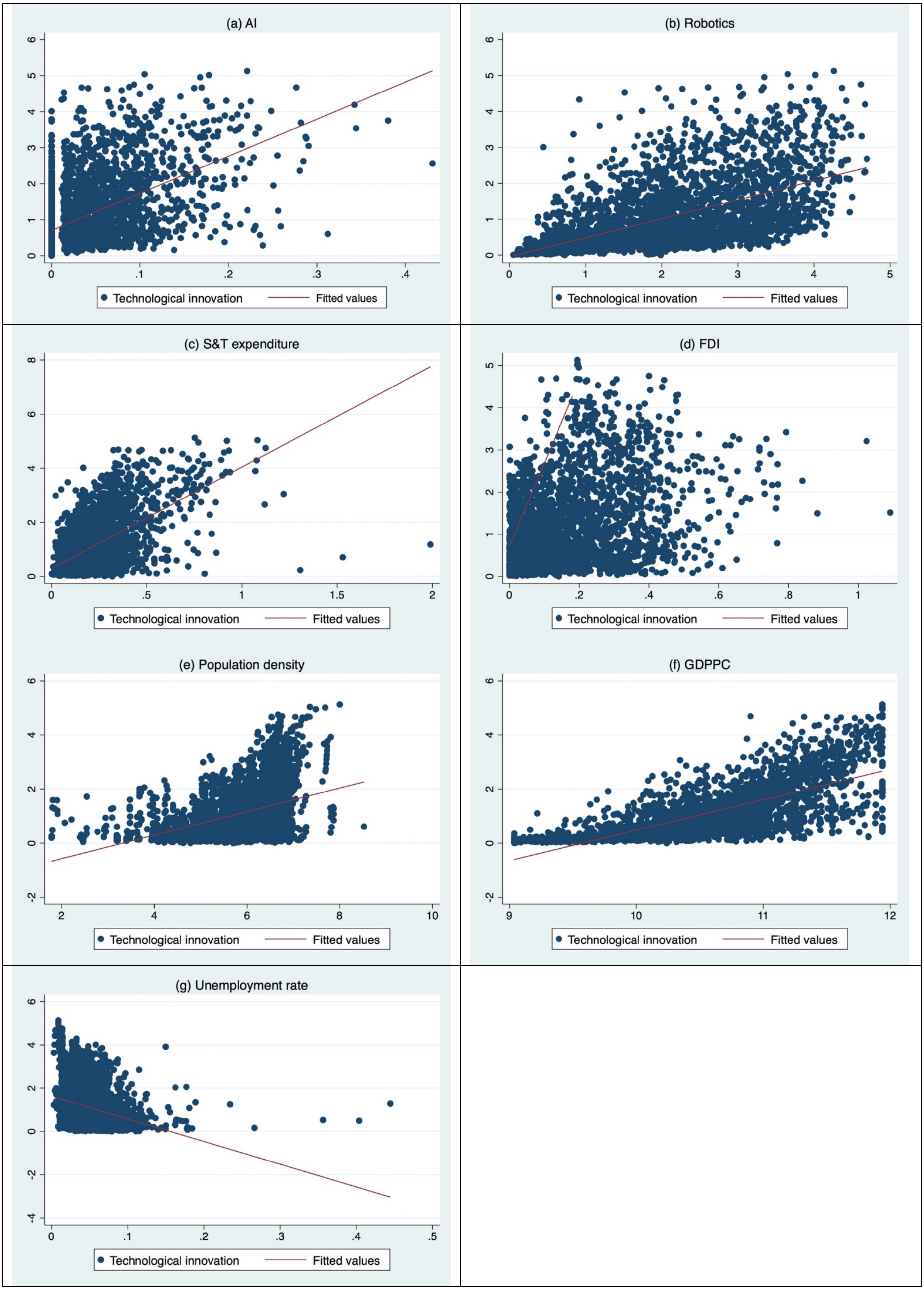


Figure 6 illustrates the correlations between various potential factors and technological innovation from 2008 to 2019. The comparisons reveal, in accordance with the linear model of innovation, a more pronounced correlation between S&T investment and technological innovation (Figure 6(c)), relative to AI (Figure 6(a)) and robots (Figure 6(b)). Additionally, Figure 6(f) demonstrates a strong and positive relationship between economic performance (GDP per capita) and technological innovation, whereas Figure 6(g) shows a negative association between unemployment and technological innovation.

4. Results

4.1 Do AI and robotics improve local technological innovation?

Table 2 displays the empirical outcomes of the OLS (columns (1)-(4)) and IV-2SLS (columns (5)-(8)) estimations. These estimations assess our first hypothesis, that is whether an emphasis on AI and robotics impinges on technological innovation across cities in China. The reliability of the IV-2SLS results is confirmed by all statistics (Anderson canonical LM statistic and Cragg-Donald F statistic) (Cameron & Trivedi, 2005). Columns (1)-(2) and (5)-(6) assess the direct effects of AI and robotics on technological innovation, while columns (3)-(4) and (7)-(8) explore their moderating roles in enhancing the impact of S&T expenditure on technological innovation.

Table 2. OLS and IV-2SLS: The impact of AI and Robotics on local technological innovation

	OLS				IV-2SLS			
Technological innovation	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
FDI	-0.733	0.326	-0.627	0.689	1.324	1.969**	-0.447	0.892*
	(0.541)	(0.505)	(0.550)	(0.515)	(1.126)	(0.787)	(0.500)	(0.491)
Population density	0.012	0.005	0.022	0.012	-0.031	0.005	0.041	0.030
	(0.051)	(0.048)	(0.048)	(0.051)	(0.077)	(0.046)	(0.043)	(0.041)
GDPPC	0.107***	0.101***	0.114***	0.112***	0.187***	0.077**	0.112***	0.101***
	(0.033)	(0.031)	(0.034)	(0.032)	(0.061)	(0.032)	(0.030)	(0.028)
Unemployment rate	-0.450*	-0.443	-0.419	-0.396	-1.046**	-0.470	-0.402	-0.352
	(0.266)	(0.276)	(0.260)	(0.271)	(0.512)	(0.288)	(0.271)	(0.257)
S&T expenditure	0.817***	0.694***	0.480***	-0.241	0.527***	0.478***	0.171	-0.741**
	(0.122)	(0.110)	(0.129)	(0.169)	(0.143)	(0.096)	(0.163)	(0.311)
AI	0.219***		0.027		2.103***		-0.144	
	(0.028)		(0.046)		(0.697)		(0.090)	
Robotics		0.558***		0.468***		1.365***		0.438***
		(0.035)		(0.036)		(0.279)		(0.042)
S&T expenditure * AI			0.701***				1.308***	
			(0.166)				(0.314)	
S&T expenditure * Robotics				0.299***				0.455***
				(0.051)				(0.098)
Constant	-1.313***	-0.988**	-1.412***	-1.072***	-1.700***	-0.387	-1.464***	-1.014***
	(0.427)	(0.392)	(0.417)	(0.402)	(0.648)	(0.432)	(0.369)	(0.350)
First stage					-0.031***	-0.048***	0.100***	0.304***
					(0.010)	(0.008)	(0.006)	(0.015)
Anderson canon. LM statistic					11.074***	41.571***	242.792***	377.297***
Cragg-Donald F statistic					10.044***	38.114***	239.699***	392.759***
Observations	2,970	2,970	2,970	2,970	2,849	2,849	2,849	2,849
R-squared	0.931	0.937	0.932	0.938	0.800	0.924	0.932	0.939
Number of city	270	270	270	270	259	259	259	259
City dummies	YES	YES	YES	YES	YES	YES	YES	YES
Year dummies	YES	YES	YES	YES	YES	YES	YES	YES

*Notes: IV: Incidence of telephones per million inhabitants in 1984. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1*

Regarding the control variables, a significant positive coefficient for GDP per capita (GDPPC) ($p<0.01$) indicates that, according to expectations, technological innovation in China is concentrated in the more developed hubs of the country (Rodríguez-Pose et al., 2021). Similarly, S&T expenditure shows, in most cases, a significant positive connection with technological innovation ($p<0.01$), aligning with the linear model of innovation and with the literature that highlights the beneficial role of S&T investment in fostering technological innovation (Bilbao-Osorio & Rodríguez-Pose, 2004; Rodríguez-Pose & Crescenzi, 2008).

