INDUSTRY 4.0 IN CHINA: THE INTERPLAY OF INNOVATION, EMPLOYMENT, AND HOUSING DYNAMICS

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PhD

The Hong Kong Polytechnic University

2024

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Industry 4.0 in China: the Interplay of Innovation, Employment, and Housing Dynamics

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A thesis submitted in partial fulfilment of the requirements for the degree of

Doctor of Philosophy

December 2023

CERTIFICATE OF ORIGINALITY

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ABSTRACT

The transition to Industry 4.0, marked by the integration of automation technologies into the fabric of industrial and socio-economic systems in China, is the research theme of this thesis. This study explores the complexities and implications of this transition, with a specific emphasis on the role of automation technologies. The research is motivated by the need to understand the evolution from Industry 3.0 to 4.0 and its implications. In addition to examining the factors influencing the adoption of these technologies, the paper also examines their broader socio-economic impacts, such as on employment dynamics and housing market conditions. The thesis is structured around four overall research questions. The first research investigates whether the transition to Industry 4.0 in China represents a path-dependent evolution or a radical shift, focusing on factors influencing technology diffusion across Chinese cities. The second research question explores whether technologically lagging countries can leverage imported products for Industry 4.0-related innovations. The third research question examines how diversity and specialization in industries affect a city's capacity to integrate automation technologies. The fourth question studies the relationship between automation and housing prices, revealing the underlying economic dynamics. Employing a quantitative research methodology rooted in econometrics, the study analyses data from multiple sources, including the China Industrial Enterprise Database, China Customs Database, China Patent Application Database, the International Federation of Robotics, and the China Statistical Yearbook. In China, Industry 4.0 adoption is primarily influenced by technological and geographical proximity. Furthermore, the research indicates that imports can catalyse innovation at the level of city-industry. A variety of factors interact with robotic adoption in ways that affect employment differently, including industrial diversity and specialisation. Furthermore, robotics adoption is associated with an increase in local housing prices, with spillover effects on neighbouring cities. In summary, this thesis contributes significant insights into the dynamics of Industry 4.0 adoption, as well as its economic and social implications. For policymakers, urban planners, and industry stakeholders, these findings offer valuable perspectives, guiding strategies for technological adaptation and managing Industry 4.0 challenges.

LIST OF PUBLICATIONS

- **Paper arising from the thesis**

Zhou, J., **Peng, H.*,** Hui, E. C. M., & Wu, Q. (2024). The relationship between robotics and housing prices: evidence from housing markets in Chinese cities. *Industry and Innovation*, 1–27. https://doi.org/10.1080/13662716.2024.2362238

- **Manuscripts under preparation**

Peng, H., Hui, E. C. M., &Zhou, J (2024). Robotic And Urban Employment: Unravelling the Interplay Of Industrial Diversity, Specialization, And Spatial Dynamics.

Peng, H. & Hui, E. C. M. (2024), The Transformation of China's Economy from Industry 3.0 to Industry 4.0.

Peng, H., Cortinovis, N. & Hui, E. C. M. (2024), From Recipient to Innovator: the Evolution of China in Industrial Robotics.

- **Other publications**

Zhou, J., Hui, E. C. M., & **Peng, H.** (2022). Chasing opportunity? Inequality of opportunity and educational self-selection of interprovincial migrants in China. *The Annals of Regional Science*, *69*(2), 281-309.

Zhou, J., Hui, E. C. M., & **Peng, H.** (2024). Are robots crowding out migrant workers? Evidence from urban China. *Habitat International*, *152*, 103154.

ACKNOWLEDGEMENTS

As I conclude my doctoral studies, I would like to take the opportunity to express my gratitude to those who gave me invaluable support.

First and foremost, I would like to express my heartfelt gratitude to my PhD supervisor, Chair Professor Eddie Hui. Our first meeting at a 2017 conference led to a recommendation letter for my Cambridge application. However, due to unforeseen circumstances, my path led me elsewhere. In 2019, he asked whether I wanted to apply to PolyU for my doctoral studies, an opportunity that has profoundly shaped my academic and professional trajectory. During the subsequent three years and a half of my PhD journey, he provided me with substantial autonomy over the direction and content of my research, entrusting me with the freedom to explore and conduct research on the topics I am interested in. Moreover, Prof. Hui's exemplary dedication as a scholar has been a source of inspiration.

Additionally, I want to thank Dr Nicola Cortinovis, my host supervisor during my attachment programme at Utrecht University. Despite the numerous challenges, Nicola's detailed guidance and steadfast encouragement mean a lot to me. I also owe a great deal of gratitude to my senior colleague, Dr Zhou Jiantao. His willingness to share his knowledge and experiences in academic studies, work, and even daily life has greatly eased my studies.

Moreover, I must express my thanks to my friends and colleagues, both near and far. To those I have stayed connected with through the internet, those I have not had the chance to meet in person for years, those I had the opportunity to meet in person after the pandemic, those who have been by my side during the challenging times of the pandemic, those who have asked me to join in hiking and other playful adventures, and those who have shared daily meals with me – your occasional care and support have been a source of immense comfort and joy. Your presence, both physical and virtual, has greatly enriched my life during these years.

Last but not least, my deepest gratitude goes to my family, whose enduring belief in me and unconditional support have been the cornerstone of my journey, providing me with the courage and strength to pursue my life.

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CHAPTER1. INTRODUCTION

1.1 Research Background

1.1.1 Policy background: toward industry 4.0

The advent of Industry 4.0, often referred to as the Fourth Industrial Revolution (FIR), marks a significant shift in the global manufacturing landscape. According to the German Federal Ministry of Education and Research, the term Industry 4.0 was first coined in 2011 as part of a strategic manufacturing roadmap to promote digital manufacturing (Walendowski et al., 2016). Industry 4.0 is characterised by an unprecedented fusion of technologies blurring the lines between the physical, digital and biological spheres. This revolution is not merely an extension of digital capabilities but a comprehensive transformation that integrates Artificial Intelligence (AI), the Internet of Things (IoT), robotics, and cyber-physical systems into the heart of manufacturing processes.

An industrial revolution is characterised by new technology finding broad application in industry and thereby fundamentally changing established practices (Zhou et al., 2015). Tracing the evolution of industrial revolutions, Industry 4.0 represents a natural progression from the third industrial revolution's digital advancements. The first industrial revolution introduced mechanisation and steam power, fundamentally altering production methods. The subsequent revolutions brought mass production and electrical power, followed by digital technology. Today, Industry 4.0 builds on this digital foundation, moving towards interconnected, intelligent, and autonomous manufacturing systems.

Globally, the adoption and integration of Industry 4.0 technologies have been rapid, particularly in developed countries. Germany's "Digital Strategy 2025," launched in 2016, exemplifies a national commitment to fostering innovation and digitising traditional industries (Klitou et al., 2017a). By December 2018, the German government had highlighted five key areas for digital transformation, including supporting SMEs and ensuring that the digital revolution benefits all citizens, while also providing solutions to its challenges. Similarly, the European Union's "Digital Single Market Strategy" and the "Industrial Digitization Plan" aim to unify and digitise the market across its member states, focusing on areas like 5G, cloud computing, IoT, and cybersecurity. This strategy, built on the individual digital initiatives of its members, evolved into the "European Industrial Digitization Strategy," aiming to establish an open, collaborative innovation system and nurture pioneering enterprises, ensuring the EU's global leadership in industrial digital transformation.

Initially, Germany promoted the concept of Industry 4.0 as a strategic issue for national development, but the concept is also becoming more widely known globally and not only within Germany (Oztemel & Gursev, 2020). Entering the era of Industry 4.0, countries have taken action and launched national manufacturing strategies. The United States, a pioneer in digital transformation, has consistently focused on developing next-generation technologies, as evidenced by strategies like the "Federal Big Data R&D Strategy" and the "National AI Research and Development Strategy." These open-innovation-based policies emphasise the transformation of traditional industries. Post-financial crisis, the U.S. sought to rejuvenate its economy with re-industrialisation initiatives such as the "Smart Manufacturing Revival Plan" and the "Advanced Manufacturing American Leadership Strategy," leveraging innovative technologies to accelerate the growth of tech-intensive advanced manufacturing, ensuring its role as an economic and national security pillar.

In Asia, Japan's 'Fifth Science and Technology Basic Plan' and China's 'Made in China 2025' initiative reflect a similar commitment to embracing Industry 4.0. Japan envisions a 'Society 5.0' with widespread automation and data-driven decision-making, while China aims to transition from a manufacturing giant to a world leader in smart manufacturing. The Chinese version of the Industry 4.0 Plan, known as "Made in China 2025", was launched in 2015. Despite China's economic miracles over the past 30 years, its manufacturing productivity is still behind the developed world's: despite 15 years of rapid growth, its productivity is only 1/5th of that of the dominant developed countries (McKinsey Greater China, 2016). China's rapid manufacturing growth in the past relied on cheap labour, capital and imitation of innovation, but these competitive advantages are now being lost. China is therefore trying to generate strong players in industries where innovation is the main driver of development. Innovation is seen as meeting unmet consumer needs or driving efficiency in manufacturing. China's Industry 4.0 development is still in its infancy: the government is acting as an active initial driver; capital is beginning to invest in Industry 4.0; and leading manufacturers are beginning to build cross-enterprise and cross-industry ecosystems for themselves. According to McKinsey (2017), in 2016, China spent almost US$200 billion (about 2% of GDP) on research and development. China graduates more than 1.2 million engineers from its universities each year, more than any other country. China has the highest number of patent applications in the world. The EU, US and UK patent offices (UK IP Office, 2013, 2014a, 2014b, 2014c) inevitably mention the growing share of Chinese patent applications when doing patent analyses of new technologies.

The United Kingdom, France, South Korea, Russia, Singapore, and Thailand have embraced the principles of Industry 4.0, rolling out strategic national blueprints to harness digital innovations for economic growth and development. Specifically, the UK and France have spearheaded digital transformation and industrial upgrades, South Korea and Russia have focused on smart manufacturing and autonomous technologies, while Singapore aims to lead in digital services and Thailand seeks international collaborations under its "Thailand 4.0" initiative.

Although Industry 4.0 policies have been developed in several countries, the concept has been criticised for a lack of clarity (Beier et al., 2020; Lasi et al., 2014; Oesterreich & Teuteberg, 2016). The main concept of Industry 4.0 lies in automating and digitally transforming the economy (Alcácer & Cruz-Machado, 2019; Oztemel & Gursev, 2020). Industry 4.0 is a transformative force that includes technologies such as additive manufacturing, artificial intelligence (AI), robotics, and sensing technologies. The World Economic Forum conducted a survey of over 800 executives and experts from related fields to compile their reports on digital transformation (World Economic Forum, 2015). The report claims that the number of robots used in manufacturing will increase to 2.4 million by 2018. In this way, implanted technologies are becoming a reality. Wearable internet devices, self-decision-making systems, autonomous problem solvers, and learning machines are just a few examples of the technology that has been impacted by this transformation. AI can learn from previous situations to provide future decision processes. 3D printing has the potential to create very complex products without the need for complex equipment. In other words, a single 3D printer will be able to do work that once required an entire factory to do and even create artificial organs. The availability of intelligent sensors makes it possible to connect literally anything to the Internet. It is expected that 1 trillion sensors will be used in human life by 2025. There is a high probability that more than 6 billion connected devices will proactively ask for support in 2018. Global spending on big data is assumed to be well over 200 billion dollars in 2020. There were 3.5 million working robots worldwide in 2021 (International Federation of Robotics, 2022a). By 2020, 59% of US manufacturers would use some sort of robotics technology (Oztemel & Gursev, 2020; World Economic Forum, 2015).

Among those technologies, the industrialisation and technological revolution led by automation and robotics technology is one of the defining factors of our current economic system. Precisely because of its fast diffusion and possible widespread impacts, automation has sparked several policy and academic debates, especially in terms of the economic impact these technologies have, especially on productivity (Bessen et al., 2020), labour markets (Acemoglu & Restrepo, 2020; Bessen et al., 2019; Filippi et al., 2023), trade and foreign direct investments (Stapleton & Webb, 2020; Yuan & Lu, 2023). Technology-induced unemployment is one of the main concerns associated with technology development. (Acemoglu & Restrepo, 2020; Brynjolfsson & McAfee, 2014; Cheng et al., 2019), which is already part of the truth and worries some workers. A report by PricewaterhouseCoopers estimates the proportion of existing jobs at high risk of automation by the 2030s to range from 20% to 25% in some East Asian countries and up to 30% in the United Kingdom (Hawksworth et al., 2018b). Frey and Osborne (2017) estimate that approximately 47% of total US employment is at high risk of computerisation by the early 2030s. Notably, Arntz et al. (2016) conducted similar research, obtaining a much lower estimate; they argue that only around 10% of jobs are vulnerable to job automation when the vulnerability of specific tasks is considered rather than the occupation as a whole. However, some scholars argue that new jobs are also created because of technological advancement to offset the disappearing jobs (Acemoglu & Restrepo, 2019; Autor & Salomons, 2018). The number of jobs that will be eliminated or created through automation remains undetermined, but research at its current stage does not provide much help to geographers and policymakers because of the perspectives (Cséfalvay, 2021).

Besides successfully adopting these technologies, the ability to develop new automation technologies is likely to play a fundamental role in the future. Investing and acquiring capabilities for developing crucial technologies is likely to provide considerable benefits, not only in terms of technological leadership and opportunities to shape the evolutionary trajectory of technologies (Freeman, 2002; Lundvall & Rikap, 2022), but more broadly in terms of participation in the global economy, competitiveness and diversification (Castellacci et al., 2020; Laffi & Boschma, 2022; Yuan & Lu, 2023).

1.1.2 Theoretical background

Economic Geography, the subfield of human geography that studies economic activity and factors affecting it, can also be considered as the intersection of spatial science and economics (Clark et al., 2003; Clark et al., 2018). It focuses on a variety of topics using different methods, including industries(Capasso et al., 2015; Frenken & Boschma, 2007), economics of agglomeration(Alumni et al., 2013; McCann, 2008; Ottaviano & Thisse, 2004), transportation(Gauthier, 1970; Lafourcade & Thisse, 2011; McCann, 2005), international trade(Grant, 1994; Krugman, 2000; McConnell, 1986), economic development(Gallup et al., 1999; Krugman, 1999), real estate(Aalbers, 2019), etc. As mentioned in the previous section, we are on the cusp of Industry 4.0, and theories and methodologies in Economic Geography that explore the mechanisms behind the distribution of industries, the concentration of economic power, and the spatial diffusion of innovation provide an indispensable tool for understanding the shifts brought about by this new industrial paradigm. The emerging landscape resulting from the convergence of technological advances is redefining the patterns of production, value creation and regional development. The way Economic Geography understanding spatial dynamics and economic activities is pivotal in revealing the complexities of Industry 4.0. It provides a lens through which the reshaping of the industrial landscape can be viewed, analysed, and contextualised within a broader narrative of economic evolution and regional transformation. This section explores different theoretical frameworks in the subfield of Economic Geography, highlighting their distinctive perspectives and methods, and subsequently explains their relevance to understanding the ongoing impact of Industry 4.0 on the global economic landscape.

Exploring the origins of a region's new industries has always been a central theme in economic geography (Scott, 1988; Walker & Storper, 1989). The study of this theme is crucial to understanding regional economic development patterns and promoting sustainable growth. Much of the early literature understands industrial development from a static perspective, relating it to the region's characteristics, such as institutional contexts (Rodríguez-Pose, 2013), localized learning capability (Maskell & Malmberg, 1999), and agglomeration externalities (Jacobs, 1969; Marshall, 1890). Such a theory is commonly known as traditional economic geography. This field has historically emphasised locational fundamentals and natural advantages (Ellison & Glaeser, 1997, 1999), setting the stage for understanding the initial distribution of industrial activities. It offers insights into the 'where' and 'why' of economic activities, presenting a geographical perspective on the economic landscape that is deeply rooted in physical space and tangible, measurable factors.

While traditional economic geography provides a foundation for understanding the spatial distribution of economic activities, New Economic Geography (NEG) presents a different perspective. Originating from economics, and integrating spatial effects, NEG offers an in-depth perspective on economic agglomeration and dispersion (Krugman, 1998, 1999, 2000), emphasising economies of scale and market dynamics (Krugman, 1991). It may be important to note, however, that NEG's analytical framework relies on a static framework and treats firms as the central unit of analysis, less on regional development, which limits its ability to provide a comprehensive understanding of the role of industrial clusters in regional economic development (Perrons, 2004). When exploring Industry 4.0, this limitation may lead to a lack of a comprehensive understanding of the interaction of Industry 4.0 technologies with the broader economic systems and global value chains. Therefore, while the NEG has contributed significantly to the understanding of spatial economic phenomena, its analytical framework needs to be further extended to include more dimensional economic and social factors in its application to explain and guide the development of Industry 4.0.

The "evolutionary turn" in economic geography has emerged in recent years, calling for a dynamic evolutionary perspective on the region's economic development (Boschma & Frenken, 2018; Boschma & Lambooy, 1999; Kogler, 2015). Evolutionary economic geography (EEG) theory emphasises cognitive proximity (or technological relatedness) between emerging industries and existing ones, as well as the impact of path dependence and the critical role of knowledge on economic systems. In the context of Industry 4.0, EEG offers an applicable framework for understanding the evolution of industries and regions, with particular emphasis on historical processes and the path-dependent nature of economic development. This aligns well with the rapid technological advancements and constant innovation that characterise Industry 4.0, making EEG an ideal theoretical framework for analysing the spatial distribution and development of industries in this new industrial era.

The differences between the theoretical perspectives of economic geography mainly lie in the ways of viewing the economic system and its focus. For example, in the case of studying the coal industry, traditional economic geography would focus on resource distribution and geographical location, while new economic geography emphasises spatial economic factors such as transportation networks and market size. In contrast, EEG focuses on the dynamics of innovation within the industry and the impact of the institutional context, such as the impact of the clean energy transition on the coal industry. These differences reflect theoretical development from static location factors to dynamic economic system evolution.

To summarise, EEG is particularly suitable for studying the context of Industry 4.0 because it emphasises the evolutionary process and path-dependent nature of economic development, which is closely linked to the rapid technological progress and continuous innovation that characterize Industry 4.0. Therefore, the selection of EEG as the main theoretical foundation of this study aims to provide an in-depth understanding of spatial distribution and industrial development in the era of Industry 4.0. This will involve scrutinising the interplay between technological innovation, regional development, and the broader economic and social context to better understand how these factors have collectively shaped the trajectory of Industry 4.0.

1.2 The context of China

This section scrutinises the historical economic development of China, with a particular emphasis on the inception and growth of its modern manufacturing sector. The seminal Reform and Opening Up in 1978 marked a major transition from a planned economy to a market economy in China. Not just a shift from an agriculture-oriented to a manufacturing-oriented economy, but, more profoundly, a fundamental reform of the economic system and the way the economy is managed (Lin, 2004). It was a transformation characterised by the liberalisation of trade policies, the establishment of special economic zones, and the encouragement of foreign direct investment (Huang, 2018). Consequently, China's manufacturing sector burgeoned, driven by an increasing amount of workforce and a strategic alignment of policies fostering industrial growth. This transition laid a solid foundation for the development of China's manufacturing sector and subsequent economic growth and became a key point in China's economic history (Liu, 2020).

Over the past 40 years, China has achieved remarkable economic success, developing into the world’s second-largest economy. Over the next four decades, following the Reform and Opening Up, China's economic output has expanded dramatically, with the overall economic volume in 2020 being 98 times that of 1978, boasting an average annual economic growth rate of 11.54%, and an average growth rate of per capita Gross National Product (GNP) of 10.51% (The World Bank Group). The value added by secondary industry in 2020 was 218.53 times that of 1978, with an average annual growth rate for the secondary industry's value-added standing at 13.68% (National Bureau of Statistics, 2023a). In 1978, China's economy was predominantly inward-orientated, with the ratio of total imports and exports to GNP being a mere 9.7% (Huang, 2018). In 2013, China surpassed the United States to become the largest goods trading nation globally. By 2020, China was the world's largest exporter and the second-largest importer. From a modest total trade value of 33.5 billion in 1978, China's total trade volume skyrocketed to 32.16 trillion yuan in 2020, 960 times larger than in 1978, with an impressive average annual growth rate of 17.76%, outpacing overall economic growth by 6 percentage points (National Bureau of Statistics, 2023b; National Development and Reform Commission, 2021). Such comprehensive transformation has been propelled by various structures, and a government-led focus on infrastructure development. During the boom years, manufacturing output witnessed double-digit growth rates, with China swiftly hinged on developing a diverse manufacturing base that span textiles, electronics, machinery, and automobiles, among other sectors.

Along with the reform and open up, China’s massive workforce paved the way for a higher economic growth rate until the 2008 global financial crisis. However, China’s traditional low-end, labour-intensive, and export-oriented production modes encountered a bottleneck following the financial crisis. Many export-oriented firms faced problems, such as dwindling orders, fierce market competition, increasing labour costs and labour shortages, and began to adopt robots to replace workers. The government started to introduce policies to encourage automation and improve the prospects of local manufacturers facing tough business conditions (Barbieri et al., 2012; Cheng et al., 2019; X. Li et al., 2019; Sharif & Huang, 2019), while promoting industrial transformation and upgrading, for instance, the “Replacing Humans with Machines” policy introduced by the Dongguan government. According to the field research of X. Li et al. (2019), the labour replacement rate in the Pearl River Delta is about 10%, while the “Replacing Humans with Machines” policy has led to the development of about 70 related industries in the region. As a result, robot adoption in China has maintained an annual growth rate of more than 30% since the early 2000s, as shown in Figure 1. In 2016, China became the world’s largest user of industrial robots, with nearly 350,000 units of industrial robots in use.