In the OLS analysis, AI displays a direct positive association with technological innovation (Column (1)) ($p<0.01$). Patent applications per 10,000 inhabitants increase by 0.219 when municipal governments incorporate an additional 1% AI keyword frequency in their work reports (per 1,000 keywords). Column (2) shows that robotics is positively and significantly linked with technological innovation ($p<0.01$), pointing to an increase of 0.558 patent applications per 10,000 residents with the addition of one more industrial robot (per 10,000 employees) in a city. The IV-2SLS estimator yields consistent findings regarding the contributions of AI and robotics to technological innovation in columns (5)-(6), indicating that the correlation is more than a mere coincidence and that a greater emphasis on AI and robotics is a trigger for higher innovation.

The analysis of AI and robotics as moderators in the relationship between S&T expenditure and technological innovation is captured by the introduction of interaction terms in columns (3)-(4) and (7)-(8). The significant positive interaction terms (columns (3) and (7)) are a symptom that AI enhances the positive effect of S&T expenditure on local technological innovation ($p<0.01$). Similarly, both the OLS and IV-2SLS estimators confirm that robotics exerts a positive moderating influence on the impact of S&T expenditure on technological innovation (columns (4) and (8)) ($p<0.01$).

Hence, the findings in Table 2 corroborate the positive influence of economic development (proxied by GDPPC), S&T investment, municipal government AI initiatives, and robotics on technological innovation within Chinese cities (Liu et al., 2020; Maclaurin, 1953; Rodríguez-Pose et al., 2021). Furthermore, AI and robotics significantly increase the effect of S&T investment on technological innovation. Overall, the results confirm Hypothesis 1(a) and Hypothesis 2(a), underscoring the role of AI and robotics in enhancing technological innovation across Chinese cities.

4.2 Are AI and robotics the solution for technological innovation in less innovative Chinese cities?

To examine if AI and robotics have different effects on technological innovation in more or less innovative cities, we use quantile estimations. We classify cities by deciles, depending on where they are placed in the Chinese innovation distribution. Figure 7 illustrates the mean variation of all variables across technological innovation percentiles, revealing a non-linear and upward trend in the mean variation of technological innovation. The figure shows that it is not only that more innovative Chinese cities innovate more but that the level of concentration of technological innovation in those cities is strong (Figure 7). AI, robotics, and S&T expenditure all exhibit increasing trends alongside the rise in technological innovation percentile.

The results of the quantile regression analysis are presented, by decile, in Table 3. Regarding the controls included in the analysis, the results reveal a significant positive connection of GDP per capita with technological innovation. However, this positive association varies with the position of the city in the ranking of urban technological innovation. The returns are strongest in cities at the centre of the innovation distribution (between the fourth and seventh decile).

Moreover, the quantile analysis underscores that S&T investment's innovation effect is far weaker in cities below the technological frontier. The regression coefficients of Table 3 are lowest for cities in the two lowest deciles (0.341, 0.483) of the urban innovation distribution. S&T are thus an important driver of technological innovation but contribute to a widening of the innovation gap across Chinese cities. The quantile regression models also suggest that the returns of AI in terms of technological innovation accrue across the whole innovation spectrum but are stronger in cities in the mid-range of the distribution, with the highest coefficient taking place right in the middle (5^{th} decile, 0.179). The coefficients for the bottom two deciles are also higher than those for the top two deciles. This is a sign that the contribution of AI to technological innovation, while positive and significant, does not lead —or leads much less— to the widening the gap in innovation performance across Chinese cities.