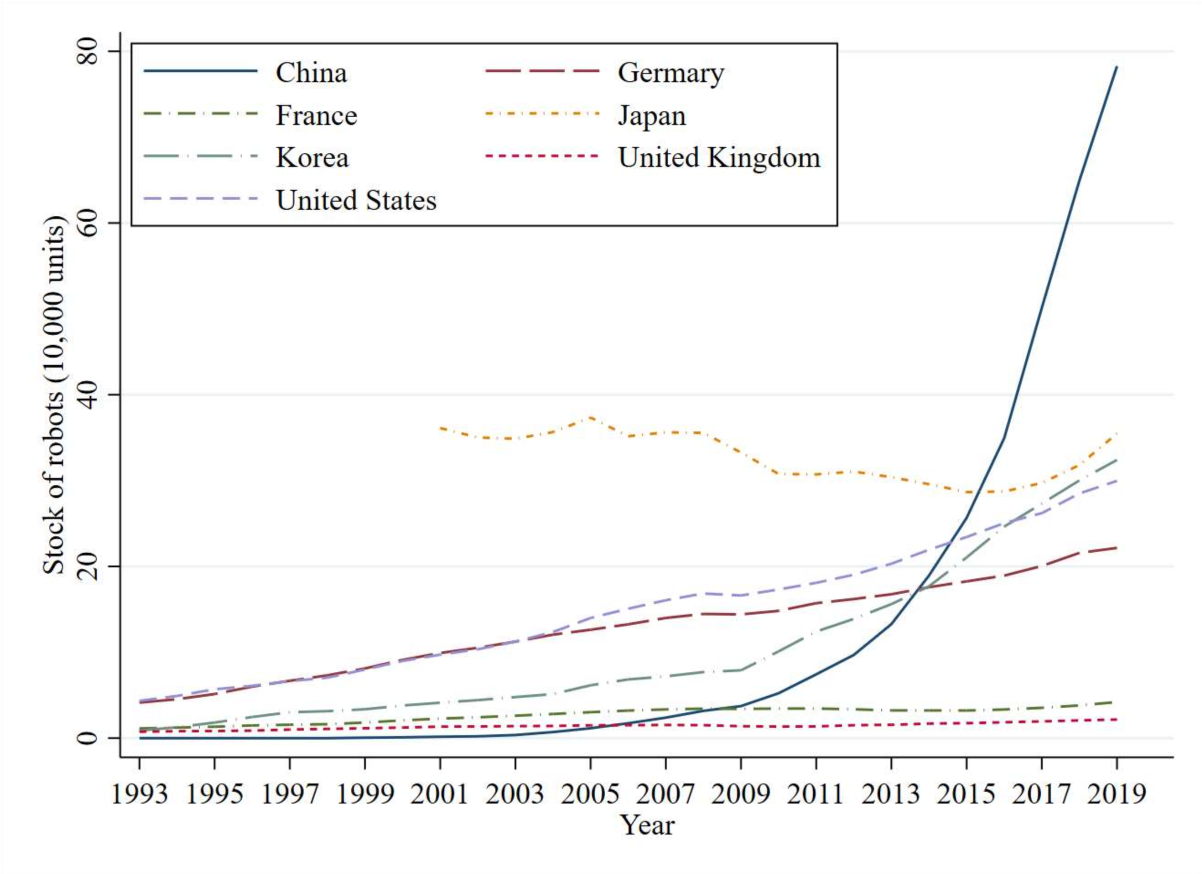


Figure 1.1 The stock of industrial robots in China and other developed countries from 1993 to 2019 (Data source: International Federation of Robotics (IFR))

Unlike developed countries such as the United States, Japan and Germany, which went through the process of production automation in the 1960s and 1970s, China must automate and upgrade its industry after completing industrialisation in just a few decades (Huang & Sharif, 2017), along with which is an emerging impact on the labour market. Studies have shown that the adoption of robotics and automation technologies to replace low-skilled workers can lead to a polarised labour market, thereby exacerbating the development of inadequate and uneven job markets, and increasing social inequality and instability (Zhou & Tyers, 2019). A study of the Chinese case may therefore provide another but valuable insight into the development of Industry 4.0 for other developing economies.

1.3 Research Aim and Objectives

This research is oriented towards achieving a comprehensive understanding of the transformative impacts of Industry 4.0 on China's economic and regional evolution. Its first objective is to analyse the diffusion and adoption of Industry 4.0 technologies within China, assessing factors like cognitive and geographical proximity in various cities. Additionally, the study aims to explore the impact of robot imports on local innovation in robotics, particularly focusing on the dynamics between imports and innovation capabilities. A significant part of the research is designed to examine the implications of automation, specifically the integration of industrial robots, on employment levels and housing markets in Chinese cities. This research will examine how automation influences local economies and societal structures, thereby providing insights into the broader economic impact of Industry 4.0 in China. This comprehensive research seeks to unravel the complex dynamics between technological advancements in Industry 4.0 and China's evolving economic geography, thus offering critical insights into the interplay between technological progress and socio-economic transformations in a rapidly evolving global context.

Building upon the overarching aim, each primary objective can be broken down into more detailed sub-objectives. The first primary objective assesses how cognitive and geographical factors influence the adoption of Industry 4.0 technologies across Chinese cities. It then analyses the interrelation between existing ICT technology and the development of novel Industry 4.0 technologies, exploring whether such a transition is path-dependent or a radical shift. It further evaluates the role of a local policy framework and the existing knowledge base in facilitating the integration of advanced technologies. This objective is integral to understanding the dynamics of Industry 4.0’s implementation in China, offering valuable insights for policymakers and industrial stakeholders navigating this technological evolution.

The second primary objective is to explore the effects of robot imports on local innovation within China's robotics sector. This objective includes investigating how robot imports directly influence the development of new robotics technologies, thereby contributing to the understanding of technological transfer and adaptation. The research will analyse the role of trade linkages in enhancing innovation capabilities, assessing how external trade relationships facilitate local technological advancements. It will also determine how the effects of robot imports vary across different economic strata, specifically between broader city-industry frameworks and more focused enterprise-level impacts. Moreover, the study will evaluate the interplay between external factors like imports and internal dynamics such as R&D and FDI, offering insights into the complexities of innovation dynamics in the robotics sector across

China. These sub-objectives collectively aim to unravel the complex relationship between global technological trends and China's local innovation systems.

The third primary objective aims to examine the relationship between automation and employment in Chinese cities, with a specific focus on how industrial externality shapes this relationship. The sub-objectives include: (1) quantifying the direct correlation between the adoption of industrial robots and local employment rates, thereby confirming the inverse relationship posited by existing literature; (2) probing into how different industrial structures-specifically related and unrelated varieties—mediate the impact of robotics on the labour market, with a hypothesis that related variety intensifies employment declines more than unrelated variety; (3) evaluating whether industrial specialization within cities serves as a buffer against the potential adverse effects of automation on employment levels; (4) investigating the spatial spillover effects of automation, examining if the employment consequences in one city have cascading impacts on neighbouring regions, and determining whether these effects are modulated by the cities' economic ties and stages of development; and (5) examining the degree to which the industrial structure's moderating effects on employment are localised, assessing the presence or absence of broader regional influences.

The fourth primary objective investigates the relationship between automation, specifically the installation of industrial robots, and housing prices in China, including examining their fluctuation patterns and underlying mechanisms. The sub-objectives include: (1) assessing the direct correlation between automation (via industrial robot installation) and housing prices in Chinese cities; (2) investigating how automation influences the housing market through its effects on local labour markets; (3) evaluating the spillover impact of robot installation on housing prices in neighbouring cities using dynamic spatial panel models and developing an asymmetric geographical-economic weight matrix to better understand spatial relationships between cities. These sub-objectives aim to provide a comprehensive understanding of how automation, as a facet of technological advancement, is influencing housing markets in China, and potentially offer insights into the effects of automation in other developing economies.

1.4 Chapter Layout

This thesis is structured to provide a comprehensive exploration of the impacts of Industry 4.0 (I4.0) technologies and automation in China, exploring various domains such as technological development, urban employment, and the housing market. Each chapter serves a distinct purpose within the broader context of the study, systematically building towards a cohesive understanding of the subject. Here we outline the layout of the four main chapters to achieve the four primary research objectives:

Literature Review and Research Framework (Chapter 2): This chapter serves to establish the theoretical and conceptual framework of the thesis. It systematically reviews existing literature, examining the diverse research on Industry 4.0 and developing a robust research framework. The framework is designed to guide the investigation across the subsequent chapters.

Knowledge Base and Technological Development (Chapter 3): This chapter is designed to explore the first primary objective. The research begins by examining how the knowledge base of cities influences the development of I4.0 technologies in China. This part establishes a foundational understanding of the technological landscape, emphasising the importance of a city's existing technological infrastructure and its relatedness to the evolution towards I4.0.

Imports of Technology and Innovation (Chapter 4): This section, aiming to address the second primary objective, expands on the technological theme by exploring whether countries can bridge technological gaps through imports to foster innovation. The focus on China as a developing economy engaging with global technological trends provides a segue from the local (city-level) technological base to a more global perspective, considering the role of imports, R&D, and foreign direct investment (FDI) in fostering local innovation.

Impact of Automation on Employment (Chapter 5): The third primary objective is tackled in this chapter. Shifting from technological development to socio-economic impacts, the study analyses the effect of industrial robots on employment in Chinese cities. This section connects the adoption of advanced technologies (as explored in the previous parts) with its tangible impacts on the labour market, a critical aspect of urban and economic development.

Automation and the Housing Market (Chapter 6): Finally, we explore an often-overlooked aspect of automation's impact: the housing market, with reference to the fourth primary objective. By linking the adoption of automation technologies with changes in housing prices, this part offers a unique perspective on how technological advancements can ripple through various sectors of the economy, extending the discussion from the labour market to broader economic effects.

In the final chapter, we systematically summarize the major findings from each chapter, draw conclusions, and discuss the implications of our study for policymakers, industry stakeholders, and future research directions. The research in these chapters is designed not only to answer the research questions posed at the outset of this thesis but also to illuminate the various impacts of automation in a rapidly evolving global economy. Furthermore, the chapter elaborates on the contribution of this study to existing knowledge, underscoring how our findings enhance or challenge the current understanding. We also critically examine the limitations of our research, acknowledging the constraints and potential areas of uncertainty. This introspection sets the stage for outlining future research directions, proposing avenues for subsequent studies to build upon, expand, or refine the work presented in this thesis.

1.5 Significance of the Research

This research provides both theoretical and practical significance. From a theoretical perspective, it contributes to the existing literature in several ways. First, the research applies the evolutionary economic geography research framework to the context of China by analysing the diffusion and adoption of Industry 4.0 technologies across Chinese cities, contributing to the knowledge of how cognitive and geographical proximity influence technology uptake. The research poses critical questions about whether the progression to Industry 4.0 is evolutionary or revolutionary, especially in the context of China, which has a unique trajectory in industrialisation. Secondly, the research explores the relationship between robot imports and local innovation in China under the evolutionary economic geography framework. The discussion about the role of trade linkages in developing capabilities for innovation in automation forms arguments and hypotheses regarding the impact of imports on innovation. The research offers a detailed understanding of innovation dynamics within China's context to the extension of existing literature. Third, the study contributes to the theoretical understanding of the intersection between automation and urban labour markets. The exploration of how a city's industrial externality moderates the impacts of automation on employment addresses theoretical questions and expands the discourse in economic geography and labour economics. The identification of spatial spillover effects and the mediating role of industrial structure on employment enhances the understanding of regional science and inter-city economic studies. Last but not least, the study extends the impact of automation from labour markets to the housing market. It shifts the traditional focus from employment patterns, skill polarization, and income disparity to explore how automation influences living expenses and housing markets, providing a fresh perspective on the broader socio-economic impacts of automation.

In terms of the practical implications, the findings of this research have some implications for regional and national planners as well. Firstly, it shifts the focus from specific technologies to the roles regions and cities play in the transition to Industry 4.0, providing insights into regional policy-making and urban planning, which are actionable and grounded in real-world applications. Secondly, the examination of how robot imports influence innovation at both city-industry (macro) and enterprise (micro) levels involves a detailed, data-driven investigation into real-world adaptation and learning processes. Unravelling the role of external trade linkages and internal factors like R&D and FDI in shaping innovation trajectories, especially in strategic sectors like robotics impact real-world innovation paths. Thirdly, the study's robust evidence demonstrating the adoption of industrial robots across Chinese cities and its empirical validation of the relationship between automation and employment can guide governmental policy designers in shaping strategies for workforce development and economic planning. By understanding the specific impacts of automation in various urban contexts, policymakers can better anticipate changes in the labour market and devise targeted interventions to support sectors and regions most affected by automation. This could involve re-skilling initiatives, incentives for industries to balance automation with job creation, or urban development policies that integrate technological advancements with sustainable employment opportunities. Lastly, the study provides important practical insights into how automated processes may inadvertently increase the costs of living for displaced workers. This finding can inform policymakers and housing market analysts about the secondary effects of automation, potentially guiding policy decisions and strategies to mitigate these challenges.

CHAPTER2. LITERATURE REVIEW

This chapter critically examines current literature relevant to the geography of Industry 4.0, its entry into the technological portfolio of a city/region, and its subsequent impacts on labour and housing markets. The review is scoped to encompass studies that explore these themes within the context of both developed and developing economies, with a particular focus on China's unique experience. By setting these boundaries, this chapter aims to provide a comprehensive understanding of the research subject of the thesis and further lay a foundation for the research foundation for the empirical studies in the following chapters.

2.1 Geography of Industry 4.0

There is widespread agreement around the emergence of Industry 4.0 will boost competitiveness and innovation across regions through the integration of new value-adding technologies into extant manufacturing activities, which marks a pivotal shift in the global manufacturing landscape (Bailey & De Propris, 2019; Klitou et al., 2017b; Lafuente et al., 2019). Central to the transformation are a group of seemingly interrelated technologies such as Robotics, 3D printing, big data and the Internet of Things, collectively steering the progression of the "Fourth Industrial Revolution" (Kagermann et al., 2013; Martinelli et al., 2021; Schwab, 2017). Despite the advancements of the technologies, emerging research underscores a significant challenge: the geographical unevenness in the distribution of Industry 4.0 initiatives, particularly evident across European regions (Muscio & Ciffolilli, 2020; Oztemel & Gursev, 2020).

The theory of EEG, particularly its core concept of path dependence, vividly illustrates regional development dynamics (Boschma & Iammarino, 2009; Boschma et al., 2012; Frenken et al., 2007), which can also explain the current uneven geographical distribution of Industry 4.0. From an evolutionary perspective, the innovative output of a region is dependent on exchanges and recombination among local pre-existing knowledge bases, leading to a path-dependent and place-dependent trajectory of cumulated technological change(Bellandi et al., 2018; Dosi, 1982; Martin & Sunley, 2006). As metaphorically described by Hidalgo and Hausmann (2009), regional development can be likened to a monkey(firm) jumping around an industry forest (an industry space), where each tree represents an industry. Monkeys are struggling to jump from a poorer part of the forest with little fruits to a richer part. However, the density of trees in this forest is heterogeneous and the distance the monkey can jump to is limited. This implies that (i) a region can only jump to a new industry that is related to the existing industries and (ii) monkeys in the density area are more likely to jump to other areas. This implies that developed countries/regions with core industries in the uneven industry space are more capable of developing new related industries but less-developed countries/regions with peripheral industries are more difficult to diversify and locked in the original less value-added industries (Boschma et al., 2012, 2013; Neffke & Henning, 2013). This metaphor effectively encapsulates the basic idea of the relatedness framework (Boschma, 2017; Hidalgo et al., 2018), which is instrumental in understanding the patterns and potentials of regions to diversify into new industries and technologies (P. A. Balland & R. Boschma, 2021). Rigby (2012) applied the concept of knowledge relatedness to understand how technological diversification and abandonment in US cities are evolving using patent data and patent citations. It shows that technological evolution in cities, influenced by their existing specializations and the cognitive proximity of new technological possibilities. The theoretical framework is further supported by empirical studies demonstrating that both the rise and fall of technological knowledge are conditioned by a city's existing technological base. (Balland et al., 2019; Boschma et al., 2015; Kogler et al., 2013). Boschma et al. (2023) analyse data from 277 European regions from 1981 to 2010, highlighting that breakthrough inventions typically combine related technologies, and regions are more likely to produce breakthroughs closely linked to their existing knowledge base.

Apart from where the monkeys stands, the distance that the monkey can jump is also very important, in another word, the proximity to the new industry. Boschma (2005) points out the necessity of some form of proximity as a precondition for successful knowledge flows and interactions. Proximity, as Huber (2012) describes, referring to the degree of closeness of actors. In the field of innovation, cognitive proximity, which Wuyts et al. (2005) define as similarity in perception, interpretation, understanding, and evaluation of the words, is particularly critical. However, Boschma and Frenken (2010) caution against the 'proximity paradox,' where excessive proximity might hinder rather than foster innovation. In an exploration of the adoption and dissemination of rDNA technology in the U.S., Feldman et al. (2015) demonstrate that the spread of leading-edge technologies in metropolitan areas is largely influenced by social, cognitive, and geographical proximity. This finding is echoed in the work of Laffi and Boschma (2022), who extend the issue to examine the regional and spatial dynamics of Industry

4.0. As pointed out by their research, the emerging 4.0 technologies are a blend of advanced 3.0 technologies with other domain-specific technologies, but there is a discontinuity between them and the 3.0 technologies.They find regions specialising in Industry 3.0 technologies have a higher likelihood of developing Industry 4.0 technologies, illustrating the importance of a pre-existing technological base and also pointing out the relatedness between Industry 3.0 technologies and Industry 4.0 technologies. However, Boschma (2005) claims that geographical proximity to other places is neither necessary nor sufficient for learning, suggesting that other forms of proximity, particularly cognitive, play a more significant role in the diffusion and adoption of new technologies.

While the concept of proximity traditionally focuses on the relationships between actors within a single region and its contribution to the adoption of new technologies, the influence of interregional linkages on such innovative activities remains less explored and understood (P.-A. Balland & R. Boschma, 2021). In the existing literature, such as Boschma (2017) and Whittle et al. (2020), the focus is largely on regional capabilities without considering how interregional linkages play a role. Literature on new path development also shows a similar trend (Trippl et al., 2018). However, transitioning to a broader perspective, the role of external factors, such as foreign goods and technologies, has historically been instrumental in shaping national development, whether through imports or foreign investments (Grossman & Helpman, 1991; Keller, 2002; Keller & Yeaple, 2009). The concept of interregional linkage aligns with the idea of path dependence, as outlined by Martin and Sunley (2006), suggesting that regions or countries lagging in technology development may struggle to build the necessary skills and capacities for cutting-edge technologies. However, these historical insights also point towards a significant opportunity: by actively investing in and embracing new technologies, regions can overcome its poor knowledge base, leveraging both internal and external linkages to catalyse technological and economic growth.

Empirical studies enrich the exploration of Industry 4.0 technologies and their adoption across Europe. P. A. Balland and R. Boschma (2021) use OECD-REGPAT data to examine Industry 4.0 technologies in Europe, finding that such technologies often reside at the knowledge space' periphery. Regions with a higher potential for I4T-related technologies between 2002 and 2016 demonstrated a greater likelihood of successful diversification into new I4Ts. This trend underscores the importance of a region's existing technological base in adopting Industry 4.0

innovations. Interestingly, the classification of Industry 4.0 technologies varies across different studies. The classification of P. A. Balland and R. Boschma (2021) includes additive manufacturing, AI, augmented reality, autonomous robots and vehicles, cloud computing, cybersecurity, machine tools, quantum computers, and system integration. This broad categorization goes beyond the general understanding of digitalization of manufacturing, expanding the understanding of Industry 4.0's scope.

Corradini et al. (2021) using patent data across European regions reveal the significance of regional absorptive capacity, cognitive, and spatial proximity in driving the flow of Industry 4.0 knowledge. Their findings highlight variations among four different Industry 4.0 technologies, with Robot and 3D Printing showing a stronger influence from cumulated technological capabilities and spatial proximity, in contrast to Big Data and IoT, which are more spatially dispersed. The spatial dynamics of these technologies are not just academically intriguing but are also crucial in understanding how regions can leverage these advancements to stimulate economic growth and undergo radical technological transformation (Evangelista et al., 2018; Hervas-Oliver et al., 2019).

When narrowing down the focus to the automation technologies only, the geography dynamics of the robotics technologies remains a major concern. The current economic system is characterised by rapid advancements in automation technologies, particularly in manufacturing, which sparks debate regarding their economic impacts (Acemoglu & Restrepo, 2020; Bessen et al., 2020; Filippi et al., 2023). Such novel technologies may reduce jobs for unskilled workers in emerging economies, but the impact remains unclear (Calì & Presidente, 2022; Diao et al., 2021; Nayyar & Hallward-Driemeier, 2018). The integration of automation and digitalisation into industrial manufacturing processes is reshaping production methods (Corradini et al., 2021; De Propris & Bailey, 2020; Martinelli et al., 2021).

The ability to develop new automation technologies plays a fundamental role in future economic competitiveness and technological leadership (Castellacci et al., 2020; Lundvall & Rikap, 2022). Historically, introducing foreign goods and technologies – either obtained through imports or foreign investments (Grossman & Helpman, 1991; Keller, 2002; Keller & Yeaple, 2009) - has been instrumental in the industrial development of nations. Empirically, various scholars have shown the crucial role of foreign direct investments and trade relations in technological diffusion and upgrading (Chen et al., 2017; Crescenzi et al., 2022). Existing studies (Ciffolilli & Muscio, 2018; Corradini et al., 2021; Laffi & Lenzi, 2023), mostly focused on advanced countries and regions, show the geography of automation and Industry 4.0 technologies is rather spatially concentrated. Other scholars highlights the importance of early adoption and pre-existing capabilities (Bloom et al., 2020; Laffi & Boschma, 2022; Xiao & Boschma, 2022). Overall, these contributions provide evidence consistent with idea of path dependence(Martin & Sunley, 2006), possibly related to high entry barriers and requirement of specific capabilities.

2.2 Industry 4.0 and its impact

Technological progress, as a key catalyst for enhancing production efficiency and spurring economic growth, has been widely discussed since Schumpeter highlighted the importance of innovation in economic cycles(Giersch, 1984; Schumpeter & Opie, 1934). Numerous studies confirm Schumpeter's insight that technological advancements have positive economic impacts. Globally, the IT industry has played a significant role in driving the third wave of economic growth (Aker & Mbiti, 2010; Arora & Athreye, 2002; Lazonick, 2004). The current wave towards the fourth technological paradigm

Although auto-replacement has manifested its effects in several arenas, scholars primarily focus on the labour market as the primary and most immediate area of impact (Acemoglu, 2002; Murphy et al., 1998), often overlooking its significant influence beyond this realm. In their study, Acemoglu and Restrepo (2019) demonstrate that as automation intensity increases, new tasks are less likely to be created, thereby reducing the demand for human labour. This conclusion is supported by a number of studies, which collectively highlight the detrimental impact of job automation on employment, wages, and productivity (Acemoglu & Restrepo, 2019, 2020; Autor & Salomons, 2018; Dauth et al., 2017; Dottori, 2021). Autor et al. (2003) suggest that the issue goes beyond skill levels and also considers tasks performed by workers from the "machine's point of view." According to their findings, automation mainly replaces routine-intensive jobs like clerical work while creating non-routine-intensive jobs that require abstract and manual labour. Building on the theory upon Autor et al. (2003), automation has two main effects on the labour market: Firstly, there is a shift in labour composition, with mid-skilled workers, typically engaged in routine-intensive tasks, being displaced. They are either rarely upgraded to high-skilled jobs or predominantly downgraded to low-skilled positions, leading to "skill polarization" in the labour market (Autor & Dorn, 2013; Gallie, 1991; Goos

& Manning, 2007). Secondly, the wage structure in the labour market undergoes a change. With the reduction in mid-skilled jobs and high barriers to high-skilled employment, displaced workers are often relegated to lower-paying, low-skilled jobs. Concurrently, the creation of more high-skilled jobs and the enhancement of skill premiums contribute to significant wage inequality, as documented in recent studies (Hémous & Olsen, 2022; Kaltenberg & Foster-McGregor, 2020; Prettner & Strulik, 2020).

Current studies examine the risk of exposure to automation and robotics technology at the occupational or national level, and little attention has been paid to the urban labour market. Similar to countries affected by automation performs differently, the impact of automation on the urban labour market varies from city to city (H. C. Chen et al., 2022; Frank et al., 2018). The heterogeneity and segmentation of cities can lead to differences in response to automation, as the industrial structure of different cities affects the factors that influence the installation of robotics technologies, the latter falling into three main categories: cost, technology and market (Bank, 2018; Li et al., 2020). Studies on US cities (Frank et al., 2018) and Swedish cities (Czaller et al., 2021) find that small cities are more susceptible to automation than large cities, as large cities house occupations less susceptible to automation, which requires stronger managerial and technical professions. Despite the burgeoning interest in the implications of automation on employment, there exists a geographic skewness in research: most of the research on job automation and robotics technology has mostly focused on developed countries, such as the United States (Autor & Salomons, 2018), Germany (Dauth et al., 2017) and Italy (Dottori, 2021). However, the varying degrees to which countries are affected by job automation and robotics technology are directly related to their industrial structure (Frank et al., 2018): developed countries are more involved in service industries; whereas developing economies have more routine, repetitive and low-skilled tasks that are often considered to be at high risk of automation and robotics technology.

As a result, recent studies have extensively documented the impact of industrial robot adoption (as a proxy of automation) on the labour market, resulting in the displacement or reinstatement of certain industries and occupations (Acemoglu & Restrepo, 2020; Dauth et al., 2017; De Vries et al., 2020; Graetz & Michaels, 2018; Hawksworth et al., 2018a; Qin et al., 2022), as well as adjustments in other aspects of the labour market (Damiani et al., 2023; Wang et al., 2022). However, while this literature has flourished considerably, there is still limited discussion on how these economic and labour market consequences spill over into other broader sectors of the economy.

2.3 Chapter Summary

The Chinese Academy of Engineering, when they planned the "Made in China 2025," analysed global manufacturing development. They assessed manufacturing strength of different countries and categorising them into three groups. The U.S. leads, followed by Germany and Japan, with the U.K., France, South Korea, and China in the third group. China is still in the process of developing Industrial 2.0 (mechanized manufacturing) and 3.0 (automation), but now faces an even greater challenge in transitioning to Industrial 4.0 (integration of automation and IT) (Yu, 2014). Despite progress in computer and information technologies, challenges remain in high-end technology development, indicating an ongoing journey into China's Industrial 3.0 phase. The country has already begun moving into an era of Industrial 4.0. In light of the existing studies that reveal the relationship between the urban knowledge bases and the relationship between industry 3.0 and 4.0 technologies and considering China's unique trajectory of entering the 4.0 era while still coping with the challenges of completing industry 3.0, a critical inquiry emerges. Accordingly, we must examine whether the transition to Industry 4.0 adheres to a path-dependent evolution, following a sequential progression from 3.0 to 4.0, or if it can be a more radical, disruptive shift, enabling discrete technological leaps.

Building on the understanding of Industry 4.0's nature and progression, the second area of this research shifts focus to the external factors influencing technological innovation, specifically in technologically lagging countries. The focus initially spans various Industry 4.0 technologies, recognising that each is influenced by different factors. Subsequently, the research narrows to specifically explore industrial robotics, a critical subset of Industry 4.0 technologies. It aims to understand if these countries can effectively learn from and innovate based on technologies acquired from more advanced nations. This is especially important for cities with weaker knowledge bases, where the challenge lies in breaking free from existing path dependencies to pave the way for innovation and growth in the realm of Industry 4.0. These considerations bring us to the first two research questions of this thesis:

Q1: Is the transition from Industry 3.0 to 4.0 in China a path-dependent evolutionary process, or a more radical and disruptive shift enabling distinct technological advancements?

Additionally, what factors influence the diffusion and adoption of Industry 4.0 technologies across various Chinese cities?

Q2: Can technologically lagging countries effectively learn from imported products and subsequently foster Industry 4.0-related innovations?

Following an exploration of factors influencing the emergence and spread of Industry 4.0, the researchers are now examining their broader impacts. Cities are becoming hubs for the development of robotics and automation technologies, transforming a variety of sectors and having an impact on economic and social life in numerous ways (Macrorie et al., 2021). Despite mixed results in research on automation and robotics technology's impact on employment, most findings suggest negative consequences. It is clear from previous research that cities facing automation have varying degrees of vulnerability and resilience. However, the exact dynamics of how diversity and specialization factor into this equation remain largely unknown. The third research question arises from this gap:

Q3: How do factors of diversity and specialisation shape a city's capacity to integrate and adopt automation technologies?

In the current academic landscape, the focus is primarily on the impact of automation on the labour market. In contrast, the impact of automation on other markets, notably the housing market, is much less frequently explored. In light of the dual nature of the housing market as a commodity and an asset, as well as the substantial economic impact of new technologies, this oversight is particularly striking. This leads to the last research question:

Q4: How does automation influence housing prices, and what are the underlying mechanisms driving this relationship?

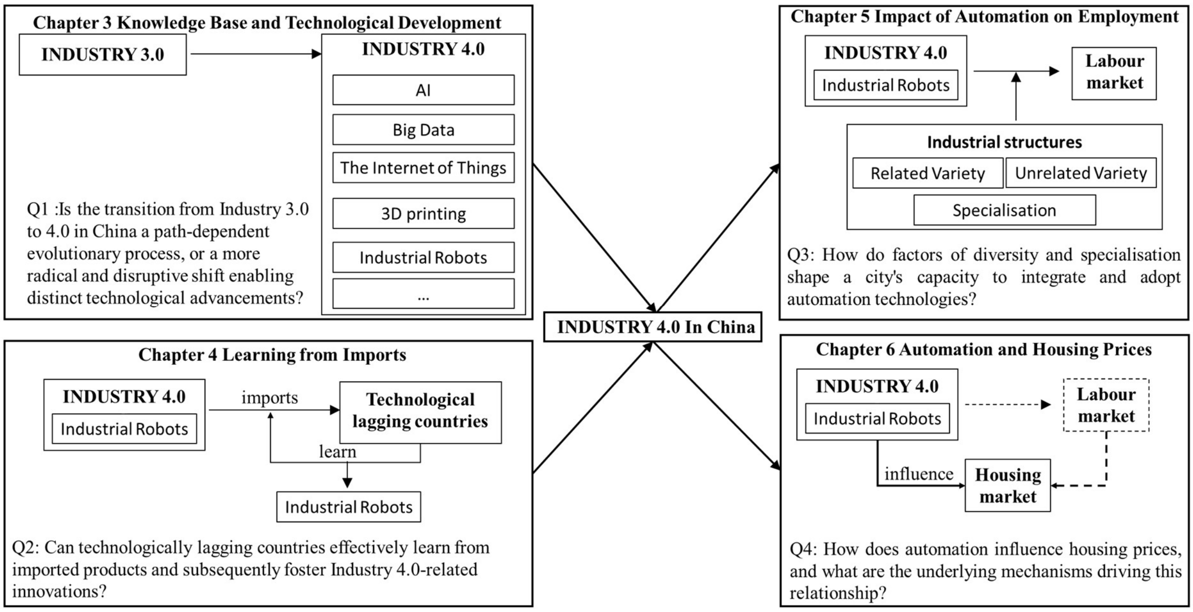


Figure 2.1 Research Framework

CHAPTER3. THE TRANSFORMATION OF CHINA'S ECONOMY FROM INDUSTRY 3.0 TO INDUSTRY 4.0.

3.1 Introduction

Knowledge production and innovation and the geographical pattern have always been a concern for European and American scholars alike (Asheim et al., 2011; Bonvillian, 2013; Boschma et al., 2015; Castaldi et al., 2015). Due to the growing popularity of Industry 4.0, geographical studies on Industry 4.0 and the technologies associated with it have developed in recent years as well (P. A. Balland & R. Boschma, 2021; Corradini et al., 2021). As a consequence, regional studies scholars and geographers have shifted their focus from the analysis of specific technologies to the analysis of the role that regions and cities play in this change: how they contribute to the process of change and how they are embedded in this era of change (De Propris & Bailey, 2020).

After mechanisation (Industry 1.0), mass production (Industry 2.0) and automation (Industry 3.0), the fourth industrial revolution is now characterised by "intelligence" (Lasi et al., 2014). Under this standard, China's manufacturing sector is still in the process of "making up for 2.0, popularizing 3.0, and developing towards 4.0". In this context, this chapter aims to solve the question: is the emergence of the 4.0 paradigm still a path-dependent process in achieving an evolution from 3.0 to 4.0, or is it a more radical and disruptive revolution where discrete leaps can be achieved? Industrial 3.0 had already been achieved prior to entering the 4.0 era in most developed countries; however, in China, which has only entered the industrial stage in the last few decades, the 3.0 and 4.0 technologies do not have separate development phases, which can be used to determine if it is a path-dependent or a path-breaking advancement.

To answer this question, we first need to test the applicability of the framework of evolutionary economic geography by analysing the role of cognitive proximity and geographical proximity in the diffusion and adoption of I4.0 across Chinese cities. To the best of my knowledge, no studies have examined the underlying assumptions that technological relatedness and geographical proximity contribute to technology entry into cities in the Chinese context. Therefore, this chapter first tests the relatedness framework by analysing the relationship between the ability of Chinese prefecture-level cities to develop new 4.0 technologies and the set of technologies that already exist in cities from 1991 to 2020. Data are obtained from the State Intellectual Property Office of the People's Republic of China (SIPO), including information on the applicant's name, the application's location, and the type of technology. We first determine their technological and geographical relatedness and then estimate them by a three-way linear probability ordinary least squares regression (OLS). The results are in line with the findings of all previous studies in other countries that have demonstrated technological relatedness at the city level, and the city's spatial proximity to other cities with relative comparative advantage is a significant driving force for Chinese cities to diversify into I4.0 technologies over the past 30 years. Based on this, we further demonstrate whether the development of I3.0 technologies is related to the development of I4.0 technologies. Finally, we test whether these effects vary across different categories of technologies. The results are robust to variations in model structure and to concerns about endogeneity.

3.2 Literature Review and Analytical framework

Studies regarding regional innovation systems have tended to emphasise the importance of localized capabilities in the production and transmission of knowledge, and this has been a dominant feature of the literature on these systems(Asheim et al., 2011; Asheim & Coenen, 2005; Zhu et al., 2019). However, the evolutionary perspective of economic geography provides a useful framework for the interrelation between space-place and time(Schamp, 2008). Evolutionary economic geography uses path dependence to explain how past choices can influence future inventions, designs, and practices - technologies embedded in machinery and product design and firm assets acquired through patents, skills, or competencies(Martin & Sunley, 2006; Walker, 2017). It does not imply a rigid succession determined by technology and the past. Instead, it implies a roadmap in which one established direction is easier to steer than another and more difficult to reverse across the board. As such, the cumulated technological capabilities of a place can be seen as a predictor of the region's ability to generate new technologies(Cohen & Levinthal, 1990; Giuliani, 2005).

In recent years, there seems to be more empirical research advancing the concept of path dependence using the concept of relatedness proposed by Hidalgo et al. (2007) to understand the process of diversification in countries and regions as a whole, for instance, the industrial development of regions (Boschma & Iammarino, 2009; Boschma et al., 2012; Frenken et al., 2007). The concept of knowledge relatedness is later applied to understand how technological diversification and abandonment in US cities are evolving using patent data and patent citations (Rigby, 2012). They find that the diversification of technology in cities is influenced both by their current practices and by the proximity of new technological possibilities to the existing specializations in the city. In other words, the rise and fall of technological knowledge are conditioned by the existing technological knowledge base in cities(Balland et al., 2019; Boschma et al., 2015; Kogler et al., 2013). Building on these foundations, some scholars have delved into the role of relatedness for specific categories of technologies. For instance, Feldman et al. (2015) explore the geography of adoption and dissemination of a leading-edge technology, rDNA technology, after its introduction in the market. They demonstrate the spread of this technology across US metropolitan areas was largely influenced by factors such as social, cognitive and geographical proximity. However, the impact of geographical proximity on interactive learning and innovation is controversial. Boschma (2005) claims that geographical proximity to other places is neither necessary nor sufficient for learning to take place. While this might hold true, a number of studies have found that proximity to other cities specialising in particular technologies could affect their ability to exploit knowledge spillovers.

Entering the era of Industry 4.0, the location and organization of manufacturing activities within value chains(Strange & Zucchella, 2017), as well as the geography of knowledge production (Ciffolilli & Muscio, 2018; Corradini et al., 2021; Patentamt et al., 2017), will be changed. Yet, little is known about the geographical distribution of I4.0, including the factors determining the readiness of a region to embed I4.0 technologies and the potential differences between I4.0 technologies of different types (Corradini et al., 2021; De Propris & Bailey, 2020). The study by Corradini et al. (2021) examines Industry 4.0's uneven spatial distribution in terms of region-specific factors and technology-specific factors. It is confirmed that regional absorptive capacity, cognitive capability, and spatial proximity are key factors influencing I4.0 knowledge flows, but they are distinct in significant ways when compared to each other. Following the relatedness framework, P. A. Balland and R. Boschma (2021) identify the future Industry 4.0 technology (I4T) centres of knowledge production in Europe. Still, some believe that Industry 4.0 technologies incorporate technologies from the Industry 3.0 paradigms with others from specific application areas. Without ICT technology from the third technological revolution, the current new technologies would not have been possible. This would mean that 3.0 technologies have not been improved significantly in a discrete manner, though that doesn't mean they haven't resulted in radical changes in new areas of application(Liao et al., 2017; Lu, 2017). A significant debate has taken place in the system change literature related to technological change concerning continuity and disruption between the third and fourth technological revolutions. Laffi and Boschma (2022) extend the issue further from a regional and spatial perspective, where they examine further how regional knowledge bases in Industry 3.0 contribute to the fostering of new technologies in Industry 4.0 across European regions. Their study shows that the probability of developing 4.0 technologies is higher in those regions that specialise in Industry 3.0 technologies.

Existing research focusing on the geography of Industry 4.0 has been concentrated in Europe. Turning to research regarding innovation in China, Andersson et al. (2014) study the geography of Chinese science and reveals its monocentric patterns regarding its scientific output. Scherngell and Hu (2011) investigated collaborative knowledge production in China from a regional perspective using Chinese scientific publications in 2007, with multiple authors' addresses coming from the China National Knowledge Infrastructure (CNKI) database. The study's findings indicate that geographical space hinders cross-regional collaborations in China. Technology proximity is more important than geography, and economic effects only play a minor role. However, their study used only one year of data, a relatively short time span, and their study used a gravity model rather than the theoretical framework of evolutionary economic geography.

According to these insights, we propose our research framework that the capacity of a Chinese city to develop its specialization in an Industry 4.0 technology depends on the knowledge base of that city, which is determined by its technological proximity to the specific Industry 4.0 technology and its geographical proximity to other cities that specialise in the specific technology. Although some consider the fourth industrial revolution to be a major technological change, the Industry 4.0 technologies still appear to incorporate ICT technologies with other fields of knowledge. For instance, the interaction systems of the industrial robots rely on information technology to communicate and interact with the external environment, while the other branch of the Industry 3.0 technology, the automated business equipment technologies, are not the basis for these Industry 4.0 technologies and therefore do not contribute significantly to their development. We, therefore, suggest that the technological development of Industry 4.0 is not a discrete jump: technology on Industry 3.0, in particular, ICT technologies, contributes to the development of Industry 4.0 technology. As the different categories of Industry 4.0

technologies have different characteristics, such as big data relying on the Internet and data mining; robotics, the IoTs and 3D Printing are highly related to manufacturing systems, we argue that when examining each sub-technology, the impact of the geographic proximity and Industry 3.0 technologies varies. However, the technological knowledge base of cities still matters significantly.

3.3 Data and methodology

Patent data is often used for research on innovation. The data employed in this study is extracted from the State of the Intellectual Property Office of the People's Republic of China (SIPO) from 2001 to 2020 with the information of applicant name, location dates of application, technology type, etc. There are three types of patents in the Chinese system: invention patent, utility models and design. An invention patent is analogous to patent rights in developed countries, as it requires the highest technological content among the three types of patents. Therefore, we use only invention patent information for our analysis. It is important to note that we are using patent filing records rather than patent grant records, as it takes a long time from filing to grant, typically over a year. The filing date is, therefore, more representative of when the technology emerged.

The first empirical challenge is to identify the Industry 4.0 technologies. The International Patent Classification (IPC) and the Cooperative Patent Classification (CPC) are two classification schemes that group inventions according to technological fields. There are studies that have listed detailed CPC codes to identify Industry 4.0 technologies (Martinelli, Mina, & Moggi, 2021; Patentamt et al., 2017). But the data from SIPO outlines only the IPC codes of each patent filing. Although CPC is an extension of the IPC, it concludes an additional section Y representing the general tagging of new technological developments. Converting CPC codes into IPC codes to filter Industry 4.0 technologies would cover non- Industry-4.0 technologies. We adopted IPC codes outlined by the previous studies (Ardito et al., 2018; Corradini et al., 2021; Martinelli et al., 2021; UK IP Office, 2013, 2014a, 2014b, 2014c) and additional keywords to filter Industry 4.0 technologies. In this chapter, the filter method used is more stringent and represents the minimum value for searching for related technologies. Despite the fact that this method cannot guarantee the retrieval of all relevant information, it is able to ensure that the patents retrieved are those that are relevant to the core technology concept. Defining whether patents belong to Industry 4.0, an emerging concept that covers a wide range of technologies is complex. We classified the I4.0 technologies into five domains: robots, 3D Printing, big data, IoT and Artificial Intelligence (AI). The detailed list of IPC codes and keywords for filtering patents can be found in Appendix.

The Industry 4.0 data extracted through the above methods are firstly used to offer some stylised facts on the geography of Industry 4.0, providing some descriptive information on the invention of the five Industry 4.0 technology groups. Then, to test the applicability of the relatedness framework, we need to estimate the probability that the relatedness density of a city affects the entry of new Industry 4.0 technologies into a city. The observation units are the 46 Industry 4.0 technologies' IPC classes within each of 285 cities in the five-year time period from 1991 to 2020. All specifications are estimated at the city-technology level. Given the binary nature of the dependent variable, we estimate the entry model using the linear probability model with fixed effects (LPMFE). Timoneda (2021) studies the trade-offs between the Linear Probability Model (LPM), logistic regression with group intercepts and the conditional logit and finds that the LPMFE produces more accurate estimates and predicted probabilities than maximum likelihood specifications when the dependent variable has less than 25 percent of occurrences, which in this case, is 17.77%. Other estimations, such as the LPM, conditional and unconditional logit models, reported as robustness checks, showing that the core results still hold by using a logit specification.

$$entry_{i,c,t} = \alpha_{i,c,t-1} + \beta_1 TechProx_{i,c,t-1} + \beta_2 GeogProx_{ic,t-1} + \boldsymbol{\beta}\, \boldsymbol{X}_{\boldsymbol{i,c,t-1}} + \boldsymbol{\beta T} + \boldsymbol{\beta C} + \boldsymbol{\beta I} + \varepsilon_{i,c,t}$$

where the dependent variable $entry_{i,c,t} = 1$ if technology *i* in which the city *c* did not have a relative technical advantage (RTA) at time *t-1*, enters the technology portfolio that the city has an RTA at time *t*; and 0 otherwise. This is applied to the five selected *i* categories. RTA is a binary variable which, when it takes the value of 1, represents that the city has a comparative advantage in a certain category, specifically in that it has a larger proportion of patents in technology class *i* than the reference region (China as a whole) at period *t:*

$$RTA_{r,i}^{t} = \begin{cases} 1, \quad if \ \dfrac{patent_{c,i}^{t} / \sum_i patent_{c,i}^{t}}{\sum_c patent_{c,i}^{t} \,/ \sum_c \sum_i patent_{c,i}^{t}} > 1 \\ 0, \qquad\qquad\qquad\qquad\qquad\qquad Otherwise \end{cases}$$

To capture the importance of cognitive proximity between knowledge bases for new knowledge creation, we construct a measure of relatedness between each technology sub-class in China. Relatedness is captured by the standardised measure of the frequency with two classes appearing on the same patent application file. In a given year, the number of individual patents that list the pair of co-classes i and j is given by the count $Nij \ = \sum_i F_{IP} F_{jp}$, where the count $F_{ip} = 1$ on individual patent p list the IPC code i, otherwise count $F_{ip} = 0$. We standardised the cooccurrence matrix *Nij* using the EconGeo R package proposed by Balland (2017) based on the probabilistic standardisation method(Eck & Waltman, 2009; Steijn, 2021). The standardised cooccurrence matrix *Sij* measures the technological relatedness between the specific Industry 4.0 technology and the broader set of patents within a city. Technological relatedness between each pair of technology sub-classes for six non-overlapping 5-year periods: 1991-1995, 1996-2000, 2001-2005, 2006-2010, 2010-2015 and 2016-2020. $\text{TechProx}_{i,c,t-1}$ is the time-lagged value of the technological proximity (in units of technological relatedness) between each Industry 4.0 technology class i and all other technology in which the city exhibits relative technological specialisation.

$\text{GeogProx}_{i,c,t-1}$ is a variable representing the time lag and spatial weighting of the knowledge spillover from other cities with a relative comparative advantage in Industry 4.0 technology class i to city c. We use different spatial matrices (i.e., adjacency and inverse distance matrices) to create different geographic lag variables.

First, a spatial matrix (258 × 258) is created based on the geographic location of each city, where the adjacency matrix takes the value of 1 when two cities share a common border of non-zero length and 0 otherwise. The inverse distance matrix uses the reverse of the distance between two cities, which is calculated based on the geographic centroid. The third spatial matrix is developed based on the inverse distance matrix, but it considers only the distances of two cities that belong to the same province. An inverse-distance matrix indicates that the near neighbours have a greater impact on the city than the distant neighbours. The diagonal of the spatial matrix constructed here takes the value of 0. Second, for each 5-year period examined, a 258 × 46 binary RTA matrix is constructed, i.e., whether these 285 cities have an RTA under the 46 Industry 4.0 technology class identified. Multiplying these two matrices yields the weighted sum of a city's neighbours exhibiting RTA. We constructed three geographic structures, the first being the adjacency matrix to capture local ties and focus only on the relative comparative advantage of adjacent neighbouring cities. The second and third are both inverse distance matrices capturing the impact of geographic distance, but one measures the impact of all domestic cities, and the other considers only the impact of cities in the same province. The coefficient β_1 and β_2 expected to be positive and significant, indicating a positive effect of relatedness to Industry 4.0 technology i in the precedent period on the probability of developing an RTA in that technology in the following period, which supports the applicability of the relatedness framework.