Figure 7. Mean variation of variables across technological innovation quantiles

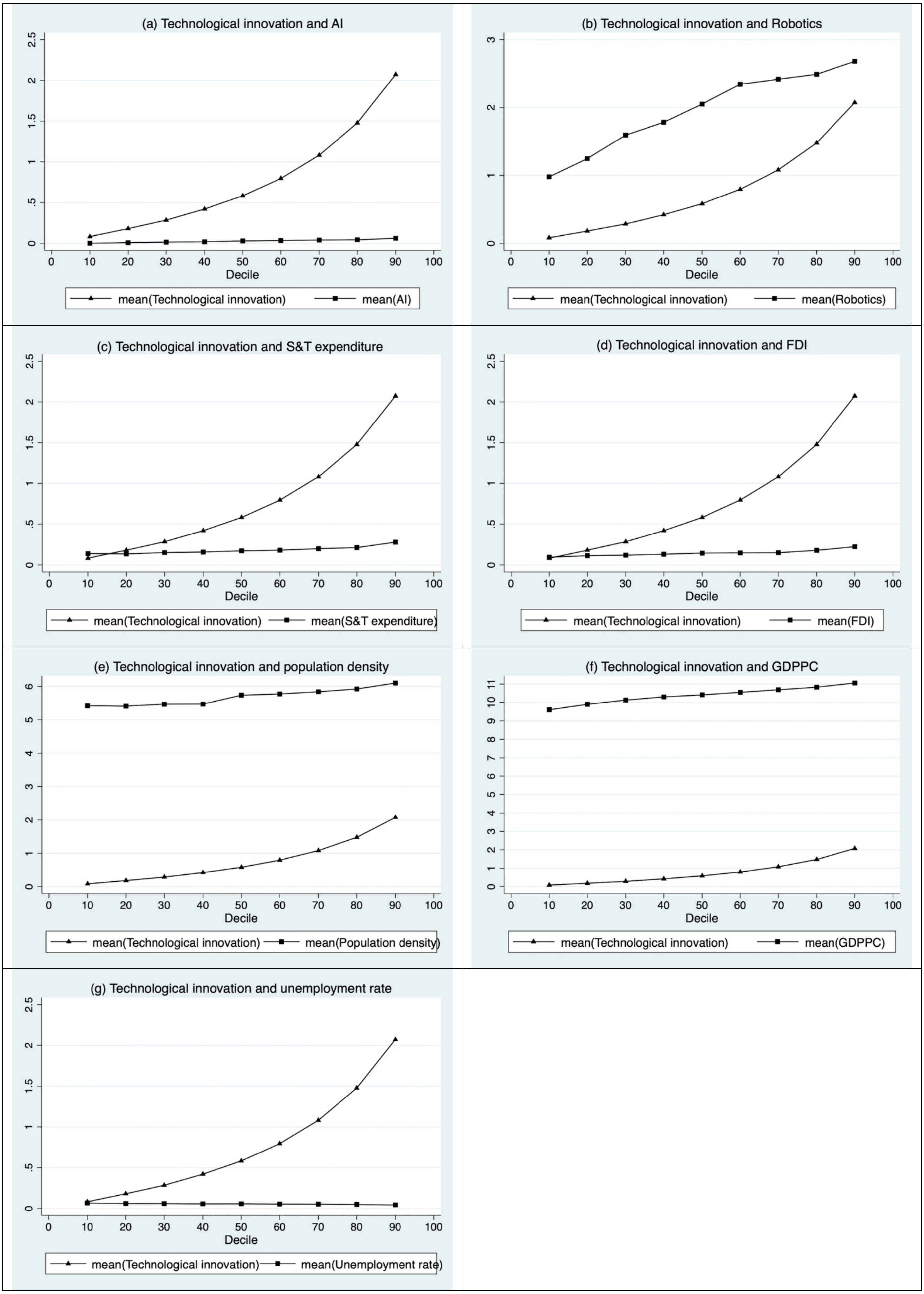


Table 3. Quantile regression: The direct impact of AI on technological innovation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Quantile regression	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
FDI	-0.756**	-1.011**	-0.788	-0.880	-1.372**	-1.740***	-1.815***	-0.935**	-0.961*
	(0.344)	(0.470)	(0.633)	(0.606)	(0.544)	(0.413)	(0.366)	(0.437)	(0.514)
Population density	-0.025	-0.043	0.008	0.081	0.079	0.122	0.148***	0.147**	0.133
	(0.054)	(0.049)	(0.104)	(0.054)	(0.099)	(0.103)	(0.055)	(0.069)	(0.102)
GDPPC	0.063***	0.067***	0.074***	0.120***	0.142***	0.149***	0.130***	0.101***	0.087***
	(0.022)	(0.023)	(0.022)	(0.033)	(0.037)	(0.034)	(0.022)	(0.021)	(0.017)
Unemployment rate	-0.285	-0.357**	-0.475***	-0.469***	-0.509	-0.540*	-0.246	-0.149	-0.015
	(0.290)	(0.152)	(0.152)	(0.125)	(0.337)	(0.299)	(0.241)	(0.189)	(0.213)
S&T expenditure	0.341***	0.483***	0.764***	0.918***	1.101***	1.069***	0.987***	0.830***	0.663***
	(0.046)	(0.111)	(0.087)	(0.112)	(0.094)	(0.099)	(0.053)	(0.090)	(0.046)
AI	0.085***	0.130***	0.133***	0.157***	0.179***	0.168***	0.151***	0.109***	0.082***
	(0.020)	(0.019)	(0.015)	(0.025)	(0.031)	(0.026)	(0.016)	(0.019)	(0.017)

*Notes: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1*

Figure 8 graphically reproduces the link between S&T and AI, on the one hand, and innovation on the other. By tracking the connection of S&T expenditure with innovation across the urban innovation distribution, S&T expenditure's impact climbs until peaking right at the centre of the distribution. Beyond that level, it shows a downward trend in more innovative cities. This result underlines the transformative nature of S&T in the more innovative Chinese hubs but suggest that more than S&T is needed in order to promote innovation in the less innovative Chinese cities (especially for cities lingering at the bottom 20% of the innovation distribution). Comparatively, AI's innovation effect is stronger in cities at the bottom of the innovation distribution, where the innovation returns of AI are similar to those at the very top (Figure 8).

Figure 8. Returns of S&T and AI expenditure across the urban innovation spectrum

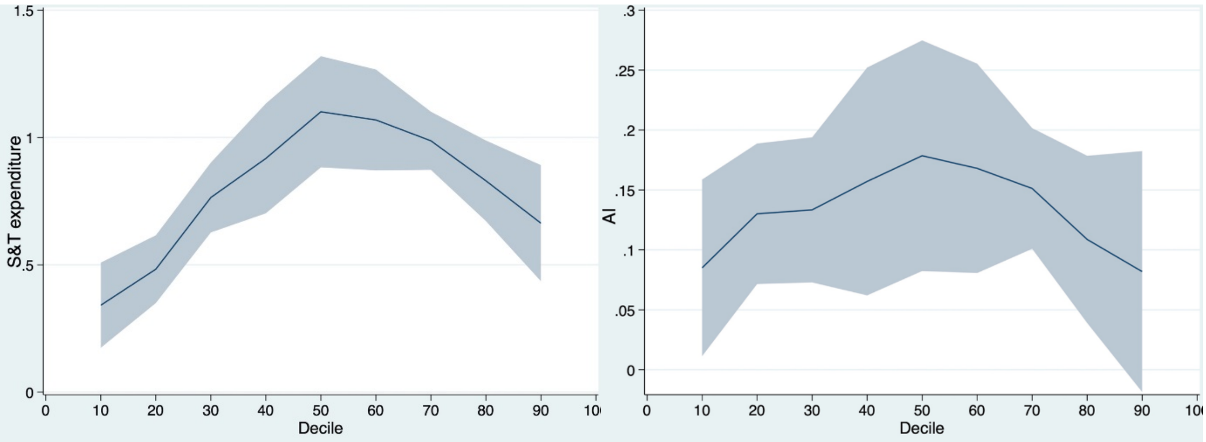


Table 4 reports the results of the same analysis for the impact of the deployment of robotics on technological innovation across the distribution of Chinese cities. The coefficients point to the introduction of robotics having a more substantial positive connection with technological innovation in cities at or below the technological frontier. The adoption of robotics is an important driver of technological innovation, particularly in cities at the lower echelons of the innovation distribution: the highest coefficients accrue to cities located between the 0.1 and 0.5 deciles of the technological innovation distribution.

Table 4. Quantile regression: The direct impact of Robotics on technological innovation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Quantile regression	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
FDI	-0.405	0.068	0.036	-0.307	-0.594	-0.435	-1.118**	-0.816*	-0.685*
	(0.362)	(0.315)	(0.255)	(0.551)	(0.625)	(0.564)	(0.481)	(0.492)	(0.401)
Population density	-0.050	-0.042	-0.027	0.065	0.066	0.077	0.098*	0.122**	0.062
	(0.049)	(0.039)	(0.081)	(0.078)	(0.063)	(0.127)	(0.052)	(0.049)	(0.085)
GDPPC	0.069***	0.061***	0.062***	0.102***	0.112***	0.132***	0.133***	0.084***	0.052***
	(0.015)	(0.020)	(0.020)	(0.029)	(0.035)	(0.035)	(0.023)	(0.026)	(0.013)
Unemployment rate	-0.526***	-0.589***	-0.570**	-0.533**	-0.583*	-0.300	-0.217	0.343	-0.062
	(0.151)	(0.160)	(0.227)	(0.216)	(0.316)	(0.368)	(0.263)	(0.264)	(0.302)
S&T expenditure	0.306***	0.424***	0.667***	0.784***	0.992***	0.987***	0.873***	0.783***	0.695***
	(0.063)	(0.087)	(0.063)	(0.098)	(0.101)	(0.079)	(0.064)	(0.045)	(0.066)
Robotics	0.496***	0.552***	0.560***	0.566***	0.558***	0.491***	0.458***	0.414***	0.378***
	(0.024)	(0.025)	(0.023)	(0.037)	(0.036)	(0.037)	(0.029)	(0.030)	(0.015)

*Notes: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1*

Figure 9 graphically depicts these results. It shows that the peak of the link between robotics and innovation is found in less-innovative cities. The innovation coefficient for robotics is lowest, on average, in the cities in the top three deciles of the innovation distribution. These results indicate that robotics significantly trigger technological innovation across the whole of China as well as a factor that reduces the innovation gap between Chinese cities.

Figure 9. Returns of robotics across the urban innovation spectrum

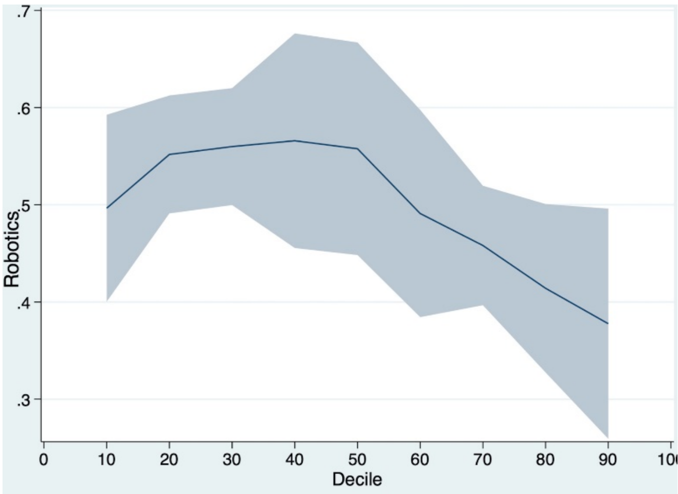


Table 5 focuses on AI's moderating effect across Chinese cities. The interaction between S&T expenditure and AI is significant and positive throughout the distribution, with the quantile regression indicating larger interaction term coefficients in less innovative cities (1.112 at 30% of the innovation distribution). Figure 10 shows this graphically. It should that AI increases the returns of S&T particularly in some of the less innovative cities of the country (second to fifth decile). The overall moderating effect of AI declines as we move up the urban innovation hierarchy in China (Figure 10). This evidence reflects that AI can enhance the return of S&T spending on technological innovation, especially in less-innovative city-regions (Liu et al., 2020).