To capture the effects of Industry 3.0 technologies, we add two city-level variables for 3.0 technological knowledge intensity. The selection of 3.0 technological patents is adopted from the classification telecommunication technologies(ht_h) and automated business equipment(ht_a) of high-tech patents from a report published by Eurostat (2016) (Laffi & Boschma, 2022). The average technological relatedness (proximity) between all pairs of I3.0 patents is calculated using the formula below.

$$AR^{c,t} = \frac{\sum_k \sum_l S_{kl}^t \times D_{kl}^{tc,t} + \sum_k S_{kk}^t \times 2D_{kk}^{c,t}}{P^{c,t} \times (P^{c,t} - 1)} \text{ for } k \neq l$$

$$D^{c,t} = \begin{bmatrix} 0 & 2 & \cdots & 0 \\ 2 & 1 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 0 \end{bmatrix}$$

A higher average relatedness score indicates that patents are located in technology classes that are relatively close to one another in the knowledge space. These are the technology classes that tend to co-occur with relatively high frequency on individual patents. A lower relatedness score would indicate that patents are distributed over technology classes that are, on average, further apart from one another in knowledge space. Average relatedness provides a useful summary measure of technological specialisation, one much more accurate than could be generated by an index such as the Herfindahl that ignores the variance in inter-class distances of categorical variables(Kogler et al., 2017).

X is the city and time-specific control variables, namely the logarithm of population density (pop_den$_{c,t}$) and the logarithm of GDP per capita (pgdp$_{c,t}$). Both variables take the average value of the 5-year period and are derived from City statistical yearbook. ***T*, *C*,** and ***I*** represent time, city and class fixed effects. The final term is an error term assumed to possess the usual properties. All the independent variables are lagged by one period to avoid potential endogeneity issues, so we have five observations per city-technology pair. Table 1 provides some summary statistics of the variables used in the econometric analysis.

Table 3.1 Summary Statistics

	N	Mean	St.Dev	min	max	t-value
Entry	19699	0.1777	0.3822	0	1	65.2381
TechProx	19699	221.6421	211.8458	0	3642.71	146.8434
LocalProx	19699	0.4457	0.7859	0	7	79.5884
GeogProx	19699	0.0351	0.0358	0	0.2636	137.866
ProvProx	19699	0.0065	0.0106	0	0.1016	86.1245
ar_a	19699	0.0001	0.0005	0	0.0079	29.7727
ar_h	19699	0.0006	0.0025	0	0.0423	33.5622
pop_den	19699	6.055	0.7692	2.3415	8.3854	1104.784
pgdp	19699	10.229	0.7154	7.8769	12.2149	2006.906

3.4 Empirical Results and Discussion

3.4.1 The geography of Industry 4.0 in China

Among the patents retrieved, there are 44,519 patent filing records for AI, 5,947 for big data, 36,256 for IoT, 10,023 for 3D Printing and 14,175 for robotics. The trends in the number of patents per year and the number of cities with each type of patent are shown in Figure 1 and Figure 2. As can be seen from both graphs, China's 4.0 technologies also began to enter a period of development and massive expansion around 2010. Prior to this, only a few cities have seen some relevant patent filing records. However, Industry 4.0 technologies are not always concentrated in those few cities. The rising trend in the number of cities implies that there is a diffusion of 4.0 technologies. Diffusion means that geographical factors are likely to play an important role.

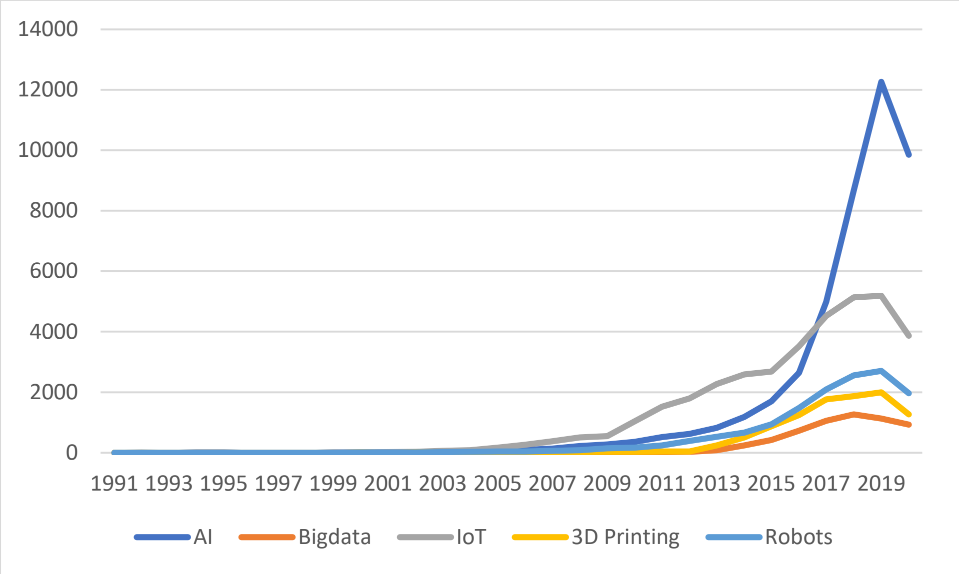


Figure 3.1 Annual counts of patent counts of I4.0 technology subgroups

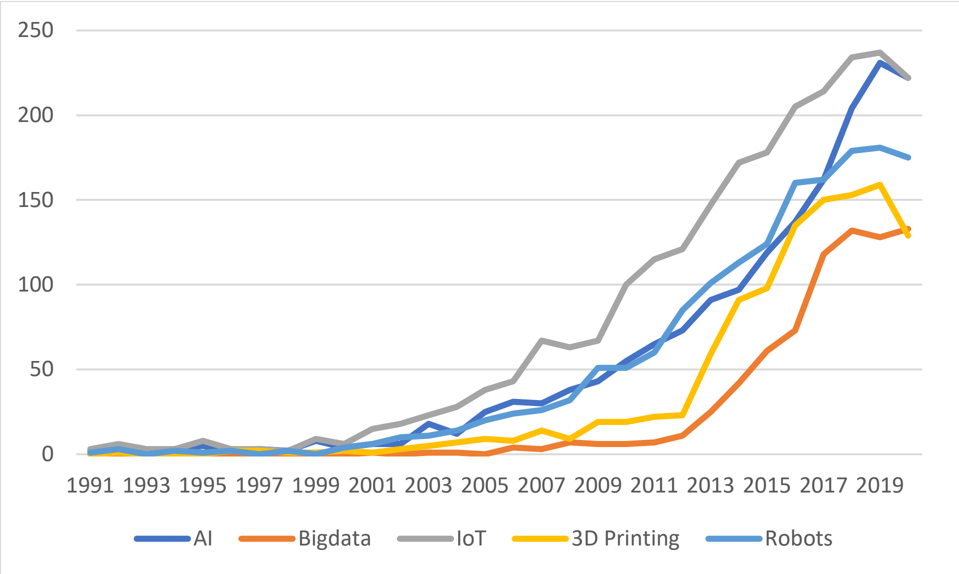


Figure 3.2 The number of cities with each I4.0 technology subgroup

By examining the geographical distribution of patents across prefectural cities in the five categories of Industry 4.0 technologies, we are able to get a sense of how the geography of Industry 4.0 is developing in China. Figure 1 shows the total number of patents of Industry 4.0 technologies for the period 1990 to 2020. In terms of spatial distribution, AI and IoT have the highest number of patent applications and are spread across most prefectural cities,

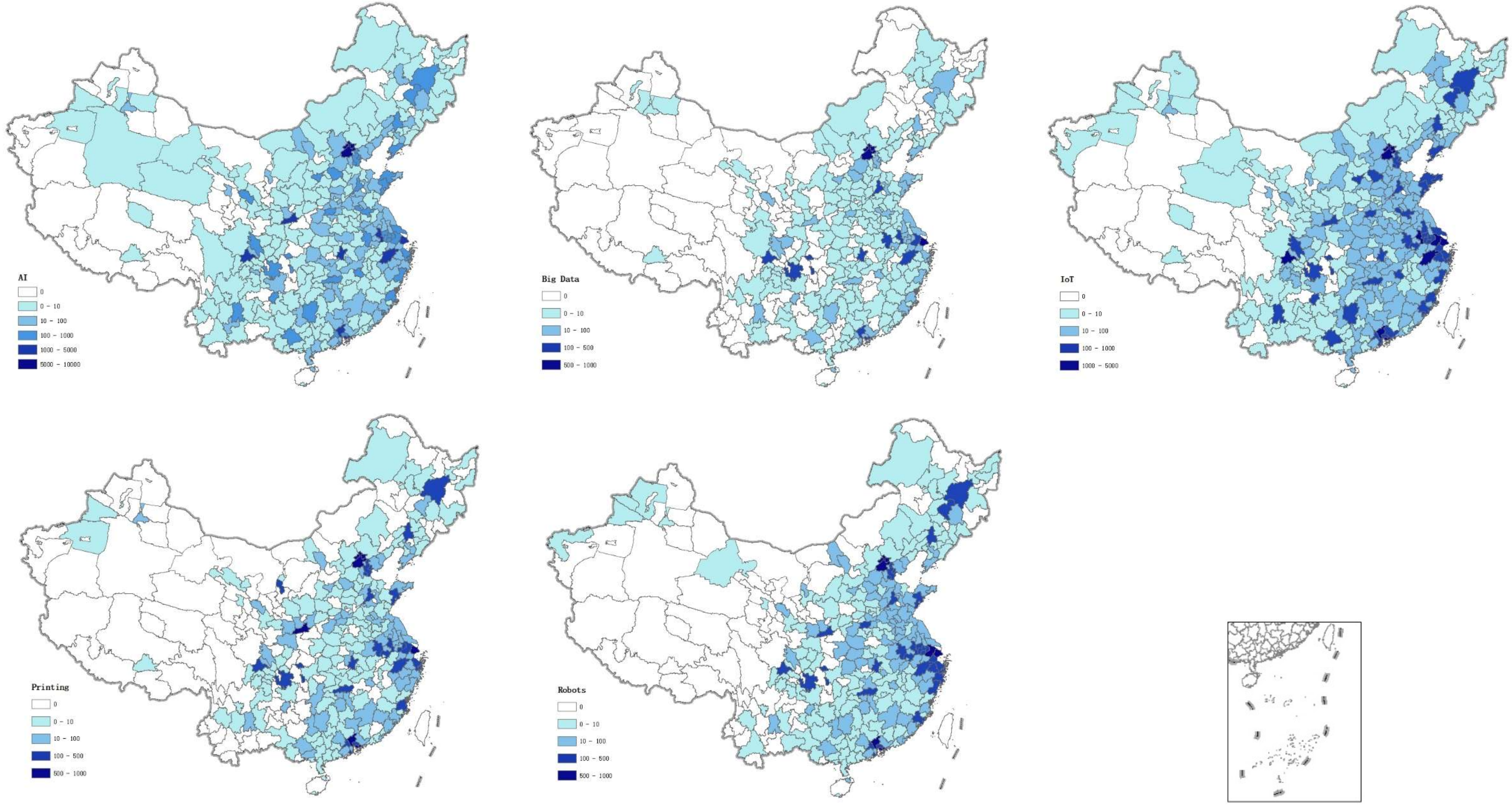
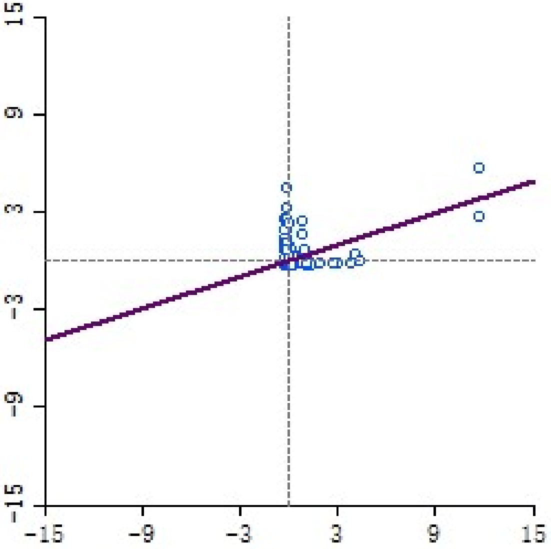
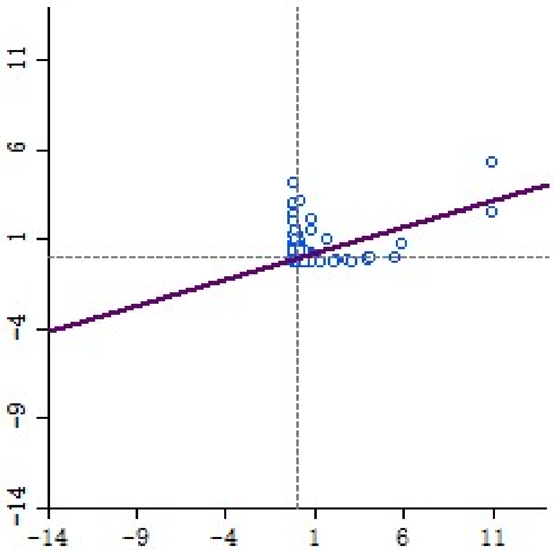


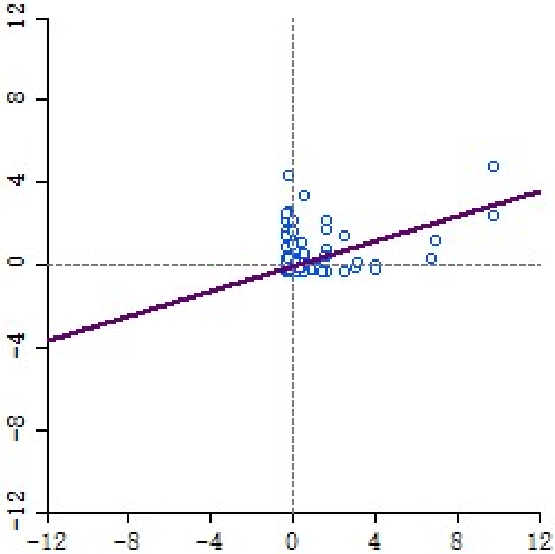
Figure 3.3 Number of patents in each technology: sum, 1990-2020



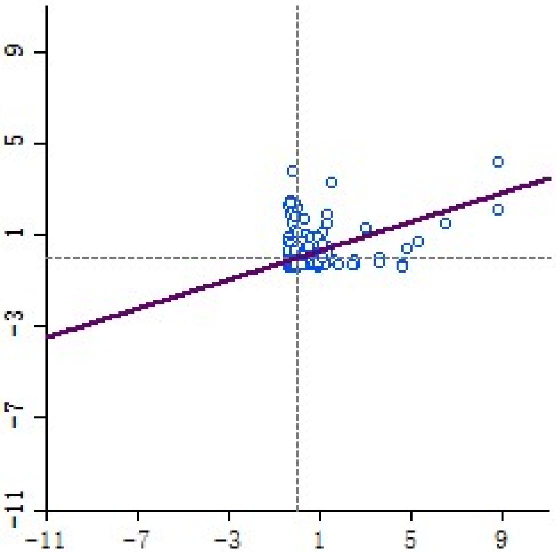
AI: Moran’s I: 0.327



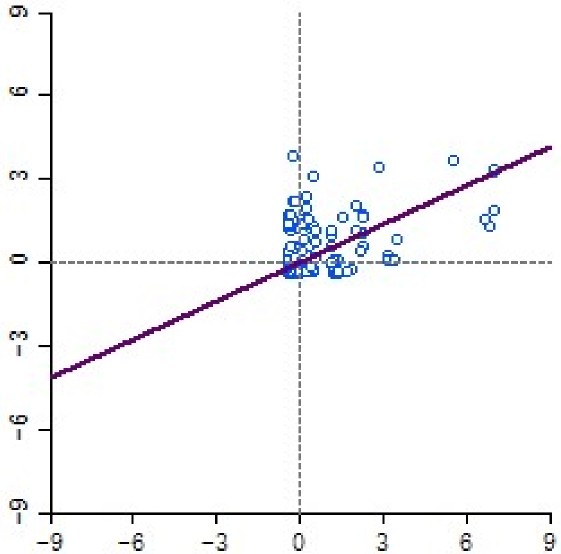
Big data: Moran’s I:0.295



IoT: Moran’s I:0.302



3D Printing: Moran’s I: 0.315



Robots: Moran’s I:0.460

Figure 3.4 Moran scatter plots and Moran’s I index for each technology

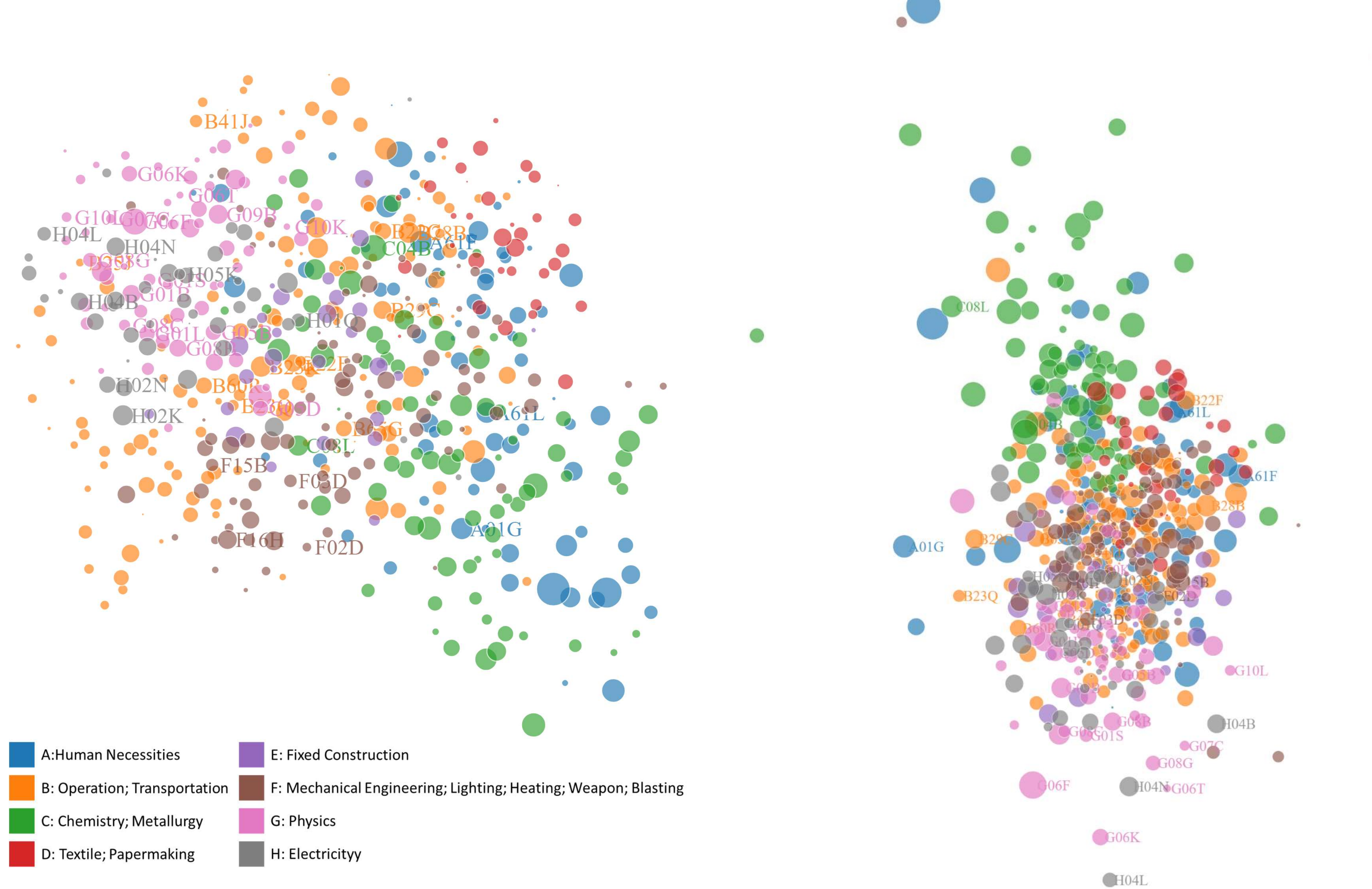


Figure 3.5 Knowledge space of China with positions of Industry 4.0 technologies (I4Ts): 1990-1995 and 2015 -2020

but AI patent activity tends to concentrate in just a few cities, whereas IoT patent inventions tend to be concentrated in some more cities. It is similar in distribution to those of the other three groups, concentrating on a few more developed cities, including developed coastal cities, Beijing, Chongqing, etc. A spatial autocorrelation analysis can further support the spatial distribution of patent applications. There is a positive spatial autocorrelation observed for all the five domains of Industry 4.0 technologies identified in Moran's I index (Figure 4), indicating that there might be a spatial spillover effect or a spatial competition effect owing to the nature of knowledge.

Figure 3.5 shows the standardised cooccurrence matrix of all patent applications in China, referred to as the knowledge space. A dot in the figure indicates an IPC category, while a colour indicates whether the category belongs to one of seven major groups. The dots are sized according to the number of patents filed. The distance between the dots is given by the inverse of the relatedness between the two categories, which means that the closer the dots are, the greater the relatedness. In the first period, the knowledge space in China was more evenly distributed and not concentrated. Most dots are small, and most of the marked IPC-related categories are distributed at the edge of the knowledge space. It should be that the intensity of patenting activity in China during this period was not strong, neither in Industry 4-related technology areas nor in other areas of knowledge production. By the end of the last period, the knowledge space in China was much more concentrated. Within the Chinese knowledge space, most of the I4Ts tend to cluster around similar technologies, while some I4Ts are more isolated, such as 3D Printing (C08L), whose location is far from other I4Ts. However, some I4Ts are more peripherally located in the knowledge space. This suggests that this part of technology is less closely related to other technologies and that such knowledge is not transferable.

3.4.2 Determinants of Industry 4.0 diffusion

Columns 1-3 of Table 3.2 present estimation results from pooled OLS, while Columns 4-6 provide coefficients estimates from the three-way FE model with all the city variables. For robustness, we present the regression results of Logit models in Columns 7-9. The variable *LocalProx* captures the effects of neighbouring cities that share a common boundary, while the variable of *GeogProx* and *ProvProx* captures capture the influence of other cities, which decreases as the distance increases. The estimators of the variable *TechProx* (models 1-9) confirm the validity of the relatedness framework for Chinese Knowledge Creation in 4.0

knowledge: cities with a knowledge base that is close, technologically, to the Industry 4.0 technology have a higher possibility of developing a specialization in that technology than cities without such a knowledge base. Similarly, the development of Industry 4.0 technology in a city is influenced by the technological dominance of other cities. The effects of spatial effect are also positive and significant at 1% confidence levels. There is a spatial spillover effect of the information flow of Industry 4.0. The coefficient of *ProvProx* is the largest among the three spatial effects in the pooled linear probability model, the fixed effects probability model and the logit model. Results regarding technological proximity and spatial effects are consistent with previous studies(Boschma et al., 2015; Corradini et al., 2021; Feldman et al., 2015; Kogler et al., 2017). Turning to the control variables, the results show a mixed effect of the population density and FDI, though not all significant. The results of both variables are not very robust. But results show that the city's economic development positively impacts the probability of developing an Industry 4.0 technology.