Table 5. Quantile regression: The moderating impact of AI on technological innovation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Quantile regression	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
FDI	-0.481	-0.592*	-0.327	-0.909**	-1.312**	-1.816***	-1.524***	-1.111***	-0.793*
	(0.325)	(0.321)	(0.288)	(0.402)	(0.520)	(0.510)	(0.378)	(0.388)	(0.425)
Population density	0.031	-0.041*	-0.005	0.081	0.096	0.132*	0.130*	0.153**	0.118
	(0.056)	(0.024)	(0.074)	(0.052)	(0.103)	(0.069)	(0.074)	(0.071)	(0.099)
GDPPC	0.070***	0.074***	0.084***	0.120***	0.146***	0.146***	0.137***	0.088***	0.085***
	(0.018)	(0.017)	(0.020)	(0.032)	(0.036)	(0.036)	(0.020)	(0.020)	(0.028)
Unemployment rate	-0.356*	-0.306**	-0.346*	-0.414**	-0.519	-0.342	-0.289	0.006	-0.066
	(0.189)	(0.122)	(0.208)	(0.210)	(0.368)	(0.260)	(0.220)	(0.235)	(0.287)
S&T expenditure	0.064	0.201***	0.229***	0.410***	0.516***	0.611***	0.614***	0.543***	0.469***
	(0.099)	(0.056)	(0.074)	(0.116)	(0.112)	(0.098)	(0.047)	(0.079)	(0.056)
AI	-0.016	-0.066***	-0.080***	-0.057*	-0.040	-0.015	-0.031	-0.040*	-0.057
	(0.047)	(0.022)	(0.020)	(0.032)	(0.039)	(0.036)	(0.023)	(0.023)	(0.037)
S&T expenditure * AI	0.454*	0.995***	1.112***	0.966***	0.907***	0.699***	0.648***	0.602***	0.557***
	(0.275)	(0.119)	(0.075)	(0.111)	(0.116)	(0.139)	(0.068)	(0.073)	(0.111)

*Notes: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1*

Figure 10. Moderating role of AI across urban innovation spectrum

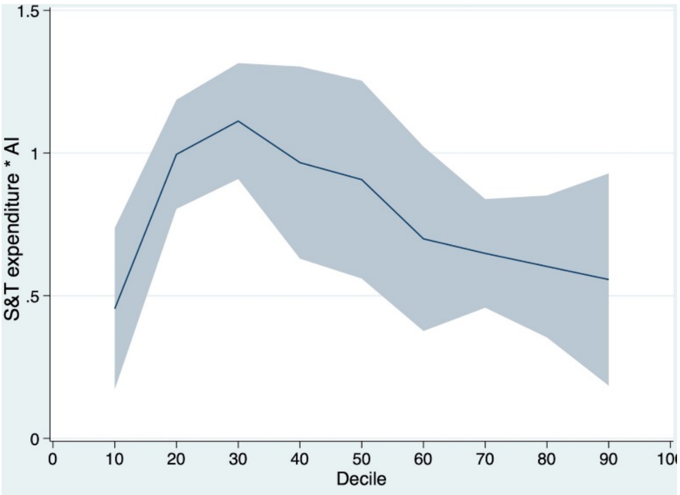


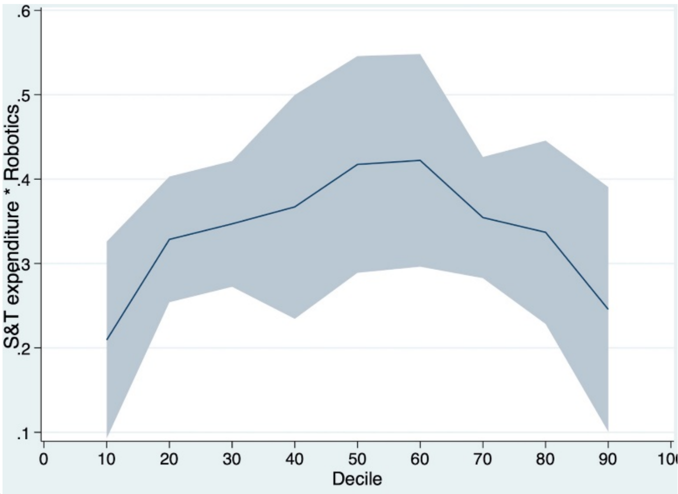
Table 6 does the same with robotics. The results confirm that robotics have a positive and significant moderating influence on the impact of S&T expenditure on technological innovation across the entire innovation distribution. The positive moderating effect of robotics is greatest at the centre of the distributions and, in particular, between the second and eight decile (Figure 11).

Table 6. Quantile regression: The moderating impact of Robotics on technological innovation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Quantile regression	**0.1**	**0.2**	**0.3**	**0.4**	**0.5**	**0.6**	**0.7**	**0.8**	**0.9**
FDI	0.294	0.271	0.511**	0.236	-0.083	-0.238	-0.804**	-0.293	-0.426
	(0.245)	(0.354)	(0.226)	(0.678)	(0.642)	(0.393)	(0.378)	(0.505)	(0.413)
Population density	-0.037*	-0.036	-0.002	0.064	0.042	0.044	0.049	0.095	0.011
	(0.020)	(0.038)	(0.071)	(0.042)	(0.065)	(0.076)	(0.064)	(0.113)	(0.050)
GDPPC	0.073***	0.060***	0.072***	0.113***	0.103***	0.124***	0.112***	0.081***	0.035**
	(0.018)	(0.020)	(0.018)	(0.030)	(0.029)	(0.030)	(0.021)	(0.027)	(0.015)
Unemployment rate	-0.475***	-0.466***	-0.500***	-0.518***	-0.532	-0.005	0.183	0.147	-0.082
	(0.139)	(0.141)	(0.191)	(0.103)	(0.392)	(0.359)	(0.193)	(0.245)	(0.289)
S&T expenditure	-0.317***	-0.470***	-0.294***	-0.234*	-0.251	-0.265**	-0.128	-0.147	-0.013
	(0.109)	(0.138)	(0.097)	(0.142)	(0.172)	(0.117)	(0.096)	(0.103)	(0.086)
Robotics	0.441***	0.477***	0.464***	0.443***	0.416***	0.384***	0.363***	0.331***	0.334***
	(0.033)	(0.023)	(0.022)	(0.041)	(0.036)	(0.032)	(0.021)	(0.028)	(0.014)
S&T expenditure * Robotics	0.209***	0.329***	0.347***	0.367***	0.417***	0.422***	0.354***	0.337***	0.246***
	(0.024)	(0.045)	(0.030)	(0.051)	(0.058)	(0.041)	(0.030)	(0.030)	(0.031)

*Notes: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1*

Figure 11. Moderating role of robotics across the urban innovation spectrum



6.

Overall, while S&T investment is a fundamental strategy for enhancing technological innovation, the vast disparity in innovation capacity among Chinese cities indicates that S&T expenditure alone is insufficient to address the huge innovation challenges confronting less innovative cities in China. AI and robotics present viable alternatives for boosting technological innovation across the whole of China. They positively impact highly innovative cities, and, on top, help narrow the innovation gap between less and more innovative cities. Furthermore, AI and robotics significantly strengthen the impact of S&T investment on technological innovation and enhance the returns of S&T to a greater extent in cities at the middle and lower ends of the innovation distributions. These findings validate Hypotheses 1(b) and reject 2(b), underscoring the important role of AI and robotics play —and can continue to play— in fostering technological innovation across the whole range of Chinese cities.

5. **Conclusion and discussion**

S&T spending has been at the heart of innovation policies (Audretsch & Feldman, 1996; Pavitt, 1982), yet, the returns of S&T investment in places lacking favourable conditions to innovate have left a lot to be desired (Rodríguez-Pose, 2001). The limited impact of S&T in the innovation 'peripheries' has created innovation divides so deep that they not just lead to a waste of talent and potential but are increasingly growing as economic, social, and political risks.

Until now, the solutions to this growing problem have been lacking. However, the development and increased use of AI and robotics represents an opportunity to not just increase the capacity of our societies to innovate, but also to put a cap on the ever-growing geographical innovation divide across many countries of the world.

We have explored the potential of AI and robotics as tools to simultaneously enhance technological innovation (Agrawal et al., 2018; Liu et al., 2020) while at the same time enhancing the innovation potential of less innovative places, following arguments that posit that these technologies can enhance innovation in less developed areas, effectively bridging territorial innovation gaps by overcoming distance limitations and redistributing resources more evenly (Coccia, 2008). We have analysed whether the development of AI and robotics increases the impact of S&T expenditure on innovation by broadening the scope of knowledge exploration and integration across various fields (Cockburn et al., 2019; Han & Mao, 2023; Laursen & Salter, 2006). And we have done this in the case of China, a country which has embarked in the last two decades and a half in a monumental innovation drive, while simultaneously embracing new technologies, such as AI and robotics.

The results of the analysis first unveil the stark disparities in innovation across Chinese cities, drawing attention to a considerable geographical polarisation in technological progress. But they also indicate that AI and robotics are not only important drivers of innovation on their own, but that they also contribute to enhance the returns of S&T, the traditional bulwark of innovation policies. They also indicate that AI and robotics, both directly and through their moderation effects on the impact of S&T can become very useful tools to bridge the innovation gulf between the more and less innovative regions in the country.

These results underline that, in terms of innovation, "one-size-fits-all" innovation strategies based on S&T do not work (Rodríguez-Pose & Wilkie, 2016). What seems to have worked in the case of China —and is likely to work elsewhere— is a combination of three factors. First, the combination in places of S&T investment with and the adoption of new technologies like AI and robotics. The interaction of these two factors is a powerful driver of innovation. Second, prioritising the development of AI and robotics in less innovative cities of China has proven a more effective innovation than the traditional focus on S&T investment. Third, the combination of AI and robotics, on the one hand, and S&T, on the other, not only increases overall innovation everywhere but also serves as a powerful combination to address the problem of the innovation gap. AI and robotics are thus versatile tools that propel innovation across the board and as a possibly more effective instrument to drive innovation there, where other policies have failed: the regions with the weakest conditions to promote innovative ecosystems.

Our analysis, centred on China, has shed light on how AI and robotics boost technological innovation amidst an uneven distribution of knowledge and economic activity. This result has considerable policy implications for countries, both developing and developed, struggling to promote innovation as well as confronted with growing innovation divides. However, more needs to be done. Future research could extend this analysis by comparing the impact of cutting-edge technologies on innovation across different types of countries. Additionally, the analysis could be refined by going beyond the AI keyword frequency and the volume of industrial robot installations as proxies for AI and robotics development. These are fields that are rapidly evolving and new metrics will emerge that provide better insights into the specific directions of technological advancement. Future studies could leverage machine learning techniques for a more detailed exploration of the development trajectories of these technologies, offering a deeper understanding of their roles in shaping the landscape of technological innovation.

References

Acemoglu, D., & Restrepo, P. (2018). The race between man and machine: Implications of technology for growth, factor shares, and employment. In *American Economic Review* (Vol. 108, Issue 6, pp. 1488–1542). American Economic Association. https://doi.org/10.1257/aer.20160696

Acemoglu, D., & Restrepo, P. (2020). *Robots and Jobs: Evidence from US Labor Markets*.

Acs, Z. J., Anselin, L., & Varga, A. (2002). Patents and innovation counts as measures of regional production of new knowledge. *Research Policy*, *31*, 1069–1085. https://doi.org/10.1016/S0048-7333(01)00184-6

Aghion, P., Jones, B. F., & Jones, C. I. (2019). Artificial Intelligence and Economic Growth. In *The Economics of Artificial Intelligence: An Agenda* (pp. 237–282). http://www.nber.org/chapters/c14015

Agrawal, A., Gans, J., & Goldfarb, A. (2018). Prediction, Judgment, and Complexity: A Theory of Decision-Making and Artificial Intelligence. In *The economics of artificial intelligence: An agenda* (pp. 89–110). University of Chicago Press.

Asian Development Bank. (2021). *The 14th Five-Year Plan of the People's Republic of China —Fostering High-Quality Development*. http://dx.doi.org/10.22617/BRF210192-2

Audretsch, D. B., & Feldman, M. P. (1996). R&D spillovers and the geography of innovation and production. *The American economic review, 86(3), 630-640.*

Autor, D. H. (2015). Why are there still so many jobs? the history and future of workplace automation. *Journal of Economic Perspectives*, *29*(3), 3–30. https://doi.org/10.1257/jep.29.3.3

Baumann, J., & Kritikos, A. S. (2016). The link between R&D, innovation and productivity: Are micro firms different? *Research Policy*, *45*(6), 1263–1274. https://doi.org/10.1016/j.respol.2016.03.008

Bilbao-Osorio, B., & Rodríguez-Pose, A. (2004). From R and D to innovation and economic growth in the EU. *Growth and Change*, *35*(4), 434–455. https://doi.org/10.1111/j.1468-2257.2004.00256.x

Brynjolfsson, E., Hui, X., & Liu, M. (2019). Does machine translation affect international trade? Evidence from a large digital platform. *Management Science*, *65*(12), 5449–5460. https://doi.org/10.1287/mnsc.2019.3388

Buarque, B. S., Davies, R. B., Hynes, R. M., & Kogler, D. F. (2020). OK Computer: The creation and integration of AI in Europe. *Cambridge Journal of Regions, Economy and Society*, *13*(1), 175–192. https://doi.org/10.1093/cjres/rsz023

Cameron, C. A., & Trivedi, P. K. (2005). *Microeconometrics: Methods and Applications*. Cambridge University Press.

Cao, C., & Suttmeier, R. P. (2017). Challenges of S&T system reform in China. In *Science* (Vol. 355, Issue 6329, pp. 1019–1021). American Association for the Advancement of Science. https://doi.org/10.1126/science.aal2515

Cao, S., Lyu, H., & Xu, X. (2020). InsurTech development: Evidence from Chinese media reports. *Technological Forecasting and Social Change*, *161*. https://doi.org/10.1016/j.techfore.2020.120277

Cicerone, G., Faggian, A., Montresor, S., & Rentocchini, F. (2023). Regional artificial intelligence and the geography of environmental technologies: does local AI knowledge help regional green-tech specialization? *Regional Studies*, *57*(2), 330–343. https://doi.org/10.1080/00343404.2022.2092610

Coccia, M. (2008). Spatial mobility of knowledge transfer and absorptive capacity: Analysis and measurement of the impact within the geoeconomic space. *Journal of Technology Transfer*, *33*(1), 105–122. https://doi.org/10.1007/s10961-007-9032-4

Cockburn, I. M., Henderson, R., Stern, S., Professor, H., Management, E., Business, H., & Morgan, S. (2019). The impact of artificial intelligence on innovation: An exploratory analysis. In *The Economics of Artificial Intelligence: An Agenda* (pp. 115–146). University of Chicago Press. http://www.nber.org/papers/w24449

Crescenzi, R., & Rodríguez-Pose, A. (2012). An "integrated" framework for the comparative analysis of the territorial innovation dynamics of developed and emerging countries. *Journal of Economic Surveys*, *26*(3), 517–533. https://doi.org/10.1111/j.1467-6419.2012.00726.x

Crescenzi, R., Rodríguez-Pose, A., & Storper, M. (2007). The territorial dynamics of innovation: A Europe-United States comparative analysis. *Journal of Economic Geography*, *7*(6), 673–709. https://doi.org/10.1093/jeg/lbm030

Davenport, T. H., Ronanki, R., Wheaton, J., & Nguyen, A. (2018). Feature Artificial Intelligence for the Real World. *Harvard Business Review*, 108–116.