We further examine the effects of Industry 3.0 technology on the development of the Industry 4.0 technology. As the *LocalProx* and *ProvProx* are constructed using different kinds of spatial matrices that capture local effects, these two variables will be included in the later regressions. Both the fixed-effect linear probability model and logit model results are presented in Table 3. The results highlight that only communication technologies (*ar_h*) have a positive effect on the probability of Industry 4.0 technology entry with a significance level of 10% level, while estimators on the impact of automated business equipment(*ar_a*) show mixed effect: cities that have a higher average relatedness with ICT technologies have a higher probability of Industry 4.0 technology entry into their technology portfolio. By leveraging the local ICT knowledge base, cities can take advantage of the cumulative dimensions of the 4.0 technology paradigm and are more likely to develop Industry 4.0 technologies; automated business devices, on the other hand, do not cultivate Industry 4.0 technologies. These results partially support our assumptions that the development of Industry 4.0 technologies still follows a path of dependence, but the dependence is on the foundation of ICT technology.

Table 3.2 I4.0 entry regression results across I4.0 technologies

	Pooled OLS			LPMFE			Logit model		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
L.TechProx	0.0001***	0.0001***	0.0001***	0.0002***	0.0002***	0.0002***	0.0003***	0.0006***	0.0003***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0001)
L.LocalProx	0.0586***			0.0108**			0.4198***		
	(0.0041)			(0.0046)			(0.0259)		
L.GeogProx		2.3006***			0.7173***			18.2238***	
		(0.0948)			(0.1708)			(0.6808)	
L.ProvProx			5.3291***			1.4192***			38.4821***
			(0.3278)			(0.4014)			(2.1184)
L.ln(pop_den)	0.0494***	0.0512***	0.0371***	-0.0488	-0.0506	-0.0564*	-0.4343	-0.4658	-0.6929**
	(0.0032)	(0.0032)	(0.0033)	(0.0317)	(0.0315)	(0.0317)	(0.3100)	(0.3173)	(0.3215)
L.ln(pgdp)	0.0588***	0.0355***	0.0496***	0.0428*	0.0462*	0.0483*	0.5541***	0.6157***	0.7541***
	(0.0036)	(0.0038)	(0.0037)	(0.0257)	(0.0257)	(0.0257)	(0.1969)	(0.2024)	(0.2004)
L.ln(fdi)	0.0196***	0.0129***	0.0155***	-0.0019	-0.0002	-0.0020	0.0118	0.0836	0.0075
	(0.0014)	(0.0014)	(0.0014)	(0.0070)	(0.0070)	(0.0070)	(0.0614)	(0.0597)	(0.0592)
Constant	-0.7690***	-0.6054***	-0.6100***	-0.0075	-0.0522	-0.0223	-5.6134*	-6.1447**	-5.5369*
	(0.0435)	(0.0445)	(0.0454)	(0.3139)	(0.3136)	(0.3132)	(2.9651)	(3.0278)	(2.9896)
Year FE	-	-	-	Yes	Yes	Yes	Yes	Yes	Yes
City FE	-	-	-	Yes	Yes	Yes	Yes	Yes	Yes
Class FE	-	-	-	Yes	Yes	Yes	Yes	Yes	Yes
N	19699	19699	19699	19699	19699	19699	19487	19487	19487
R^2	0.044	0.072	0.050	0.141	0.141	0.140			
pseudo R^2							0.085	0.119	0.092

Notes: 1) The L prefix shows that the independent variables are lagged one time period; 2) Robust standard errors are clustered at the city-technology level and reported in parentheses; 3)***, **, * represent significant levels at 0.01, 0.05, and 0.1 levels, respectively.

Table 3.3 I4.0 entry LPMFE regression results across I4.0 technologies

	LPMFE					
	(10)	(11)	(12)	(13)	(14)	(15)
L.TechProx	0.00017***	0.00017***	0.00017***	0.00017***	0.00017***	0.00017***
	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)
L.LocalProx	0.01082**	0.01081**	0.01082**			
	(0.00463)	(0.00463)	(0.00463)			
L.ProvProx				1.41965***	1.43453***	1.43425***
				(0.40181)	(0.40174)	(0.40174)
L.ar_a	1.65155		-1.93331	2.23998		-1.49706
	(4.96794)		(5.34354)	(4.93029)		(5.31194)
L.ar_h		3.63163*	3.74548*		3.81950*	3.90764*
		(1.98324)	(2.07526)		(1.99241)	(2.08531)
L.ln(pop_den)	-0.04874	-0.04906	-0.04942	-0.05601*	-0.05651*	-0.05678*
	(0.03173)	(0.03167)	(0.03174)	(0.03175)	(0.03170)	(0.03177)
L.ln(pgdp)	0.04517*	0.05194*	0.05132*	0.04953*	0.05647**	0.05599**
	(0.02648)	(0.02661)	(0.02673)	(0.02649)	(0.02663)	(0.02675)
L.ln(fdi)	-0.00180	-0.00198	-0.00220	0.00001	-0.00023	-0.00040
	(0.00714)	(0.00704)	(0.00713)	(0.00714)	(0.00704)	(0.00713)
Constant	-0.01444	-0.08194	-0.07117	-0.03716	-0.10497	-0.09662
	(0.32056)	(0.31674)	(0.32075)	(0.31982)	(0.31596)	(0.31999)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Class FE	Yes	Yes	Yes	Yes	Yes	Yes
N	19699	19699	19699	19699	19699	19699
R^2	0.140	0.141	0.141	0.141	0.141	0.141

*Notes: 1) The L prefix shows that the independent variables are lagged one time period; 2)) Robust standard errors are clustered at the city-technology level and reported in parentheses; 3)***, **, * represent significant levels at 0.01, 0.05, and 0.1 levels, respectively.*

Table 3.4 Regression results by each I4.0 technology

	AI		Big Data		IoT		3D Printing		Robots	
	(16) LPMFE	(17) Logit	(18) LPMFE	(19) Logit	(20) LPMFE	(21) Logit	(22) LPMFE	(23) Logit	(24) LPMFE	(25) Logit
L.TechProx	0.0001***	0.0017***	0.0007	0.0085*	0.0003***	0.0018***	0.0001***	0.0004*	0.0002***	0.0024***
	(0.0000)	(0.0004)	(0.0006)	(0.0050)	(0.0001)	(0.0005)	(0.0000)	(0.0002)	(0.0000)	(0.0002)
L.ProvProx	1.2588*	3.2721	2.1736	12.9917	2.7258***	10.8374**	0.0019	0.2030***	1.7609***	44.5235***
	(0.6765)	(4.8375)	(2.0464)	(12.7256)	(0.8570)	(4.8267)	(0.0087)	(0.0727)	(0.5528)	(4.5474)
L.ar_a	7.5120	17.8052	-98.1400**	-4078.49*	-25.45	-345.76**	-33.8649***	-2762.82***	-14.7252**	-375.8346**
	(10.0599)	(152.5934)	(39.0094)	(2325.7917)	(16.9490)	(166.9373)	(9.8992)	(1045.9115)	(7.2194)	(178.9740)
L.ar_h	1.1085	8.6951	6.7403	-218.5973	1.2621	-9.7730	5.0139	35.0885	4.0191*	61.0374*
	(3.9217)	(32.3590)	(10.3723)	(157.8290)	(6.3742)	(46.4200)	(3.9434)	(23.9029)	(2.1618)	(31.2232)
L.ln(pop_den)	-0.0839*	-1.1880	0.3061	-3.1474	-0.0001	-0.0004	-0.0209	-0.9910	-0.0209	-0.0577
	(0.0510)	(0.8603)	(0.2502)	(3.6701)	(0.0001)	(0.0005)	(0.0543)	(0.6354)	(0.0316)	(0.8430)
L.ln(pgdp)	0.1343***	1.3822***	-0.0574	0.0733	-0.0000**	-0.0000***	-0.0011	0.2638	-0.0061	0.1540
	(0.0451)	(0.4693)	(0.1798)	(1.3696)	(0.0000)	(0.0000)	(0.0456)	(0.4627)	(0.0331)	(0.5793)
L.ln(fdi)	-0.0245*	-0.1862	-0.0064	0.1594	0.0012	0.0312	0.0085	16.5935***	0.0083	0.2784*
	(0.0125)	(0.1304)	(0.0446)	(0.3574)	(0.0188)	(0.1322)	(0.7573)	(5.3612)	(0.0086)	(0.1566)
Constant	-0.4828	-8.0803	-1.0426	11.7344	0.2488	-4.6214**	0.2406	1.5370	0.1240	-11.2622
	(0.5213)	(7.2348)	(2.0821)	(29.6403)	(0.1913)	(1.8736)	(0.5575)	(7.0227)	(0.3907)	(7.6245)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Class FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	5735	5584	758	681	3118	2887	5933	5722	7085	6451
R^2	0.169		0.278		0.199		0.161		0.182	
pseudo R^2		0.218		0.241		0.177		0.209		0.160

Notes: 1) The L prefix shows that the independent variables are lagged one time period; 2) Standard errors in parentheses; 3)***, **, * represent significant levels at 0.01, 0.05, and 0.1 levels, respectively.

The above results consider the five domains of Industry 4.0 technologies as a whole; however, the nature of Industry 4.0 technologies is complex and diverse. Factors affecting one technology may have an opposite effect on another technology: considering them as a whole may offset some of the opposite effects. Table 4 shows the results of the regressions for each technology group individually. The results further confirm the importance of a city's technology proximity (*TechProx*) to Industry 4.0 technology entry, although the coefficient estimated in Model 18 is not significant. Possibly this is due to the fact that big data technologies did not become available until after 2000. Therefore, in Models 18-19, we only used data after period 3, i.e. after 2000. On the other hand, geographical proximity does not present a significant positive effect for all technology groups as in Models 13-15. The estimator of geographical proximity in the technology category of Big Data is not significant. This is also related to the nature of this technology, where Big Data technologies are least constrained by geographical distance. Big Data technology research is mainly based on data mining-related algorithms and theoretical research, and the accumulation and transfer of relevant knowledge are not dependent on geographical proximity. Similarly, we can see that the coefficient estimates for geographical proximity for AI technologies are only significant at the 10% confidence interval of the LPMFE model and are not significant in the logit model. A significant part of AI technology is also related to algorithms, information recognition and processing technologies, and therefore the diffusion and spread of this technology are not limited by geographical distance. In contrast, the development of IoT, 3D Printing, and robotics relates more to the development and manufacture of industrial components and is more dependent on cluster effects, which underlines the important role of geography even in the 4.0 era.

The variables capturing the effect of Industry 3.0 technologies show very different results. The estimators of automated business equipment(*ar_a*) in Model 18-20, 22 -25 are negative and significant at the 5% level. This suggests that the greater the average technological relatedness of a city in automated business equipment, the more likely it will influence the development of big data, IoT, 3D Printing and robotics in that city negatively. That is, the development of automated business equipment is in competition with the development of these Industry 4.0 technologies. On the other hand, the regression results also show positive, but not significant, impacts from communication technologies on each specific technology other than robotics. This result is rather counterintuitive. A possible explanation is that telecommunication technology relates to Industry 4.0 technologies, but it is neither necessary nor sufficient to develop these technologies.

3.5 Chapter Summary

This chapter has explored the role of a city's knowledge base in the development of I4.0 technologies in China over the past 30 years through a comprehensive review of all SIPO patent application records in 258 cities in China. First, we determined the applicability of the relatedness framework in the Chinese context: the results confirm that cities with a knowledge base that is close, technologically, to the 4.0 technology have a higher possibility of that technology entry in China. The same applies to cities that are geographically close to other cities specialising in that technology. Then we further investigated whether 3.0 technologies are necessary on the development path to 4.0 technologies in China, that is, whether the development of 4.0 technologies can break the path dependence. We find that the overall development of 4.0 technologies still follows a path of dependence, but the dependence is on the foundation of ICT technology, not on the automated business equipment, which is in line with the conclusion of Laffi and Boschma (2022). Finally, we examined whether these implications are consistent across various 4.0 technological categories. Results further confirm the role of technological proximity. However, the pattern of contribution of geographical proximity and 3.0 technologies changes when it comes to sub-categories. The development of AI and big data is not constrained by geographical distance. And the development of automated business devices competes with big data, IoT, 3D printing and robotics technology. In other technologies than robots, ICT technology becomes insignificant.

Here lies a key debate of whether Industry 4.0 represents a major technological transformation that reflects a radical departure from existing technologies, particularly 3.0 technologies. The history of the industrial revolution reveals several social transformations, from an agricultural society to an industrial society (Industry 1.0), from Industry 1.0 to 2.0, then to 3.0 and currently developing to 4.0. It should be noted that the Chinese manufacturing industry has not undergone a gradual transition from the third to the fourth industrial revolution, as has been the case in developed countries such as the United States and Europe, where most evolutionary economic geographers have studied. There are still a number of factories in the manufacturing industry that are at or below mass production levels (industry 2.0), which makes the status quo a highly complex situation. In contrast to previous studies(Laffi & Boschma, 2022), which aimed to assess whether a region specialised in Industry 3.0 technology would contribute to the development of Industry 4.0 technology, this study significantly improves the indicator of Industry 3.0 technology. As a means of capturing the city's cumulative knowledge, we used the average relatedness between ICT technology and automated business equipment technology. By studying China's case and adopting a relatedness framework, we were able to gain new insights into this debate. Overall, ICT technology contributes to the development of Industry 4.0 technologies, while automated business equipment technology does not. Path dependence still applies. Due to the heterogeneity and disruptive nature of Industry 4.0 technologies, Industry 3.0 technologies are not the only path for all Industry 4.0 technologies. The local knowledge base in ICT technology allows the region to take advantage of the cumulative Industry 3.0 technology paradigm, making it easier to generate those types of Industry 4.0 technologies that are more relevant to the 3.0 paradigm, while the specialisation of automated business equipment can compete with the development of the Industry 4.0 technology paradigm and thus negatively contribute to the entry of Industry 4.0 technology.

Our results provide important insights for city policymakers focused on Industry 4.0. Cities' own capabilities provide their own opportunities and set limits to what can be achieved. The most important aspect of whether Industry 4.0 technologies can enter a city's technology mix is the city's pre-existing technology endowment. Policymakers should have a comprehensive understanding of a city's resource endowment, including its knowledge base. If a city inherits a weak knowledge base, leading to a lack of clarity about the city's technological capabilities, the differential role of spatial proximity suggests that technology spillovers from neighbouring cities or cities in the same province can break the local technology lock and thus proliferate Industry 4.0, while ICT technologies also facilitate the development of a city's policies out of Industry 4.0. More importantly, our findings also point to the heterogeneity of Industry 4.0 technologies, i.e., the technological paradigm may also differ significantly between Industry 4.0 technologies. Factors that influence one technology may have an opposite effect on another and considering them as a whole will counteract some of the opposite effects, and cities should focus on factors that influence the development of a well-defined technology if they aim to develop that technology. For example, cities specialised in AI do not spill over to their nearer cities. Those cities at the centre of the 3.0 technology paradigm can use their 3.0 knowledge base to develop a robotics industry.

CHAPTER4. FROM RECIPIENT TO INNOVATOR: THE EVOLUTION OF CHINA IN INDUSTRIAL ROBOTICS

4.1 Introduction

Historically, introducing foreign goods and technologies – either obtained through imports or foreign investments (Grossman & Helpman, 1991; Keller, 2002; Keller & Yeaple, 2009) - has been instrumental in the industrial development of nations. Empirically, various scholars have shown the crucial role of foreign direct investments and trade relations in technological diffusion and upgrading (Chen et al., 2017; Crescenzi et al., 2022). However, as automation technologies involves complex and diverse, it remains uncertain whether technologically lagging countries can learn from imported products and innovate. Existing studies (Ciffolilli & Muscio, 2018; Corradini et al., 2021; Laffi & Lenzi, 2023), mostly focused on advanced countries and regions, show the geography of automation and Industry 4.0 technologies is rather spatially concentrated. Other scholars highlight the importance of early adoption and pre-existing capabilities (Bloom et al., 2020; Laffi & Boschma, 2022; Xiao & Boschma, 2022). Overall, these contributions provide evidence consistent with the idea of path dependence (Martin & Sunley, 2006), possibly related to high entry barriers and the requirement of specific capabilities.

This chapter focuses on a less explored but nonetheless important issue for low- and middle-income countries concerning the effect of the adoption of automation on the local innovation capabilities in robotics and related technologies. We contribute to this debate and study the relation between import of robots and local innovation in robotics, focusing on the case of China in the period 2000-2020. We argue that this is a highly relevant question to address since it pertains to the role of trade linkages in developing capabilities for innovation in automation, a key set of technologies. Our empirical approach leverages a comprehensive dataset integrating information from the China Industrial Enterprise Database, China Customs Database, and China Patent Application Database. This allows us to analyse the intricate relationship between robot imports and innovation outcomes.

4.2 Literature Review and Theoretical framework

4.2.1 Automation technologies and the geography of innovation

Current research on industrial robots focuses on the effect of its application on employment (Acemoglu & Restrepo, 2020; Dauth et al., 2017; Hawksworth et al., 2018b), productivity and economic growth(Autor & Salomons, 2018; Cséfalvay, 2021), there is limited insight into how robot adoption impacts innovation activities. Automation, robots and I4.0 as technologies that are redefining what, how and where manufacturing production takes places. By doing so, however, these technologies start changing the capabilities present in a region and in this way, they also reshape local innovation dynamics.

Laffi and Boschma (2022) analyse patenting in European regions and show that developing a specialisation in Industry 4.0 technologies – which included automation technologies – is positively related to pre-existing capabilities in Industry 3.0. In the case of the US, (Bloom et al., 2020) show that, also in the case of emerging digital technologies, the location where a technology first emerges maintains a dominant position even when the technology has diffused to and has been adopted by other locations. These findings are consistent with the idea of path dependence (Martin & Sunley, 2006) and suggest that late-coming countries and regions may face difficulties in building the skills and capabilities required for developing existing automation technologies. These findings suggest that despite the difficulties of technology diffusion, there is still great potential for active investment in automation technologies.

At the same time, the benefits of investing and acquiring capabilities in such crucial technologies are likely to be considerable. The ability to develop new automation technologies provides an opportunity to acquire technological leadership and play a role in shaping the evolutionary trajectory of technologies that are key for the present and the future (Lundvall & Rikap, 2022). Aside from the relevance of such central positions, being at the technological frontier in terms of automation technologies may facilitate a radical transformation of the economy, making it more productive and competitive in the global context (De Propris & Bellandi, 2021) as suggested by (Yuan & Lu, 2023). In this sense, some scholars suggest that late-developing countries can leapfrog development by capitalizing on technological spillovers and diffusion from developed countries (Yu et al., 2019; Corradini et al., 2021). Furthermore, from an evolutionary perspective, capabilities in key technologies like automation are likely to foster diversification opportunities both in related technologies, as discussed by Laffi and Boschma (2022), but also in new type of activities (Castellacci et al., 2020; Santoalha et al., 2021).

Recent studies begun to shed light on this less-explored area of how industrial robot adoption influences innovation activities in the Chinese context. Gan et al. (2023) analysed Chinese manufacturing firms from 2011 to 2019 and found that industrial robots significantly boost green innovation, particularly in firms with stringent environmental regulations and high R&D investment. Wang et al. (2023) examined Chinese manufacturing firms from 2011 to 2019 as well, finding a significant positive correlation between robot adoption and capacity utilisation rates, with the impact most pronounced in non-state-owned enterprises, low-tech, labour-intensive, and financially constrained firms. Luo and Qiao (2023) extended the timeline to 2020 and found that robot adoption significantly enhances technological innovation, evidenced by a substantial increase in invention patent applications, with this effect being mediated by improvements in human capital, notably in education and allocation to R&D roles. However, these studies, relying on data from the International Federation of Robotics, face limitations due to the data's lack of city or firm-level granularity, which could affect the depth of insight into the specific impacts of robot adoption on innovation despite the valuable insights they provided.

4.2.2 External linkages and robot adoption

Innovation is commonly known as one of the key drivers of economic growth and competitiveness. However, there is little understanding of how interregional linkages may affect development of such new activities within regions(P.-A. Balland & R. Boschma, 2021). Existing research, such as by Boschma (2017) and Whittle et al. (2020), mainly focuses on regional capabilities but overlooks the role of interregional linkages. A similar trend is also evident in literature on new path development (Trippl et al., 2018).

However, recent studies have begun to emphasise the importance of international trade and imports in fostering innovation, as highlighted by Feng and Li (2021) and Keller (2010). For instance, Baldwin and Harrigan (2011) argue that imports play a crucial role in spreading new technologies and ideas, enhancing productivity, and promoting innovation. Keller (2010) found that imports expose firms to new technologies and ideas, providing complementary inputs and knowledge, thereby spurring innovation. However, there are also studies indicating that import competition can reduce domestic firms' capacity for innovation (as noted by Aghion et al., 2019) and decrease investment in R&D (as shown by Blanes et al., 2020).

While research has traditionally focused on the role of domestic R&D in fostering innovation, recent studies have begun to highlighted the importance of international trade and imports in fostering innovation(Feng & Li, 2021; Keller, 2010). For instance, Baldwin and Harrigan (2011) argue that imports play a crucial role in the diffusion of new technologies and ideas, which can lead to productivity gains and innovation. Similarly, Keller (2010) finds that imports can enhance innovation by exposing firms to new technologies and ideas, and by enabling them to access complementary inputs and knowledge. However, there are also studies indicating that import competition can reduce domestic firms' capacity for innovation (as noted by Aghion et al. (2019)) and decrease investment in R&D (as shown by Blanes et al. (2020)).

It is important to note that such complex relationship between imports and innovation is context dependent, including firm-level factors, such as absorptive capacity and technological capabilities, in determining the impact of imports on innovation (Kafouros et al., 2008). Other studies have emphasised the role of industry-specific factors, such as the degree of competition and the level of technological change, in shaping the relationship between imports and innovation (Acemoglu et al., 2016). In the meantime, there are fewer understandings on the import behaviours generating technology spillovers, given the fact the around half of the world trade is between unaffiliated parties and knowledge transfer is hard to measure (Keller, 2010). In addition, technology embodied in intermediate goods or final goods is not easily accessible. Liu and Qiu (2016) find that the decrease in input tariff drop results in less innovation undertaken by Chinese firms as high-quality input imports substitute for innovation. Chen et al. (2017) has studied the import behaviour of Chinese firms and find that importing intermediates stimulate domestic firm's R&D intensity.

4.2.3 Theoretical Framework

This study is designed to explore the impact of external economic factors – specifically imports, R&D investment, and FDI – on innovation outputs in both city-industry and enterprise level within the Chinese economic setting. China's rapid industrial growth, increasing R&D expenditure, and its status is now a major player in global trade. It examines how these external economic factors interact with local economic structures and innovation ecosystems at both the city-industry and enterprise levels, acknowledging China's unique developmental trajectory and regional diversities.

We assume that imports still play a crucial role in driving innovation in the case of industrial robots. Import acts as pipelines for new ideas, technologies, and practices, which can spur innovation activities. Drawing on the theory of international trade, innovation geography and evolutionary economic geography, we hypothesised that:

Hypothesis 1: Higher levels of imports are positively associated with greater innovation outputs in terms of patent applications.

The study further explores the interaction between imports and R&D investments. Building on the concept of absorptive capacity from innovation economics, it is proposed that R&D investment not only bolsters a firm's internal innovation capabilities but also enhances its ability to leverage and integrate imported technologies. The combination of imports and robust R&D efforts more effectively translates into innovation outputs.

Hypothesis 2: The interaction between imports and R&D positively influences innovation, suggesting a synergistic effect where R&D enhances the ability to leverage imported technologies.

Recognizing the dynamic nature of innovation processes, the study further hypothesises a time-lagged positive relationship between imports and innovation at the enterprise level. We assume that there is an initial adaptation period required for assimilating imported technologies, during which firms may adjust their strategies, processes, and human capital. This adaptation is followed by a phase where the assimilated knowledge and technologies manifest in increased innovation outputs. Given that, we propose the following hypothesis:

Hypothesis 3: There is a time-lagged positive relationship between imports and innovation at the enterprise level, with an initial adaptation period followed by increased innovation outputs.

4.3 Data sources and model specification

4.3.1 Data sources

We will analyse the factors that affect the innovation of industrial robots in Chinese manufacturing companies. To do this, we will use three databases: the China Industrial Enterprise Database, the China Customs Database, and the China Patent Application Database. The China Industrial Enterprise Database contains information on both state-owned and non-state-owned enterprises with annual sales of at least RMB 5 million (or RMB 20 million since 2011). These enterprises account for 98% of the manufacturing industry's exports. This database provides comprehensive data on company operations and financial statistics such as sales, exports, employment, and total assets. The China Customs Database covers import and export trade information for 280,282 enterprises from 2000 to 2016. It includes enterprise name, product name amount, quantity and price, etc. Finally, the China Patent Application Database is extracted from the State Intellectual Property Office of the People’s Republic of China (SIPO) from 2000 to 2020 with the applicant's name, location, dates of application, technology type, etc. There are three types of patents in the Chinese system: invention patent, which requires the highest technological contents among three types; utility models; and design patents, which are analogous to patent rights in developed countries. We only use invention application data proxy for innovation on robotic technologies with high technological barriers.

4.3.2 Data process

We first filtered import and export records containing the word "robot" from commodity names in the customs database, obtaining eight specific types of industrial robots and their customs codes (see Appendix). Next, we merged the product data at the "enterprise-product" level to obtain Chinese enterprise-level industrial robot import data. We followed a three-step process to analyse the innovation of industrial robots in Chinese enterprises from 2000 to 2020. First, we filtered out invention patents related to industrial robots using keywords in the patent database. Second, we split applicants in cases where multiple units or individuals jointly apply for patents in the patent database. Finally, we removed personal applicants and adjusted enterprise names in both databases so that patent data could be matched with enterprise import data through enterprise names. After matching the industrial enterprise database and enterprise import data between 2000-2013, an unbalanced panel including 3,495 companies was obtained to describe China's behaviour in trade and innovation of industrial robots from 2000-2020. We used a moving average method to fill in the missing values in the industrial enterprise. City-industry data is obtained by aggregating enterprise-level data by industry, city, and year. To create a more balanced panel data at the city-industry, missing values are filled in by assigning a value of 0 to represent the absence of related activities in a specific industry, city, and year. However, for years without any available data (e.g., importing activities after 2016), the corresponding cells are left blank. 3.3 Model specification:

$$Patent_{i,c,t} = \alpha + \beta_1 IMP_{i,c,t} + \boldsymbol{\beta_2}\, \boldsymbol{X_{i,c,t}} + \boldsymbol{\beta_3}\, \boldsymbol{T} + \boldsymbol{\beta_4}\, \boldsymbol{I} + \boldsymbol{\beta_5} \boldsymbol{C} + \varepsilon_{i,c,t}$$

$Patent_{i,c,t}$ denotes the number of two-digit manufacturing industry i's robotics patent application in city *c* during year *t*. In accordance with established literature, the natural logarithm of $Patent_{i,c,t}$ is utilised to gauge their level of innovation in the present year. The variable $IMP_{i,c,t}$ represents the amount of robotics product imports of Industry in city *c* in the year *t*, with $\boldsymbol{X_{i,c,t}}$ as the industry-city level control variables, including: *R&D* refers to the total annual research and development expenses of all enterprises in that industry. *FDI* refers to the total amount of foreign capital received by the industry in that year, as well as direct investment from Hong Kong, Macao, and Taiwan into enterprises of that industry. FC refers to the number of foreign-funded enterprises among all enterprise types in the industry. To avoid the omission of important explanatory variables, this study also includes fixed effects for year, industry, and city. The year fixed effect $\boldsymbol{T}$ is introduced to control for the impact of specific events that may occur in certain years. The industry fixed effect $\boldsymbol{I}$ and city fixed effect $\boldsymbol{C}$ are included to absorb the influence of individual differences among industries and cities on the results.

In this study, we further calculated another variable called $Related\_Imports_{i,c,t}$, which is the total amount of robot imports associated with industries considered related to the specific industry *i* within a given year. In other words, this variable represents a weighted sum of imports from industries that are related to the particular industry of interest (industry *i* in the formula) within a city at a given time. This variable captures not just the volume of imports related to an industry, but also the relevance of these imports in terms of industrial ecosystem and potential knowledge and technology spillovers. The weights to sum up the imports are determined by the industrial relatedness between two industries, which represents the tendency for two industrial sectors to co-occur. To quantify the relatedness, we first calculate a correlation matrix for the manufacturing industry. The matrix encapsulates correlation values between each pair of industries. Diagonal entries in the matrix representing self-correlation measures (i.e., relationships between an industry and itself) are excluded from our calculations to avoid self-influence. The relatedness between two industries i and j is computed as a ratio of observed co-occurrences versus expected co-occurrences assuming independence between industries i and j. Observed co-occurrences corresponded to the number of cities specialise in both industries i and j.

$$LQ_{i,c,t} = \left(\frac{E_{i,c,t}/E_{*c,t}}{E_{i*,t}/E_{**,t}} \right) \text{ and } x_{i,c,t} = \begin{cases} 1\,, if\ LQ_{i,c,t} > 1 \\ 0\,, otherwise \end{cases}$$

$$\varphi_{i,j,t} = \frac{C_{ij,t}}{\left[\left(\frac{S_{i,t}}{T_t}\right) \times \left(\frac{S_{j,t}}{T_t - S_{i,t}}\right) + \left(\frac{S_{j,t}}{T_t}\right) \times \left(\frac{S_{i,t}}{T_t - S_{j,t}}\right) \right] \times \left({T_t}/{2} \right)}$$

$$Related\_Import_{i,c,t} = \sum_{i \neq j} \varphi_{i,j,t} \times Import_{i,c,t}$$

On the other hand, expected co-occurrence is calculated based on overall sector occurrence. The relatedness between industries has been row-standardized in the calculation, which adjusts the correlation values so that each row of the correlation matrix sums up to one. This technique ensures that the measure of relatedness across different industries is relative and comparable within each year. The use of row-standardization controls that for any given industry, the relatedness measure represents the proportion of its connections to all other industries, thereby allowing for a more accurate representation of the relational importance of each industry to the others.

Next, we use these measures as weights to aggregate information about industry import totals. To avoid capturing the potential noise in the data that might arise from yearly recalculations, which is possibly brings about by industry dynamics, relatedness is calculated every five years in this study. By doing this, the study assumes that the inter-industry relatedness does not change significantly on a year-to-year basis but may evolve more slowly over longer periods. This interval is selected based on the premise that significant evolutionary changes in industries' core competencies, technologies, supply chains, and customer bases develop over more extended periods. For each industry within a given year, we sum up its related industries' import values with each import value scaled according to its corresponding industry's relatedness with respect to the focal industry. More closely related industries contributed more heavily towards overall related imports.

To analyse the long-term impact of innovation activities, we will incorporate lagged variables in our regression analysis. However, there are different time spans for the patent and customs databases - the former covers 2000 to 2020 while the latter only goes up to 2016. Since innovation is a long-term process with delayed effects, we also examine how company behaviour affects future innovation outcomes. To optimize data usage and assess long-term effects, we have chosen to lag the dependent variable instead of using all lagged independent variables when presenting our findings. Table 1 presents descriptive statistical data on the city-industry level.

4.3.3 Industrial robots in China

China's dominance in the global market for industrial robots has grown significantly since 2000. In that year, China accounted for less than 1% of industrial robots shipped worldwide. However, by 2013, China had become the world's largest market for industrial robots with a share exceeding 20%. As of 2021, more than half of all installations of industrial robots globally are in China (International Federation of Robotics, 2022b). As a major manufacturing hub and recipient of orders from around the world, Chinese companies face increasingly demanding and specific customer requirements due to technological advances elsewhere. To meet these challenges and take advantage of government incentives to "replace human with machine," manufacturers have been introducing automated and intelligent equipment into their production processes. This trend is reflected in Figure 1 which shows that robot adoption rates in China have maintained an annual growth rate exceeding 30% since the early 2000s.

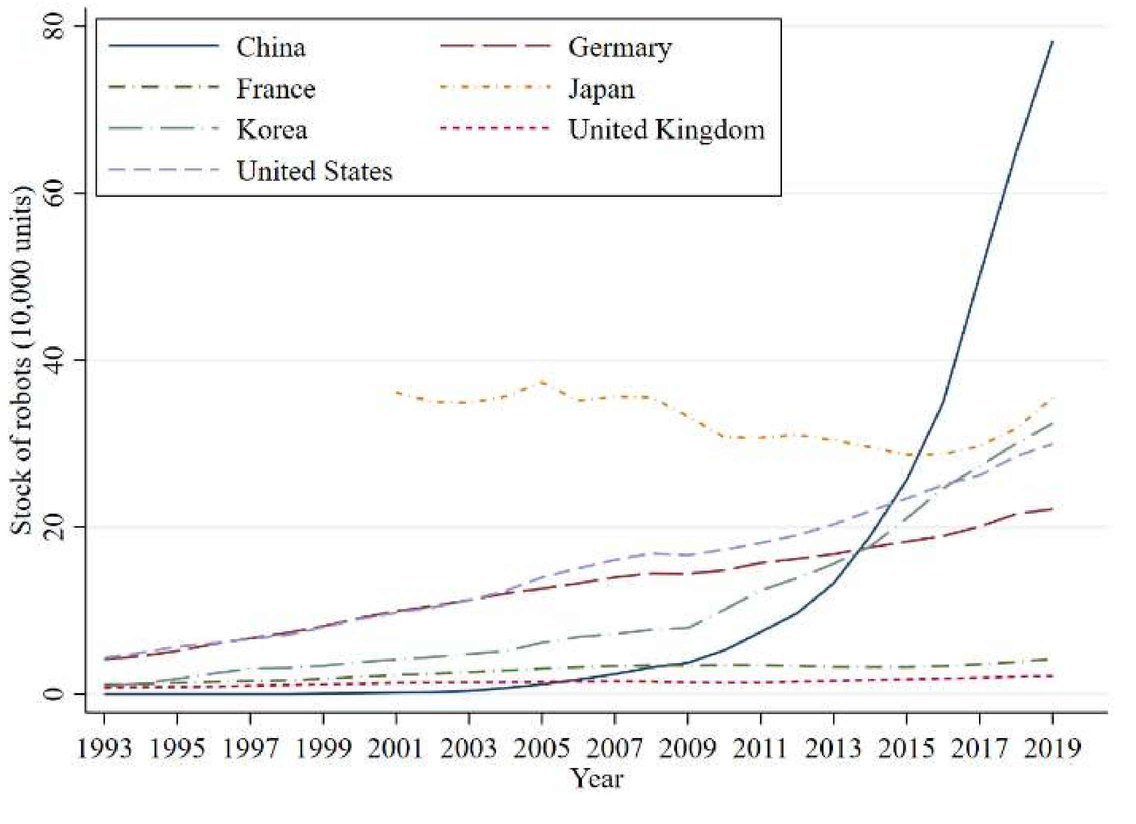


Figure 4.1 The stock of industrial robots in China and other developed countries from 1993 to 2019

(Data source: International Federation of Robotics (IFR))

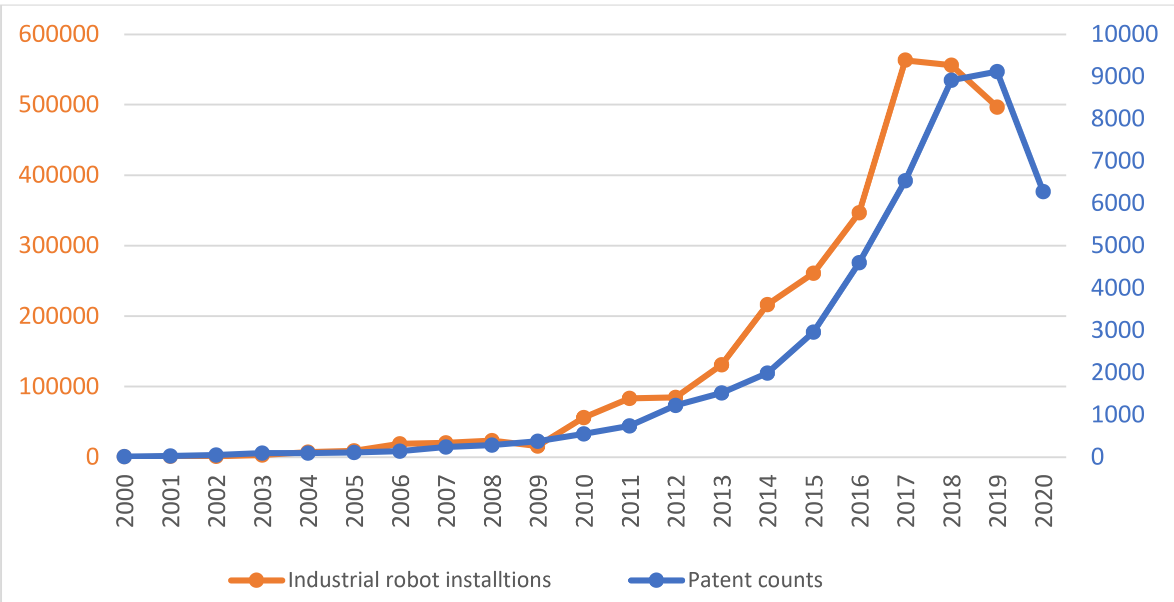


Figure 4.2 Industrial robot installations and robotics patent application in China from 2000-2020

(Data source: IFR and State Intellectual Property Office of People's Republic of China (SIPO))

From 2013 onwards, the International Federation of Robotics began including data from Chinese industrial robot suppliers. This indicates that prior to this year, robot installations in China were imported. However, since then, there has been a rapid increase in domestically produced robots. In just five years, from 2012 to 2017, domestic production increased by over twenty times - from about 5,800 units to an annual rate of 131,000 units. Of these annually produced robots in China, approximately 29% (27,800 units) are manufactured locally. Therefore, it can be concluded that during this period robot technology had already penetrated China.

Table 4.1 The descriptive statistics of variables

Variables	Observations	Mean	Std. Dev	Min	Max
Patent	11,435	0.33	1.45	0	49
Import	11,435	482,100.06	44,90,576.68	0	211,639,142
FDI	11,435	440,464.24	1,785,260.95	0	42,331,089
R&D	11,435	44,097.42	261,610.16	0	7152,291
Related_Import	11,435	1,177,051.6	14,681,357.11	0	520,271,148
FC	11,435	2.09	7.36	0	184

4.4 Regression results

4.4.1 Baseline model

The three-way fixed effect model estimation results enable us to analyse the technological innovation in the field of industrial robots in China from 2000 to 2020. As mentioned above, this period witnessed the growth of China's industrial robot market from almost negligible to the largest user in the world, showing a huge demand for robotics technology and rapid development in intelligent manufacturing. Results show that the quantity of imported robot products has a significant positive correlation with the number of patent applications related to industrial robots, with the coefficient gradually increasing and peaking after two years before gradually diminishing. This suggests that the import of robotic products has played a positive role in promoting technological innovation, likely because the introduced technology and knowledge have helped improve domestic industrial technology. This aligns with the demands from complex customers around the world faced by Chinese companies and the government's incentive policies.

Table 4.2 Regression results of baseline model

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variables:	Y	F. Y	F2. Y	F3. Y	F4. Y	F5. Y
Log (Import)	0.00505***	0.00683***	0.00726***	0.00689***	0.00646***	0.00406***
	(0.00108)	(0.00119)	(0.00130)	(0.00135)	(0.00123)	(0.00120)
Log (FDI)	0.00100**	0.00084**	0.00135***	0.00194***	0.00225***	0.00299***
	(0.00040)	(0.00041)	(0.00044)	(0.00048)	(0.00050)	(0.00053)
Log (R&D)	0.00715***	0.00680***	0.00842***	0.01052***	0.01223***	0.01419***
	(0.00064)	(0.00064)	(0.00073)	(0.00080)	(0.00085)	(0.00091)
Log (FC)	0.00626***	0.00759***	0.00916***	0.01072***	0.01284***	0.01485***
	(0.00124)	(0.00130)	(0.00136)	(0.00134)	(0.00142)	(0.00138)
Constant	0.00155***	0.00292***	0.00359***	0.00414***	0.00419***	0.00341***
	(0.00025)	(0.00030)	(0.00034)	(0.00038)	(0.00039)	(0.00040)
City_FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry_FE	Yes	Yes	Yes	Yes	Yes	Yes
Year_FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	113050	113050	113050	113050	113050	106400
R^2	0.15355	0.16491	0.18743	0.20843	0.23516	0.26563
Adjusted R^2	0.15182	0.16320	0.18577	0.20681	0.23360	0.26403

Notes: 1) Standard errors in parentheses; ; 2) ***, **, * represent significant levels at 0.01, 0.05, and 0.1 levels, respectively.

Similarly, foreign direct investment also shows a significant positive effect in the models. The results imply the positive contributions of foreign capital in introducing new technologies, maybe management experience and integration with global markets for manufacturers. The estimated coefficients for research and development expenditure are significant and continually increasing across models 1 to 6, reflecting the importance of R&D activities in enhancing technological innovation capability. Considering the predictive effect on the patent application as shown in models 2 to 6, it can be inferred that the innovation results of R&D investments have a time lag, with stronger long-term effects. Moreover, the number of foreign-invested enterprises also showed a similar trend, with its positive impact on patent applications, increasing from 0.00626 to 0.01485, indicating that foreign-invested enterprises play an active role in transferring advanced technologies and innovative practices. Overall, the explanatory power of the models increased from an R^2 of 15.355% to 26.563%. The inclusion of fixed effects for city, industry, and year, along with the clustering of standard errors at the city-year level, suggests that the model accounts for unobserved heterogeneity across these dimensions and corrects for possible correlations within groups overtime.

4.4.2 Robustness Tests

To enhance the credibility of our results, we have conducted a series of robustness tests to ascertain the consistency of our findings across various methodological conditions. Initially, we modified the dependent variable in our baseline model to reflect the count of patents. We then transitioned to utilising Poisson regression, an optimal choice for modelling count data that consists of non-negative integers. The Poisson regression's particular suitability stems from its proficiency in handling data where events occur with moderate frequency and are not excessively large in number. This approach mitigates biases that might arise from the distributional assumptions or inherent constraints of linear regression techniques when dealing with count data. Moreover, the Poisson model accounts for unobserved heterogeneity by controlling for city, industry, and year fixed effects, as detailed in Table 4.3.

Table 4.3 Robustness test results using Poisson regression

	(7)	(8)	(9)	(10)	(11)	(12)
Dependent Variables:	Patent	F. Patent	F2. Patent	F3. Patent	F4. Patent	F5. Patent
Log (Import)	0.03714***	0.04951***	0.04440***	0.03170***	0.02617**	0.00959
	(0.01372)	(0.01248)	(0.01125)	(0.01053)	(0.01326)	(0.01123)
Log (FDI)	0.02888	-0.00493	-0.00433	-0.00104	-0.00048	0.03757**
	(0.01944)	(0.01815)	(0.01505)	(0.01603)	(0.01702)	(0.01625)

Log (R&D)	0.04184**	-0.02271	-0.01120	0.00388	0.03552	0.07862***
	(0.02087)	(0.01734)	(0.01664)	(0.01779)	(0.02169)	(0.02142)
Log (FC)	-0.00817***	-0.00365	-0.00393	-0.00206	0.01072***	0.04074***
	(0.00278)	(0.00335)	(0.00264)	(0.00223)	(0.00300)	(0.01219)
Constant	0.03714***	0.04951***	0.04440***	0.03170***	0.02617**	0.00959
	(0.01372)	(0.01248)	(0.01125)	(0.01053)	(0.01326)	(0.01123)
Observations	7276	8194	9367	10659	11237	10560
City_FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry_FE	Yes	Yes	Yes	Yes	Yes	Yes
Year_FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: 1) Standard errors in parentheses; ; 2) ***, **, * represent significant levels at 0.01, 0.05, and 0.1 levels, respectively.

The analysis reveals that the estimated coefficients for Log (Import) consistently maintain statistical significance across different model specifications, underscoring the robustness of this variable. However, variations emerge with other variables. For instance, Log (FDI) does not exhibit significance in the short term and surprisingly indicates a negative relationship with patent counts in the immediate one or two-year period. Contrastingly, a significant positive effect occurs in the long-term forecast, particularly in the five-year mark as presented in model (12). This pattern suggests that FDI's beneficial influence on patent production may require an extended incubation period to manifest. Similarly, Log (R&D) initially exhibits a positive correlation with patent counts in model (7) but transitions to a negative (though not significant) association in the immediate subsequent periods (models 8 to 10). By the fifth period (F5. Patent in model 12), the relationship turns strongly positive and significant, hinting at a delayed positive impact of R&D investment on patent generation, likely due to the research period necessary for R&D activities to culminate in patentable outputs. Log (FC), indicative of foreign-capital enterprises, starts off with a negative and significant coefficient, possibly reflecting an initial crowding-out effect or adaptation phase. Nevertheless, this variable shifts to a positive and significant stance in the more extended term models (models 11 and 12), implying that over time, the presence of foreign-funded enterprises may indeed foster higher patent counts.

Collectively, the robustness test outcomes above not only corroborate our primary linear regression findings but also shed light on the temporal dynamics of impact. Factors like FDI and R&D investments may exhibit delayed effects, materialising in patent increases only over an extended horizon.