European Commission. (2020). *Europe 2020*. https://eur-lex.europa.eu/legal-content/EN/ALL/?uri=celex:52010DC2020

Feldman, M. P., & Florida, R. (1994). The Geographic Sources of Innovation: Technological Infrastructure and Product Innovation in the United States. *Annals of the Association of American Geographers*, *84*(2), 210–229. https://doi.org/10.1111/j.1467-8306.1994.tb01735.x

Felten, E., Raj, M., & Seamans, R. (2021). Occupational, industry, and geographic exposure to artificial intelligence: A novel dataset and its potential uses. *Strategic Management Journal*, *42*(12), 2195–2217. https://doi.org/10.1002/smj.3286

Freeman, C., & Soete, L. (2009). Developing science, technology and innovation indicators: What we can learn from the past. *Research Policy*, *38*(4), 583–589. https://doi.org/10.1016/j.respol.2009.01.018

Furman, J. L., Porter, M. E., & Stern, S. (2002). The determinants of national innovative capacity. *Research Policy*, *31*(6), 899–933. https://doi.org/10.1016/S0048-7333(01)00152-4

Furman, J., & Seamans, R. (2019). AI and the Economy. *Innovation Policy and the Economy*, *19*(1), 161–191.

Glaeser, E. (2011). *Triumph of the city: How urban spaces make us human*. New York: Pan Macmillan.

Goldfarb, A., & Trefler, D. (2019). Artificial Intelligence and International Trade. In *The Economics of Artificial Intelligence: An Agenda* (pp. 463–492). University of Chicago Press. http://www.nber.org/chapters/c14012

Griliches, Z. (1980). R&D and The Productivity Slowdown. *The American Economic Review*, *434*, 413–420.

Griliches, Z. (1986). Productivity, R&D, and Basic Research at the Firm Level in the 1970s. *American Economic Review*, *76*(1), 141–154.

Grossman, G. M., & Helpman, E. (1994). Endogenous Innovation in the Theory of Growth. *Journal of Economic Perspectives, 8*(1), 23-44.

Haenlein, M., & Kaplan, A. (2019). A brief history of artificial intelligence: On the past, present, and future of artificial intelligence. *California Management Review*, *61*(4), 5–14. https://doi.org/10.1177/0008125619864925

Han, F., & Mao, X. (2023). Artificial intelligence empowers enterprise innovation: evidence from China's industrial enterprises. *Applied Economics*. https://doi.org/10.1080/00036846.2023.2289916

Hervás-Oliver, J. L., Parrilli, M. D., Rodríguez-Pose, A., & Sempere-Ripoll, F. (2021). The drivers of SME innovation in the regions of the EU. *Research Policy*, *50*(9). https://doi.org/10.1016/j.respol.2021.104316

Jaffe, A. B. (1993). Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations. *The Quarterly Journal of Economics*, *August*. https://doi.org/10.7551/mitpress/5263.003.0010

Laursen, K., & Salter, A. (2006). Open for innovation: The role of openness in explaining innovation performance among U.K. manufacturing firms. *Strategic Management Journal*, *27*(2), 131–150. https://doi.org/10.1002/smj.507

Lee, C. C., Qin, S., & Li, Y. (2022). Does industrial robot application promote green technology innovation in the manufacturing industry? *Technological Forecasting and Social Change*, *183*. https://doi.org/10.1016/j.techfore.2022.121893

Li, X. (2009). China's regional innovation capacity in transition: An empirical approach. *Research Policy*, *38*(2), 338–357. https://doi.org/10.1016/j.respol.2008.12.002

Liu, F., & Sun, Y. (2009). A comparison of the spatial distribution of innovative activities in China and the U.S. *Technological Forecasting and Social Change*, *76*(6), 797–805. https://doi.org/10.1016/j.techfore.2008.12.002

Liu, J., Chang, H., Forrest, J. Y. L., & Yang, B. (2020). Influence of artificial intelligence on technological innovation: Evidence from the panel data of china's manufacturing sectors. *Technological Forecasting and Social Change*, *158*. https://doi.org/10.1016/j.techfore.2020.120142

Liu, X., Liu, F., & Ren, X. (2023). Firms' digitalization in manufacturing and the structure and direction of green innovation. *Journal of Environmental Management*, *335*, 117525. https://doi.org/10.1016/j.jenvman.2023.117525

Lundvall, B. Å., & Rikap, C. (2022). China's catching-up in artificial intelligence seen as a co-evolution of corporate and national innovation systems. *Research Policy*, *51*(1). https://doi.org/10.1016/j.respol.2021.104395

Maclaurin, W. R. (1953). The sequence from invention to innovation and its relation to economic growth. *The Quarterly Journal of Economics, 67*(1), 97-111.

Madan, R., & Ashok, M. (2023). AI adoption and diffusion in public administration: A systematic literature review and future research agenda. *Government Information Quarterly, 40*(1), 101774.

Mcbride, J., & Chatzky, A. (2019). *Is "Made in China 2025" a Threat to Global Trade?* https://www.cfr.org/backgrounder/made-china-2025-threat-global-trade

Mergel, I., Dickinson, H., Stenvall, J., & Gasco, M. (2023). Implementing AI in the public sector. *Public Management Review*. https://doi.org/10.1080/14719037.2023.2231950

Mikko, M., Stein, Ø., & Jaakko, S. (2021). Machine learning and the identification of Smart Specialisation thematic networks in Arctic Scandinavia. *Regional Studies*, *0*(0), 1–13. https://doi.org/10.1080/00343404.2021.1925237

Motohashi, K., & Yun, X. (2007). China's innovation system reform and growing industry and science linkages. *Research Policy*, *36*(8), 1251–1260. https://doi.org/10.1016/j.respol.2007.02.023

National Science and Technology Council. (2020). *Advancing America's Global Leadership in Science & Technology*. https://www.whitehouse.gov/ostp/nstc/reports/

Neumann, O., Guirguis, K., & Steiner, R. (2022). Exploring artificial intelligence adoption in public organizations: a comparative case study. *Public Management Review*. https://doi.org/10.1080/14719037.2022.2048685

Ning, L., Wang, F., & Li, J. (2016). Urban innovation, regional externalities of foreign direct investment and industrial agglomeration: Evidence from Chinese cities. *Research Policy*, *45*(4), 830–843. https://doi.org/10.1016/j.respol.2016.01.014

Openshaw, S. (1992). Some suggestions concerning the development of artificial intelligence tools for spatial modelling and analysis in GIS. *The Annals of Regional Science*, *26*, 35–51.
Pakes, A., & Griliches, Z. (1980). Patents and R&D at the firm level: A first report. *Economics Letters*, *5*(4), 377–381. https://doi.org/10.1016/0165-1765(80)90136-6
Parteka, A., & Kordalska, A. (2023). Artificial intelligence and productivity: global evidence from AI patent and bibliometric data. *Technovation*, *125*. https://doi.org/10.1016/j.technovation.2023.102764
Pavitt, K. (1982). R&D, patenting and innovative activities A statistical exploration. *Research Policy*, *11*, 33–51.
Rampersad, G. (2020). Robot will take your job: Innovation for an era of artificial intelligence. *Journal of Business Research*, *116*, 68–74. https://doi.org/10.1016/j.jbusres.2020.05.019
Roberts, H., Cowls, J., Morley, J., Taddeo, M., Wang, V., & Floridi, L. (2021). The Chinese approach to artificial intelligence: an analysis of policy, ethics, and regulation. *AI and Society*, *36*(1), 59–77. https://doi.org/10.1007/s00146-020-00992-2
Rodríguez-Pose, A. (2001). Is R&D investment in lagging areas of Europe worthwhile? Theory and empirical evidence*. *Papers in Regional Science*, *80*(3), 275–295. https://doi.org/10.1111/j.1435-5597.2001.tb01800.x
Rodríguez-Pose, A., & Crescenzi, R. (2008). Research and development, spillovers, innovation systems, and the genesis of regional growth in Europe. *Regional Studies*, *42*(1), 51–67. https://doi.org/10.1080/00343400701654186
Rodríguez-Pose, A., & Wilkie, C. (2016). Putting China in perspective: A comparative exploration of the ascent of the Chinese knowledge economy. *Cambridge Journal of Regions, Economy and Society*, *9*(3), 479–497. https://doi.org/10.1093/cjres/rsw018
Rodríguez-Pose, A., Wilkie, C., & Zhang, M. (2021). Innovating in "lagging" cities: A comparative exploration of the dynamics of innovation in Chinese cities. *Applied Geography*, *132*(May). https://doi.org/10.1016/j.apgeog.2021.102475
Rodríguez-Pose, A., & Zhang, M. (2019). Government institutions and the dynamics of urban growth in China. *ce*, *59*(4), 633–668. https://doi.org/10.1111/jors.12435
Romer, P. M. (1986). Increasing Returns and Long-Run Growth. *Journal of Political Economy*, *94*(5), 1002–1037. https://www.jstor.org/stable/1833190
Shanghai. (2017). *Opinions on the Implementation of this City's New Generation of AI Development*. http://www.shanghai.gov.cn/nw2/nw2314/nw2319/nw12344/u26aw54186.html
Stiglitz, J. E. (2014). *Unemployment and Innovation*. (No. w20670). national bureau of economic research.
Tian, H., Zhao, L., Yunfang, L., & Wang, W. (2023). Can enterprise green technology innovation performance achieve "corner overtaking" by using artificial intelligence?—Evidence from Chinese manufacturing enterprises. *Technological Forecasting and Social Change*, *194*. https://doi.org/10.1016/j.techfore.2023.122732
Wang, L., Zhou, Y., & Chiao, B. (2023). Robots and firm innovation: Evidence from Chinese manufacturing. *Journal of Business Research*, *162*. https://doi.org/10.1016/j.jbusres.2023.113878
Wang, Q. J., Feng, G. F., Chen, Y. E., Wen, J., & Chang, C. P. (2019). The impacts of government ideology on innovation: What are the main implications? *Research Policy*, *48*(5), 1232–1247. https://doi.org/10.1016/j.respol.2018.12.009
Wirtz, B. W., & Müller, W. M. (2019). An integrated artificial intelligence framework for public management. *Public Management Review*, *21*(7), 1076–1100. https://doi.org/10.1080/14719037.2018.1549268

Yang, C., & Huang, C. (2022). Quantitative mapping of the evolution of AI policy distribution, targets and focuses over three decades in China. *Technological Forecasting and Social Change*, *174*. https://doi.org/10.1016/j.techfore.2021.121188

Zeng, J. (2021). China's Artificial Intelligence Innovation: A Top-Down National Command Approach? *Global Policy*, *12*(3), 399–409. https://doi.org/10.1111/1758-5899.12914

Appendix

Appendix A. The Statistical Description of *AI* Measure

Table A1. All frequencies of 31 AI keywords from Work Reports of Municipal Governments (2008-2021)

Keywords	**Frequency**
Smart city	2310
Intellectual manufacturing	1551
Cloud computing	1353
Digital economy	1345
Internet of thing	1269
Robots	906
Artificial intelligence	816
Industrial Internet	617
Internet finance	513
Cloud platform	321
Smart transport	301
Wise Information Technology of med (WITM)	220
Smart grid	207
Industrial digitalization	184
Cyber security	180
Fintech	101
Smart Senior Care	80
Home automation	72
Virtual Reality	48
Autonomous vehicles	26
Smart warehousing	17
Intellectual technology	17
Digital finance	15
Smart wear	13
Global Positioning System	12
Smart village	10
Smart sustainability	9
Decision Support Systems	3
Data mining	3
Digital supply chain	1
Computer vision	1

Figure A1. The sample of the annual work report of Shanghai Municipal People's Government

Home / Government Affairs Open / Municipal Government Information Open Catalog / Various Reports Submitted by the Municipal Government to the Municipal People's Congress and its Standing Committee for Consideration / Municipal Government Work Report

Source: Liberation Daily

Font size: Large medium small

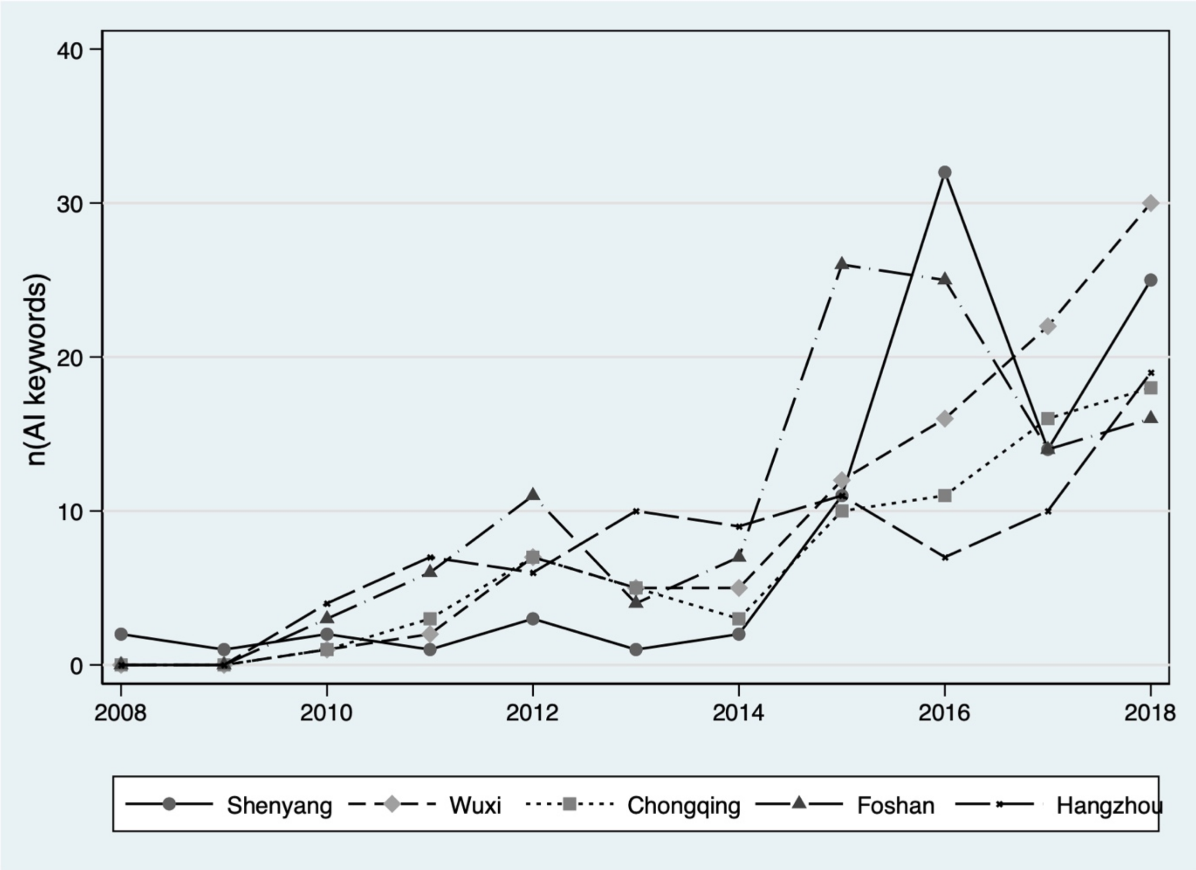
Home | Government service | News | Open government affairs | Government-citizen interaction | Into Shanghai