Table 4.4 Robustness test results using logic regression

	(13)	(14)	(15)	(16)	(17)	(18)
Dependent Variables:	Patent_D	F. Patent_D	F2. Patent_D	F3. Patent_D	F4. Patent_D	F5. Patent_D
Log (Import)	0.02580**	0.03083***	0.02722***	0.01723**	0.01666	-0.00323
	(0.01153)	(0.01053)	(0.00986)	(0.00828)	(0.01034)	(0.00905)
Log (FDI)	0.02674	-0.01231	-0.00804	0.00565	0.02290**	0.05112***
	(0.01681)	(0.01447)	(0.01147)	(0.00948)	(0.01163)	(0.01251)
Log (R&D)	0.05654***	-0.02408	-0.02096*	-0.00664	0.01277	0.06058***
	(0.02039)	(0.01854)	(0.01218)	(0.01436)	(0.01238)	(0.01181)
Log (FC)	0.00238	0.01479**	0.02033**	0.03004***	0.04235***	0.08672***
	(0.00708)	(0.00659)	(0.00990)	(0.01131)	(0.01439)	(0.02999)
Constant	0.02580**	0.03083***	0.02722***	0.01723**	0.01666	-0.00323
	(0.01153)	(0.01053)	(0.00986)	(0.00828)	(0.01034)	(0.00905)
Observations	7276	8194	9367	10659	11237	10544
City_FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry_FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: 1) Standard errors in parentheses; ; 2) ***, **, * represent significant levels at 0.01, 0.05, and 0.1 levels, respectively.

We further expanded our investigation into the determinants of patent activity by performing logistic regression analyses. The logistic approach facilitates a different angle of analysis, concentrating on the probability of an industry engaging in patenting activity. These models use a binary dependent variable that signifies whether an industry has filed for patents in a given year, offering a dichotomous perspective on patent activity as opposed to the count data previously examined. The logistic regression results are presented in Table 4.4, featuring dependent variables from Patent_D to F5. Patent_D, representing the current and future year patent filing status.

For Log (Import), we observed significant positive effects in the immediate term, but this influence diminishes over time, as reflected by the loss of significance in the long-term lag (F5. Patent_D), which does not hold as the baseline models and Poisson models do. The coefficients for Log (FDI) remain non-significant in the short run, yet as the forecast horizon extends, their significance and positive impact intensify, particularly notable in the five-year forecast model (18), confirming a lagged response to FDI. The trajectory of Log (R&D) presents a compelling narrative, with a strong initial positive impact that momentarily dips, only to rise significantly again in the long-term forecast. This pattern indicates the evolving and delayed effects of R&D investments on the likelihood of patent filings. The variable Log (FC) initially shows an insignificant impact, but over time, its influence grows markedly, reaching high significance levels in the long-term model. This trend may reflect the increasing propensity for industries with foreign capital involvement to file patents as they establish more robust operations and R&D roots in the domestic market.

The logistic regression analysis complements our robustness checks and underscores the complex temporal dynamics of the determinants of patent filings. The diminishing effect of imports over time juxtaposed with the strengthening influence of FDI and foreign capital presence on the probability of patent filings necessitates a nuanced understanding of the policy implications. R&D investment displays a non-linear effect on patent activity, further highlighting the intricate relationship between innovation investments and patenting outcomes. Collectively, these logistic regression outcomes validate the robustness of our original findings and enrich our understanding of the factors influencing patent filings.

4.4.3 Impact of imports from related industry

While we try to explore the intricacies of industrial dynamics and their influence on innovation, it is important not only to consider the isolated activities within a given sector, but also the symbiotic relationships among industries. The variable calculated at section 4.3.2 are taken into account the later analysis, offering a nuanced view of inter-industry interactions. By including *Related_Imports* in the regression model, we aim to shed light on the extent to which interconnected trade activities fuel inventive outcomes. This subsection delves into the empirical exploration of how imports from related industries bolster the propensity for

Table 4.5 Regression results including *Related_Imports*

	(19)	(20)	(21)	(22)	(23)	(24)
	Log (Patent)	F. Log (Patent)	F2. Log (Patent)	F3. Log (Patent)	F4. Log (Patent)	F5. Log (Patent)
Log (Import)	0.00505***	0.00683***	0.00727***	0.00690***	0.00646***	0.00406**
	(0.00113)	(0.00137)	(0.00163)	(0.00179)	(0.00179)	(0.00169)
Log (Related_Import)	0.00089***	0.00091***	0.00110***	0.00103***	0.00091***	0.00060**
	(0.00022)	(0.00025)	(0.00025)	(0.00030)	(0.00027)	(0.00027)
Log (FDI)	0.00094	0.00078	0.00127*	0.00187**	0.00218**	0.00295***
	(0.00061)	(0.00069)	(0.00070)	(0.00078)	(0.00085)	(0.00095)
Log (R&D)	0.00713***	0.00678***	0.00840***	0.01050***	0.01222***	0.01419***
	(0.00101)	(0.00106)	(0.00122)	(0.00144)	(0.00158)	(0.00169)
Log (FC)	0.00626***	0.00758***	0.00915***	0.01072***	0.01284***	0.01484***
	(0.00194)	(0.00209)	(0.00243)	(0.00272)	(0.00312)	(0.00374)
Constant	-0.00014	0.00117	0.00149	0.00218*	0.00245**	0.00226*
	(0.00079)	(0.00090)	(0.00099)	(0.00116)	(0.00117)	(0.00125)
N	113050	113050	113050	113050	113050	106400
City_FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry_FE	Yes	Yes	Yes	Yes	Yes	Yes
Year_FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.15421	0.16548	0.18809	0.20890	0.23550	0.26576
Adjusted R^2	0.15247	0.16375	0.18641	0.20727	0.23392	0.26416

Notes: 1) Standard errors in parentheses; ; 2) ***, **, * represent significant levels at 0.01, 0.05, and 0.1 levels, respectively.

innovation, which is captured by patent activities as the empirical analysis above. Table 4.5 shows results of regression models including the variable of *Related_Import.*

The estimated coefficient of *Related_Imports* in the regression models reveals a consistently positive and statistically significant effect on patenting activities across all specifications. Result suggest that not only do imports influence innovation, but there is also an incremental effect of industries that are related to the industry import robotics. The diminishing magnitude of the coefficients over time may suggest that the immediate impact of related imports on innovation is stronger than its long-term effect.

The results indicate that while overall imports and R&D continue to be important predictors of patenting activities, which supports our baseline model. In addition to that, the relatedness of imports plays a distinct and significant role in innovation outcomes. The positive coefficients for *Related_Imports* suggest that industries draw innovative insights from inputs sourced from industries that share a close relationship with them. The R-squared values increase with the inclusion of the *Related_Imports*, indicating that these models explain more variation in patent outputs than baseline models.

4.4.4 Synergistic dynamics between imports and economic activities

In this subsection, we look into the synergistic dynamics between imports and economic activities —research and development (R&D) and foreign direct investment (FDI). By introducing interaction terms into our regression models, we aim to elucidate the combined effects these variables may have on patent outputs. The regression results presented in Table 4.6 explore the interaction between imports and two key investment areas: research and development (R&D) and foreign direct investment (FDI)

The consistently positive and significant coefficients estimated for the interaction terms for import and R&D across all models indicate a complementary relationship between imports and R&D. It suggests that as firms increase their investment in R&D, the positive impact of imports on patent outputs becomes stronger. This could be due to imported technologies providing new ideas or essential components that enhance domestic R&D efforts. The interaction term for imports and FDI becomes significant and positive from model (28) onwards, implying that the positive effect of imports on patent outputs is enhanced when coupled with FDI. This may be reflective of FDI providing additional resources, knowledge, or networks that amplify the benefits of imports. The R-squared values increase with the inclusion of the interaction terms, indicating that these models explain more variation in patent outputs than models without interaction terms. Overall, the results suggest that while imports have a nuanced impact on innovation, the interaction with R&D and FDI investments can significantly enhance this effect.

Table 4.6 Interaction Effects of Imports with R&D and FDI on Patent Outputs

Dependent Variables:	(25) Log (Patent)	(26) F. Log (Patent)	(27) F2. Log (Patent)	(28) F3. Log (Patent)	(29) F4. Log (Patent)	(30) F5. Log (Patent)	(31) F6. Log (Patent)
Log (Import)	0.00052	0.00092*	0.00080	-0.00160**	-0.00450*	-0.00638**	-0.01018***
	(0.00048)	(0.00053)	(0.00058)	(0.00063)	(0.00250)	(0.00265)	(0.00257)
Log (Import) × Log (R&D)	0.00069***	0.00088***	0.00097***	0.00107***	0.00103***	0.00103***	0.00115***
	(0.00004)	(0.00004)	(0.00005)	(0.00005)	(0.00021)	(0.00022)	(0.00021)
Log (Import) × Log (FDI)	0.00004	0.00006	0.00007	0.00020***	0.00045*	0.00038	0.00048**
	(0.00004)	(0.00005)	(0.00005)	(0.00006)	(0.00023)	(0.00025)	(0.00024)
Log (FDI)	0.00141***	0.00136***	0.00192***	0.00252***	0.00267***	0.00344***	0.00390***
	(0.00014)	(0.00015)	(0.00017)	(0.00018)	(0.00045)	(0.00047)	(0.00048)
Log (R&D)	0.00593***	0.00525***	0.00671***	0.00863***	0.01043***	0.01253***	0.01417***
	(0.00019)	(0.00021)	(0.00023)	(0.00025)	(0.00075)	(0.00078)	(0.00081)
Log (FC)	0.00529***	0.00633***	0.00777***	0.00905***	0.01095***	0.01308***	0.01388***
	(0.00014)	(0.00015)	(0.00017)	(0.00018)	(0.00117)	(0.00115)	(0.00123)
Constant	0.00184***	0.00329***	0.00401***	0.00464***	0.00475***	0.00393***	0.00352***
	(0.00027)	(0.00030)	(0.00033)	(0.00036)	(0.00025)	(0.00024)	(0.00024)
City_FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry_FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year_FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	113050	113050	113050	113050	113050	106400	99750
R2	0.15647	0.16872	0.19113	0.21254	0.23946	0.26928	0.29148
Adjusted R2	0.15473	0.16701	0.18946	0.21091	0.23789	0.26768	0.28983

Notes: 1) Standard errors in parentheses; ; 2) ***, **, * represent significant levels at 0.01, 0.05, and 0.1 levels, respectively.

4.4.5 Enterprise-Level Determinants of Innovation Performance

This subsection focuses on the granular impact of imports and innovation at the enterprise level. It complements the city-industry perspective by examining how individual firms' import activities correlate with their patent outputs, offering a microcosmic view of the innovating activities. While the core methodology of our analysis remains consistent with the overarching study as we shift from the broader industry model to the intricacies of enterprise-level data, we adapt our regression models to capture the dynamics of firm-specific innovation drivers. Here, we introduce an adjusted econometric model that integrates enterprise-specific variables, such as Total Factor Productivity (TPF) and R&D intensity, to scrutinize their role in shaping patent applications.

$$Patent_{i,t} = \alpha + \beta_1 IMP_{i,t} + \boldsymbol{\beta_2}\, \boldsymbol{X_{i,t}} + \boldsymbol{\beta_3}\, \boldsymbol{T} + \boldsymbol{\beta_4}\, \boldsymbol{I} + \varepsilon_{i,t}$$

$Patent_{i,t}$ denotes the number of firm *i*'s patent application during year *t*. In accordance with established literature, the natural logarithm of $(Patent_{i,t} + 1)$is utilised to gauge their level of innovation in the present year. The variable $IMP_{i,t}$ represents the amount of robotics product imports of firm *i* in the year *t*, with $\boldsymbol{X_{i,t}}$ as the enterprise-level control variable, including: *Total Factor Productivity* (TFP). We use the industrial enterprise database to calculate the TFP. However, some key indicators were missing from this database. To address this issue, we supplemented and calculated these indicators by referring to Yu et al. (2018) and applying Levinsohn and Petrin (2003) method in accordance with standard accounting principles. *R&D* refers to the annual Research and Development expenses of the enterprise. *FDI* refers to the direct investment of foreign capital and Hong Kong, Macao and Taiwan capital in enterprises. *Scale* refers to total employment of the company at year-end. *Capital per employee* (capital/labour) is determined by dividing fixed assets with total number of employees. To avoid the omission of important explanatory variables, this study also includes fixed effects for year, enterprise, and city. The year fixed effect ***T*** is introduced to control for the impact of specific events that may occur in certain years. The enterprise fixed effect ***I*** is included to absorb the influence of individual differences among enterprises on the results. Table 4.7 presents descriptive statistical data on this unbalanced panel.

Table 4.7 The descriptive statistics of variables

Variables	Observations	Mean	Std. Dev	Min	Max
Patent	39,476	0.1	0.63	0	45
Import	39,476	139,649.77	2,225,306.25	0	211,639,142
TPF	39,278	8,827.02	61,797.55	2.98	5,143,400.5
R&D	35,358	14,261.38	133,909.25	0	7,142,497
FDI	39,476	127,589.13	458,014.33	0	14,622,627
Scale	39,476	1,557.22	6,192.32	0	236,035
Capital	39,476	760.35	7,060.94	0	442,676.5

After describing the model and descriptive statistics, we proceed to present the results at the firm level. Table 4.8 presents the enterprise-level regression results, exploring the determinants of innovation as reflected by patent application activity. The coefficients on Log (Import) suggest an evolving relationship between import levels and innovation. Initially, the relationship is significantly negative (model 32), implying that higher import levels may be associated with lower innovation output. However, this effect diminishes and turns positive (though less significantly) in later years (models 34-37), potentially indicating a lagged positive impact of imports activity on innovation or an adaptation period for firms to effectively leverage imported technologies. TPF is positively related innovation output, with significance peaking in the one-year lag. The variation in significance across columns may reflect fluctuations in the efficiency with which inputs are utilized year over year. Notably, the positive and significant coefficients in models 32 and 35 indicate that, at least in certain years, TPF is a robust predictor of innovation.

Investment in R&D consistently shows a positively significant effect across all models, underscoring its crucial role in driving firm-level innovation. The stability and strength of the R&D coefficients confirm the widely accepted view that R&D activities are central to the innovative process. The impact of FDI on innovation is mixed. Initially, FDI does not appear to have a significant impact (model 32 in Table 4.8), but it becomes negatively significant in subsequent years (models 34-36). This could reflect a complex interaction between foreign investment and domestic innovation activities, where FDI may not always align with the firm's innovation strategies.

Table 4.8 Regression results at the enterprise level

	(32)	(33)	(34)	(35)	(36)	(37)
Log (Import)	-0.0042***	-0.0006***	0.0001	0.0005*	0.0004*	0.0005**
	(0.0007)	(0.0002)	(0.0003)	(0.0003)	(0.0002)	(0.0002)
Log (TPF)	0.0036*	0.0047***	0.0032	0.0031**	0.0026	0.0027
	(0.0021)	(0.0011)	(0.0021)	(0.0015)	(0.0028)	(0.0028)
Log (R&D)	0.0027***	0.0034***	0.0037***	0.0035***	0.0040***	0.0038**
	(0.0007)	(0.0007)	(0.0009)	(0.0008)	(0.0010)	(0.0014)
Log (FDI)	-0.0003	-0.0006*	-0.0012***	-0.0013***	-0.0021***	-0.0011**
	(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.0006)	(0.0005)
Log (Scale)	0.0005	0.0035	0.0059	0.0066**	0.0049	0.0051
	(0.0033)	(0.0022)	(0.0039)	(0.0028)	(0.0056)	(0.0069)
Capital	0.0000***	0.0000**	0.0000***	0.0000	0.0000**	-0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Constant	0.0235*	-0.0262*	-0.0208	-0.0151	0.0166	0.0234
	(0.0137)	(0.0134)	(0.0187)	(0.0167)	(0.0264)	(0.0350)
Year_FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm_FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	39473	33535	30437	27299	24323	21327
R^2	0.6523	0.5764	0.5689	0.6025	0.6567	0.6942
Adjusted R^2	0.6179	0.5267	0.5119	0.5438	0.5982	0.6334

Notes: 1) Standard errors in parentheses; ; 2) ***, **, * represent significant levels at 0.01, 0.05, and 0.1 levels, respectively.

The variable Log (Scale) does not show a consistent pattern, suggesting that the size of the firm, as measured by employment, does not have a uniform effect on innovation. This aligns with the notion that the advantages of scale for innovation may be contingent on other factors, such as industry characteristics or the nature of the firm's market. Capital per employee exhibits mixed results, with a positive association in the short term (models 32-33 in Table 4.8), but a negative impact in the longer term (model 37). This may reflect a nuanced relationship where initial capital investment supports innovation, but over time, excessive capital intensity without corresponding efficiency gains may hinder innovation.

In comparison to the city-industry level results, the enterprise-level findings offer a more different view, revealing the complexity of the relationship between imports and innovation. At the city-industry level, imports consistently spur innovation activity, suggesting that at a broader scale, the influx of imported goods or technologies directly correlates with increased innovative outputs, likely due to wider access to diverse technologies and competitive pressures stimulating local innovation. Conversely, the enterprise-level analysis reveals a more micro and temporally lagged relationship between imports and innovation. Initially, higher levels of imports are associated with reduced patent output, as indicated by the negative coefficients in the early models of Table 4.8. First, there may be an initial phase where firms adapt to integrate imported technologies, which might temporarily divert resources or focus away from their own innovation activities. Additionally, firms might initially use imports as substitute for local innovation, relying on external technologies rather than developing their own. However, as time progresses, this relationship becomes positive, suggesting that after an adaptation period, firms begin to effectively leverage imported technologies to enhance their own innovation capabilities. This lagged effect can reflect a learning curve where firms gradually learn from and build upon imported technologies, eventually leading to its breakthrough, which is in the presence of patent applications. The shift from a negative to a positive relationship highlights the importance of considering time lags in understanding how imports affect firm-level innovation.

4.5 Chapter Summary

In a global landscape where automation technologies are rapidly evolving, a critical question emerges: can countries with technological gaps leverage imports to foster innovation? This issue is particularly pressing for low- and middle-income countries, where existing research, often centred on more advanced nations, suggests a concentrated distribution of automation and Industry 4.0 technologies. This disparity raises concerns about path dependency and the barriers to adopting and innovating with these technologies. Recognizing the importance of early adoption and the development of existing capabilities, this study aims to bridge this research gap by focusing on China, a key example of a developing economy engaging with these global technological trends. Specifically, it examines the impact of imports, R&D, and FDI on local innovation capacities in robotics technologies.

The research initially undertakes a city-industry level analysis to examine how imports, R&D, and FDI influence the number of patent applications. Subsequently, the study shifts to an enterprise-level analysis, exploring the microeconomic implications of these factors on firm-level innovation. To affirm the robustness of the findings, various checks, including Poisson regression and logistic regression, were performed.

Our research finds that at the broader city-industry level, imports provide an immediate impetus for innovation, possibly due to a diffusion of ideas and competitive dynamics. In contrast, at the enterprise level, the impact of imports on innovation is contingent upon a firm's ability to absorb and integrate external knowledge, which may vary widely depending on the firm's existing capabilities, resources, and strategic orientation. Across both levels, R&D investment consistently proved crucial for driving innovation. The impact of FDI on innovation varied across different times and analysis levels, reflecting its complex nature.

CHAPTER5. ROBOTIC AND URBAN EMPLOYMENT: UNRAVELLING THE INTERPLAY OF INDUSTRIAL DIVERSITY, SPECIALISATION, AND SPATIAL DYNAMICS

5.1 Introduction

Similar to countries affected by automation performing differently, the impact of automation on the urban labour market varies from city to city (H. C. Chen et al., 2022; Frank et al., 2018). Findings from previous studies categorise cities by city size (Czaller et al., 2021; Frank et al., 2018); however, this does not apply to Chinese cities (Chen et al., 2021). Before reform and opening up, China had experienced a long period of top-down planned economic development (Logan, 2018), which directly influenced the trajectory of urban development in China. In the context of a planned economy, the ability of cities to access more resources for development determines the subsequent development path of cities (Barbieri et al., 2012). Cities with government support lead to a diversified industrial structure, and those without government support lead to speciality cities (H. C. Chen et al., 2022; Zhu et al., 2017). Therefore, this chapter raises a more specific question in the Chinese context: whether cities endowed with different industrial structures behave differently under robotic exposure.

H. C. Chen et al. (2022) argue that cities with access to more resources are more resilient to automation due to a more diverse industrial structure. This is in line with the regular theme concerning agglomeration, discussing the impact of diversification versus specialisation. (Glaeser et al., 1992). Later there is a conceptual framework that defines and categorises diversification into related and unrelated varieties by introducing the concept of cognitive proximity (Boschma, 2015; Boschma & Iammarino, 2009; Frenken et al., 2007; Porter, 2003). Knowledge spillover mainly occurs when two industries are cognitively close to each other (Nooteboom, 2000), but only to a limited extent among unrelated sectors (Frenken et al., 2007).

Accordingly, this chapter examines the effects of industrial specialisation and (un)related variety in China using data from the China Annual Survey of Industrial Firms and the International Federation of Robotics (IFR). Due to data availability, this study was conducted in the context of China's transition, based on panel data of 271 prefectural-level cities from 2008 to 2015.

5.2 Literature review and Hypotheses development

Automation and robotics, central to the fourth industrial revolution, are significantly altering employment landscapes. Acemoglu and Restrepo (2019) provide evidence of the potential influence of such advancements: the increasing intensity of automation is coupled with a decrease in new task creation, which ultimately leads to a diminished demand for human labour. Such conclusion finds resonance in various studies, which collectively underline the pressing consequences of job automation on employment, wages and productivity (Acemoglu & Restrepo, 2019, 2020; Autor & Salomons, 2018; Dauth et al., 2017; Dottori, 2021).

Furthermore, while much of the study emanates from Western studies, China's burgeoning engagement with automation offers a pertinent case in point. Despite its recent development as the world's preeminent industrial robot user (Li et al., 2020), research focusing on China's automation trajectory is relatively nascent. This development is partly informed by the Lewis turning point, a juncture where the nation began to face with labour shortages and increasing labour costs, prompting industries pivoted towards automation as a substitute for human labour (Du and Wei, 2020).

Central to the discussion on automation's impact on employment are two competing narratives: 'displacement effect', where robots replace human jobs, and the 'reinstatement effect', where new roles emerge as a consequence of automation. Drawing from empirical studies on the Chinese labour market (Giuntella and Wang, 2019, Du and Wei, 2021) and in line with the broader literature, we posit our primary hypothesis:

Hypothesis 1: The adoption of industrial robots in a city is inversely correlated with the employment rate in that city's labour market.

While the direct consequences of robot adoption employment lay the basic foundation of this discourse, it is crucial to recognise the intricate interplay of the modern economic landscape. Recent research has underscored the significance of industrial structures, more specifically, industrial diversity and specialisation in determining a city's resilience or vulnerability to automation. Frank et al. (2018) highlighted the interplay between urban agglomeration and the employment consequences of automation, noting shat smaller cities are particularly vulnerable. Similarly, Crowley et al. (2021) explored regional susceptibility to job automation in the context of agglomeration externalities across Europe.

Beyond such mere agglomeration externalities, the structural composition of industries within an economy can play a profound role. The way cities react to external stimuli can often be traced back to their foundational make-up; in this case, the industrial structure of an economy might shape its responses to technological advancement.