Delegates:

- The new momentum for development has accelerated. The "four major brands" have continued to develop, and the "five-type economy" has been fully developed. The proportion of the total output value of industrial strategic emerging industries in the total output value of industries above designated size has increased from 30.8% in 2017 to about 42%, and the scale of the three leading industries of integrated circuits, biomedicine, and artificial intelligence has reached 1.40 trillion yuan. In the past five years, a total of 2.251 million new market entities of various types have been established, an increase of 52.7% over the previous five years, and the number of enterprises per thousand people has increased to 111.1, ranking first in the country.

Continue to promote the functional upgrading of the "five centers". Strengthen the industrial support of the international economic center, insist on focusing on the real economy for economic development, accelerate the construction of a modern industrial system, deepen and upgrade the "Shanghai Plan" for the three leading industries, improve the innovation and development capabilities of integrated circuit equipment, materials and design, promote the application and promotion of biomedical innovative products, optimize the ecology of artificial intelligence autonomous and controllable software and hardware, accelerate innovation breakthroughs in six key industries, continue to promote new energy vehicles, civil aviation, space information and other industries to make up the chain and strengthen the chain. Accelerate the development of the marine industry on Changxing Island, vigorously develop four new tracks of digital economy, green low-carbon, meta-universe, and intelligent end point, and accelerate the layout in the five major fields of future health, future intelligence, future energy, future space, and future materials. Strengthen the resource allocation capabilities of the international financial center, deepen the construction of a global asset management center and an international reinsurance center, accelerate the construction of an international financial asset trading platform, promote more innovations in commodity futures and financial derivatives, support the establishment of more headquarters-type and functional Financial Strengthen the concentration radiation energy level of the International Trade Center, implement a new round of support policies for the regional headquarters of multinational companies, and actively create a demonstration area for the innovative development of service trade. Strengthen the position of the international shipping center as a hub, and accelerate the development of the north side of Xiaoyang Mountain, the first phase of the renovation of Luojing Port Area, the east extension of the Dalu Line waterway, and the fourth phase of Pudong International Airport. Start the construction of Shanghai East Railway Station, an integrated transportation hub in the East, and develop high-end shipping services. Strengthen the innovative source function of the International Science and Technology Innovation Center, further promote the construction of a comprehensive national science center in Zhangjiang, strengthen the service guarantee of national laboratories in Shanghai, accelerate the cultivation of a number of national laboratory bases in Shanghai, cooperate with the promotion of the reorganization of national key laboratories, vigorously develop new R & D institutions, improve the platform system of scientific research bases, start the construction of major national scientific and technological infrastructure such as the magnetoinertia pre-research project, and continue to build facilities in the fields of photonics, life sciences, and oceanography

Figure A2. Annual trends of China's Top 5 Cities for the AI development (2008-2018)



Appendix B. The Statistical Description of Robotics Measure

Table B1. Industry classification (GB/T4754-2017)

The first class	Name	The second class	Name
A	Agriculture, forestry, animal husbandry and fishery	1	Agriculture
		2	Forestry
		3	Animal husbandry
		4	Fishery
		5	Auxiliary activities
B	Mining	6	Coal mining and washing
		7	Oil and gas extraction industry
		8	Ferrous metal mining and processing industry
		9	Non-ferrous metal mining and processing industry
		10	Non-metallic mineral mining and processing industry
		11	Mining professional and supporting activities
		12	Other mining industries
C	Manufacturing	13	Agricultural and side-line products processing industry
		14	Food manufacturing
		15	Wine, beverage, and refined tea manufacturing
		16	Tobacco products
		17	Textile industry
		18	Textile, clothing, and apparel industry
		19	Leather, fur, feathers and their products and shoemaking
		20	Wood processing and wood, bamboo, rattan, palm and straw products industry
		21	Furniture manufacturing industry
		22	Paper and paper products industry
		23	Printing and recording media reproduction
		24	Culture, education, industrial arts, sports, and entertainment products manufacturing
		25	Petroleum, coal, and other fuel processing industry
		26	Chemical raw materials and chemical products manufacturing industry
		27	Pharmaceutical manufacturing
		28	Chemical fiber manufacturing
		29	Rubber and plastic products
		30	Non-metallic mineral products
		31	Ferrous metal smelting and rolling processing
		32	Non-ferrous metal smelting and rolling processing
		33	Metal products
		34	General equipment manufacturing
		35	Special equipment manufacturing
		36	Automobile manufacturing
		37	Railway, shipbuilding, aerospace, and other transportation equipment manufacturing
		38	Electrical machinery and equipment manufacturing
		39	Computer, communications, and other electronic equipment manufacturing
		40	Instrument manufacturing
		41	Other manufacturing
		42	Comprehensive utilization of waste resources
		43	Metal products, machinery, and equipment repair industry
D	Electricity, heat, gas and water production and supply	44	Electricity and heat production and supply industry
		45	Gas production and supply industry
		46	Water production and supply industry

E	Construction	47	House construction industry
		48	Civil Engineering Construction Industry
		49	Construction and installation industry
		50	Architectural decoration, renovation, and other construction
F	Wholesale and retail	51	Wholesale industry
		52	Retail industry
G	Transportation, warehousing and postal services	53	Railway transportation
		54	Road transport
		55	Water transport
		56	Air transport
		57	Pipeline transportation
		58	Multimodal transport and transportation agency
		59	Loading, unloading, handling and warehousing
		60	Postal industry
H	Accommodation and catering industry	61	Accommodation industry
		62	Catering industry
I	Information transmission, software, and information technology services	63	telecommunications, radio and television, and satellite transmission services
		64	Internet and related services
		65	Software and information technology services
J	Finance	66	Money and financial services
		67	Capital Market Services
		68	Insurance industry
		69	Other financial industries
K	Real estate	70	Real estate
L	Leasing and business services	71	Leasing industry
		72	Business services industry
M	Scientific research and technical services	73	Research and Experimental Development
		74	Professional and technical services industry
		75	Technology promotion and application service
N	Water conservancy, environment, and public facilities management	76	Water conservancy management industry
		77	Ecological protection and environmental management
		78	Public facilities management
		79	Land management
O	Residential services, repairs, and other services	80	Residential services
		81	Motor vehicle, electronic products, and daily product repair industry
		82	Other service industries
P	Education	83	Education
Q	Health and social work	84	Hygiene
		85	Social work
R	Culture, sports, and entertainment	86	Press and publishing industry
		87	Radio, television, film, and sound recording production
		88	Culture and art industry
		89	Sports Industry
		90	Entertainment Industry
S	Public administration, social security, and social organizations	91	Organs of the Communist Party of China
		92	State agencies
		93	CPPCC, Democratic Parties
		94	Social Security
		95	Mass organizations, social groups and other member organizations
		96	Grassroots mass self-government organizations and other organizations
T	International organizations	97	International organizations

Notes: According to GB/T4754-2017 classification, the industry is divided into three categories including primary industry, secondary industry, and tertiary industry in turn. Most of the data we included is from primary industry (A01-04), secondary industry (B-E, except 11, 43), and education of tertiary industry (83).