A recurring theme in literature discussing the industrial structure of an economy is the dichotomy of between diversified and specialised industries(Glaeser et al., 1992). Among the debates, Jacobs (1969) put forward that firms co-located with those from diverse industries benefit from diversification, leveraging both formal and informal information exchanges to spur innovation. Frenken et al. (2007) further developed the concept of diversification by differentiating between related and unrelated varieties, suggesting that not all diversities lead to knowledge spillovers (Boschma, 2015; Boschma & Iammarino, 2009; Frenken et al., 2007; Porter, 2003). The specificity of these varieties becomes even more pertinent in the context of automation and its effects on the labour market.

Related variety refers to the diversity of industries within an economy that share a common knowledge base or technological relatedness, promoting knowledge spillovers and synergies(Nooteboom, 2000). While related variety is often associated with regional growth (Boschma & Iammarino, 2009; Boschma et al., 2012; Falcıoğlu, 2011; Quatraro, 2010; Saviotti & Frenken, 2008), its role in buffering or exacerbating external shocks, such as those from automation, is debated. Some studies suggest that cities with a high degree of related variety might be more vulnerable to such shocks due to intertwined information networks(He et al., 2021; Martin, 2012).

To illustrate the potential impact of related variety on external shocks, consider two hypothetical cities, one with high related variety and the other with low. Assuming that industries in these cities are interconnected, an external shock to one industry could ripple through to related industries. In a city with high related variety, this ripple effect could be more pronounced, leading to a more widespread impact. This conceptual framework suggests that while related variety can facilitate knowledge spillovers, it might also transmit risks more efficiently between industries.

Unrelated variety in a city's industrial structure is often posited as a protective mechanism against external shocks. The logic is akin to a portfolio diversification strategy in finance: a diverse set of unrelated industries can shield a city from the adverse effects of shocks in any single industry (Frenken et al., 2007; Haug, 2004; Van Oort et al., 2015). Although this diverse set of unrelated industries can act as a buffer, mitigating the immediate adverse effects of shocks in any single industry, its inherent structural separation might not completely insulate cities from automation risks. Instead, while the ripple effects of automation might be less pronounced due to fewer inter-industry linkages, the overall macro impact on employment could still be negative. Additionally, while unrelated variety can spur breakthrough innovations, leading to the creation of entirely new industries (Castaldi et al., 2015), such innovation is rare. The net employment gains from such innovations might not compensate for jobs lost to robots in the short to medium term.

Marshall (1890) proposed that specialised cluster, providing specific goods and services, offer firms distinct advantages, a notion later formalised as the Marshall-Arrow-Romer (MAR) model by Glaeser et al. (1992). Such specialised cities, often rooted in traditional industries or those transferred from coastal metropolises, are shaped by local resources and comparative advantages. While conventional wisdom may suggest that such cities, due to their narrow industrial focus, could be susceptible to path dependency and technological lock-in(Boschma, 2015; Boschma & Iammarino, 2009; Boschma et al., 2012; Caragliu et al., 2016; Frenken et al., 2007), there is a contrasting perspective that such specialisation might serve as a shield. Given the nature of specialisation often centres on core competencies and professional skills, cities with higher degree of specialisation might not be as vulnerable to the sweeping impacts of automation as believed. Particularly, industries rooted deeply in specialised knowledge or unique craftsmanship might remain resilient against robot adoption, as opposed to sectors dominated solely by routine tasks. Given the discussed complexities surrounding industrial diversification and specialisation, we put forward our next hypothesis:

Hypothesis 2a: The adverse effect of industrial robot adoption on employment is intensified in cities with greater industrial diversity. Among diverse industrial structures, the related variety (RV) has a more significant negative impact on employment compared to unrelated variety (UV) when industrial robots are introduced.

Hypothesis 2b: A higher degree of specialization within a city's industrial structure will buffer or reduce the negative impact of industrial robots on its employment levels.

The influence of economic activities in one locale often transcends its borders, affecting adjacent regions—a phenomenon widely recognized in economic geography as spatial externalities(Hu & Li, 2015; Rodríguez-Pose & Crescenzi, 2008). Modern economies, with their intertwined supply chains and shared labour markets, are no exception. With the diffusion of technology, such as industrial robots, it's plausible to expect that cities adjacent to early adopters may experience secondary effects. The automation trend in one city, for instance, could lead to reduced demand for manually produced goods from its neighbouring city, affecting the latter's employment. Empirical studies have shown how technological adoption in central regions often pushes low-skilled jobs to peripheral areas, only to later shrink those jobs with the spread of technology(Zhou, 2022).

While technological advancements may initially seem disruptive, their effects are multifaceted. Cities that are on similar economic trajectories might find synergies amidst technological disruptions. For instance, while one city adopts robots and reduces certain job roles, it might simultaneously generate demand for other roles, which could be supplied by neighbouring cities with similar economic structures.

Hypothesis 3a: The negative employment effects due to industrial robot utilization in one city will spill over to negatively influence neighbouring cities' employment levels.

Hypothesis 3b: Cities with similar economic development stages will experience a positive employment spillover from neighbouring cities, even when those neighbours have increased industrial robot adoption.

The role of a city's industrial structure in mediating the effects of technological advancements is crucial. However, the degree to which these moderating effects propagate to adjacent regions remains underexplored. Given the unique characteristics of each city's industrial landscape, the buffering or amplifying impacts of a particular industrial structure might be deeply localized, influenced by specific regional policies, historical trajectories, and local business ecosystems.

Hypothesis 4: The moderating effects of a city's industrial structure on the impact of robot adoption on employment are localized, with no spillover effects on neighbouring cities.

5.3 Method and data

5.3.1 Empirical design

The primary dataset for our analysis is derived from the China Annual Survey of Industrial Firms, which captures information on over 300,000 industrial firms across 31 two-digit industries and 171 three-digit industries. Data on robot usage were obtained from the International Federal of Robotics (IFR) and the second *China Enterprise Economic Census* in 2008. Other supplementary data is extracted from the China City Statistical Yearbook spanning the years 2009–2016. These data provide a comprehensive perspective on China's industrial milieu. The sample for this study encompasses 282 cities in China spanning from 2008 to 2015. This chpater seeks to address the question: "Will the impact of industrial robots on urban labour markets be moderated by industrial specialization, related variety, and unrelated variety?" Therefore, we first capture the direct effect of robot adoption on Employment, then we measure the mediation effect through interaction terms with industrial structures:

$$\begin{aligned} ER_{i,t} = {} & \alpha_0 + \alpha_1 RE_{i,t} + \alpha_2 \left(RE_{i,t} \times IndustrialStructure_{i,t}\right) \\ & + \alpha_3 IndustrialStructure_{i,t} + \boldsymbol{\alpha_4 X_{i,t}} + \boldsymbol{\alpha_5}\, \boldsymbol{T} + \boldsymbol{\alpha_6 C} + \varepsilon_{i,t} \end{aligned} \tag{1}$$

where$ER_{i,t}$ is the employment rate of city *i* in year *t.* $RE_{i,t}$ denotes the degree of robot adoption of city i in year *t.* $IndustrialStructure_{i,t}$ measures for specialisation($SPE_{i,t}$) , related variety($RV_{i,t}$), and unrelated variety ($UV_{i,t}$) respectively in city *i* in year *t.* The calculation of these indicators is described in Section 3.2. $\boldsymbol{X_{i,t}}$ are city-specific control variables. $\boldsymbol{T}$ and $\boldsymbol{C}$ are fixed effects for years and cities respectively. The error terms $\varepsilon_{i,t}$ capture unobserved shocks. All nominal variables underwent inflation adjustments using the GDP deflator, with 2008 set as the base year. Standard errors are adjusted for clustering at the city level.

5.3.2 Variable Calculation

(1) Robot exposure (RE)

Following the studies of Acemoglu and Restrepo (2020) and Dauth et al. (2017), we construct a Bartik-style indicator to calculate the level of robot exposure for each city. The IFR publishes annual statistics on worldwide robotics industrial robots, which contains data on robot installations by type, country, industry and application. The data is collected as primary data from most industrial robot suppliers worldwide or as secondary data through national robotics associations. Hence, only country-level industrial breakdown data is available. We then calculate the level of robot exposure for each city based on employment data by industry and city as weights, which are derived from the second *China Enterprise Economic Census* in 2008. Because there are differences between the industrial classifications of China and IFR, we re-match the two standards into 19 sectors: agriculture, forestry, fishing; Mining and quarrying; food and beverages; Textiles, wood and furniture; paper and printing; plastic and chemical products; minerals; basic metals; metal products; electrical and electronics; industrial machinery; automotive; other vehicles; other manufacturing production; electricity, gas, water supply; construction; education, research, and development; other services. Following Equation (2), we aggregate employment and robot installation/stock according to this industry classification and calculate the Robot Exposure (RE) index across Chinese prefecture-level cities.

$$\boldsymbol{RE}_{it} = \sum_{j=1}^{J} \left(\frac{emp_{i,j,t=base}}{emp_{j,t=bas}} \times \frac{Robot_{j,t}}{emp_{i,t=bas}}\right) \tag{2}$$

Where $Robot_{kt}$ denotes the number of installed robots in industry *j* and city *i* at time *t*. $emp_{i,j,t}$ is the employment in industry *j* and city *i* at year *t*. This calculation is based on two assumptions: The penetration of industrial robots within a country is commensurate, and the distribution of employment across industries has not changed significantly since the base year. Higher RE values represent higher robot density (units per 1,000 workers) and robot penetration rates.

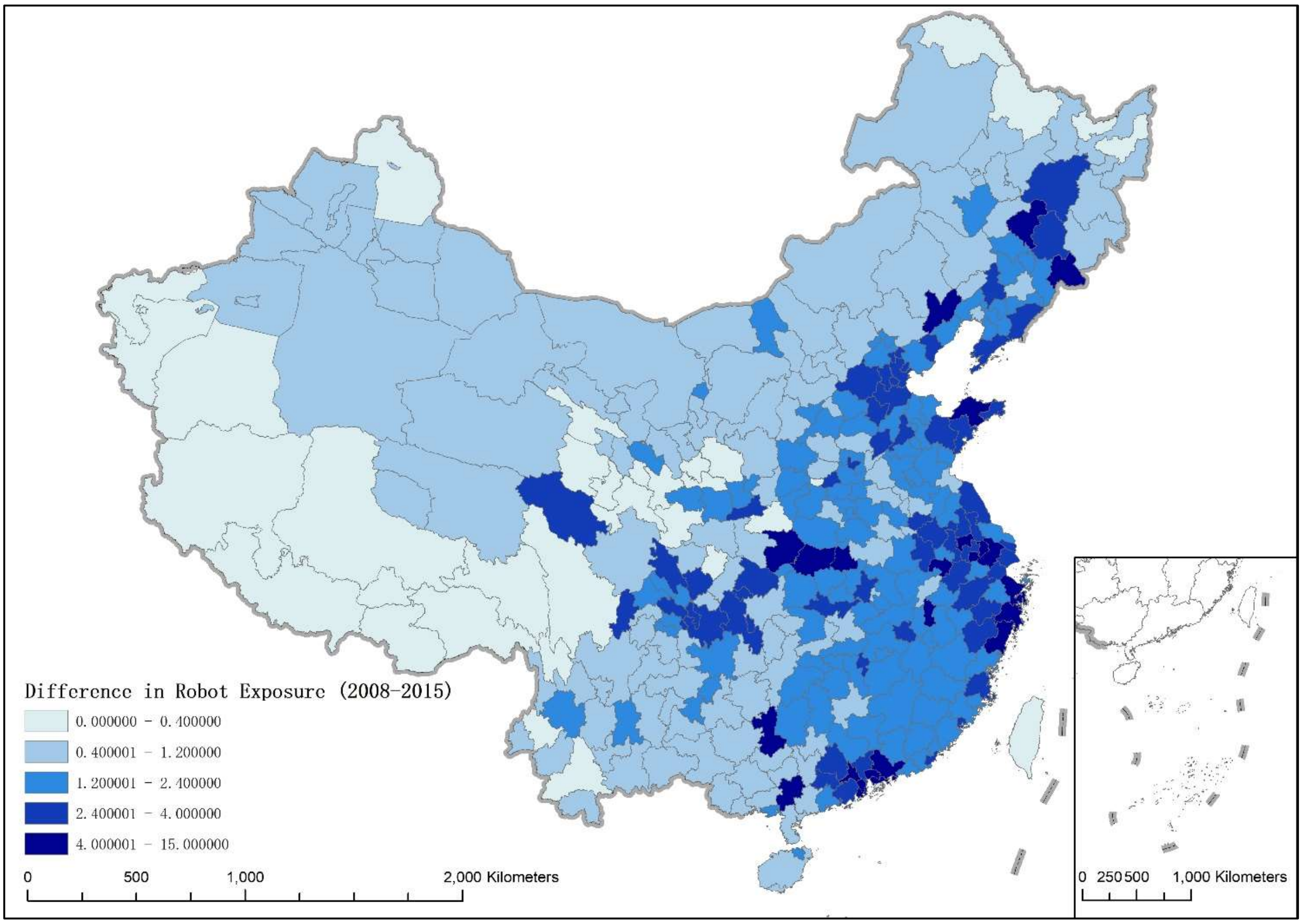


Figure 5.1 Robot exposure (stock difference) across Chinese prefecture-level cities, 2008-2015

Figure 2 draws the city-level robot exposure (stock) difference between 2008 and 2015, demonstrating the robot penetration conditions in this period. Coastal cities employ significantly more industrial robots than inland cities, except for some cities in Hubei Province. This is due to the agglomeration of manufacturing industries in coastal cities and their access to imported goods. In addition, the manufacturing sector has been expanding to some interior cities like cities in Hubei Province. Cheng et al. (2019) conducted a China Employer-Employee Survey on robot adoption. Their survey data on the probability of using robots by industries versus the share of robot units across industries in the IFR data in the data have a correlation coefficient of 0.97, which provides a support for our index calculation.

(2) Specialisation (SPE)

The data source for calculating the industrial externalities (Specialisation, Related Variety and Unrelated Variety) is the *China Annual Survey of Industrial Firms* provided by the State Statistical Bureau. This dataset contains data on more than 300,000 industrial enterprises, including all state-owned industrial companies and non-state-owned industrial enterprises covering31 two-digit industries and 171 three-digit industries, the sales revenues of which are above the specific level (above 5 million yuan before 2011 or 20 million yuan from 2011) in China. In the manufacturing sector, the average size of firms is generally larger because of increasing returns to scale (Guo et al., 2016). Large and medium-sized manufacturing firms have access to sufficient financial support in R&D and thus have a strong research capability, which significantly impacts whether new technologies are used in the manufacturing process(Tang et al., 2021). Therefore, the estimated bias may be minimal even if there were only including only above the designated sized companies as the sample.

Equation (3) displays the calculation method for specialisation:

$$SPE = \frac{1}{N}\sum_i \left| \frac{emp_{i,j} / \sum_i emp_{i,j}}{\sum_j emp_{i,j} / \sum_i \sum_j emp_{i,j}} \right| \tag{3}$$

where $emp_{i,j}$ represents the total employment in three-digit industry $i\ (= 1,2,\dots,I)$ within city $j = (1,2,\dots J)$.This index measures the sum of the absolute value of the difference between the specialisation coefficient of each industry in a given city and the degree of specialisation of the corresponding sector in other cities of the country. N is the number of industries in each city and is used to normalise the specialisation value.

(3) Related variety (RV) and unrelated variety (UV):

The measure of the effect of related and unrelated varieties follows Frenken (2007), who used the entropy measure to indicate both variables at different levels of sectoral aggregation using the manufacturing profile of each location. Related variety is measured as the weighted sum of entropy at the three-digit industry level within each two-digit industry class, denoted by $g = (1,2, \dots G)$.

$$RV = \sum_{g=1}^{G} P_g H_g \tag{4}$$

where the two-digit industry share P_g can be derived by summing the three-digit industry shares P_i:

$$P_g = \sum_{i \in S_g} P_i \tag{5}$$

$$H_g = \sum_{i \in S_g} (p_i / P_g) \ \ln(P_g / P_i) \tag{6}$$

where P_i represents the three-digit sector share of gross industrial outputs within a location j. The assumption here is that three-digit sectors (e.g. sub-branches in automotive manufacturing) in the same two-digit industry class (e.g. automotive manufacturing industry) have a lower cognitive distance. Meanwhile, there are certain degrees of cognitive distance due to differences at the three-digit level. Consequently, the greater the variety at the three-digit industry level within the two-digit industry class in the city, the more the learning opportunities, the more the knowledge spillover, and the more the city will benefit from such a set of different but related sectors. The higher the degree of related variety, the greater is the knowledge spillover expected within the city.

Unrelated variety per city is indicated by the entropy of the two-digit distribution. This indicator measures the extent to which different types of manufacturing sectors characterise a city. The more manufacturing sectors there are at the two-digit industry level, the higher a city's endowment with unrelated variety.

$$UV = \sum_{g=1} P_g \ \ln\left(1/P_g\right) \tag{7}$$

(4) Other control variables

Along with our focus on robot exposure and industrial agglomeration externality variables, we included a series of city-level control variables to control for various factors that may affect a city's employment. We control the economic performance of each city, measured by the natural logarithm of GDP per capita; labour input is an essential factor in the development of the manufacturing industry, measured as the natural logarithm of average wages. FDI is an important channel to bring technology and capital to manufacturing. It is challenging to promote manufacturing development based on abundant resources alone effectively. Knowledge and technology spillovers from FDI are an important factor in the early development of manufacturing; as we focus on the externalities of firms due to industrial structure, we use the natural logarithm of population density to control for agglomeration effects arising from density(Crowley et al., 2021); government spending in support of science and technological development is controlled for to represent government intervention. All nominal variables were deflated to real data using a GDP deflator to ensure comparability of data, with 2008 as the base year. Some of the data were taken natural logarithms. Missing values are filled with moving averages to ensure balanced panel data The independent variable used in this study and their descriptive statistics is summarised in Table 1.

Table 5.1 Summary statistics of key variables

Variables	N	Mean	Std. Dev	Min	Max
ER	2,256	97.6	2.18	59.02	100
RE	2,256	0.10	0.11	0.01	1.55
RV	2,256	0.79	0.30	-4.34	1.39
UV	2,256	2.30	0.53	0.15	3.07
SPE	2,256	3.72	8.57	0.70	251.98
Log (GDP per capita)	2,256	10.51	0.69	8.19	13.24

Log (Wage)	2,256	10.62	0.4	9.37	12.82
Log (FDI)	2,256	16.02	3.37	0	21.24
Log (Density)	2,256	5.72	0.93	1.6	7.88
Log (Firm)	2,256	0.10	0.11	0.01	1.55
Log (Science)	2,256	0.79	0.30	-4.34	1.39

5.4 Empirical results

5.4.1 Baseline results

Table 2 presents all linear panel model results on the relationship between the adoption of industrial robots and urban employment rates, and the moderating role of different industrial structures.

According to our hypothesis **H1** proposed in Section 2, we expect that cities with higher levels of robot exposure should experience lower employment rate. Table 2 reports all baseline results for Equation (1), which controls for city-level characteristics, year-fixed effects and city-fixed effect. Model 1 accounts for 55.3% of employment rate.

Results from model 1 supports our **Hypothesis 1**, that there exists a significant negative relationship between the degree of robot exposure and the employment rate. Special, a unit increase in robot exposure per 1,000 workers is associated with a 1.67% decline in the employment rate. Model 2 to 5 capture the mediation effect between robot adoption and city's industrial structure. The results in model 2 imply that in cities with a higher degree of related variety, the adverse effect of robot adoption on employment rate intensifies. In other words, higher related variety magnifies the negative impact of robot adoption on employment. The underlying reason could be that cities with higher related variety encompass industries with overlapping or complementary skillsets. As robots penetrate these markets, they could potentially supplant jobs across multiple interconnected sectors, exacerbating the overall employment loss. Model 3 introduces the interaction of robot adoption with the city's unrelated variety (UV). The coefficient of the interaction term there is negative and significant at the 1%

level. This outcome aligns with **Hypothesis 2a** and suggests that in cities characterized by a greater unrelated variety, the adoption of industrial robots tends to amplify the decline in the employment rate. Even if industries in these cities don't share direct skill or knowledge linkages, the disruption in one sector, triggered by robot adoption, could instigate a domino effect, imperilling jobs across diverse sectors.

In contrast, Model 4 highlights a positive and significant coefficient for the interaction between robot adoption and the degree of specialization (SPE) of a city. This suggests that in cities where the economy leans heavily towards particular industries (high specialization), the negative repercussions of robot adoption on employment are mitigated. In certain scenarios, it might even be conducive to employment. This outcome bolsters **Hypothesis 2b**. One plausible explanation is that specialized cities have industries that are potentially more resilient or adaptive to technological advancements. In other words, in industries where specialisation is paramount, robot adoption might lead to job evolution rather than job elimination. The workers' specific expertise and the industry's unique demands could make complete automation less feasible, thereby preserving employment rates. Another perspective could be the symbiotic relationship between specialized workers and robots. In specialized sectors, robots might be augmenting human tasks rather than replacing them. This synergistic collaboration could be leading to increased efficiencies, possibly giving specialized cities a competitive edge, and thus stabilizing employment.

Model amalgamates all the industrial structure variables and their corresponding interaction terms. While the direct effect of robot adoption on employment diminishes and is not significant (compared to the standalone models), the interaction terms retain their anticipated signs and significance that support our hypotheses.

Table 5.2 Regression results of robot exposure's local effects

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	ER	ER	ER	ER	ER

RE	**-1.670****	**-0.972****	**-1.968*****	**-0.247**	**-0.441**
	(-2.48)	**(-2.11)**	**(-3.39)**	**(-0.31)**	**(-0.62)**
RV		-0.157			-0.135
		(-0.89)			(-0.96)
RE× RV		**-4.278*****			**-2.914*****
		(-3.57)			**(-2.60)**
UV			-0.116		-0.093
			(-0.56)		(-0.45)
RE× UV			**-1.987*****		**-0.999***
			(-3.32)		**(-1.96)**
SPE				0.044***	0.029**
				(2.79)	(2.07)
RE×SPE				**0.580****	**0.367***
				(2.58)	**(1.82)**
Log(GDP per capita)	0.629**	0.574**	0.588**	0.555**	0.522**
	(2.44)	(2.22)	(2.27)	(2.16)	(2.01)
Log (Wage)	-0.099	-0.143	-0.101	-0.108	-0.136
	(-0.28)	(-0.42)	(-0.28)	(-0.31)	(-0.40)
Log (FDI)	-0.071**	-0.071**	-0.078**	-0.075**	-0.077**
	(-2.26)	(-2.27)	(-2.46)	(-2.37)	(-2.42)
Log (Density)	-3.359***	-3.184***	-3.203***	-3.131***	-3.018***
	(-2.94)	(-2.86)	(-2.78)	(-2.85)	(-2.77)
Log (Firm)	0.133	0.132	0.103	0.124	0.115
	(1.44)	(1.42)	(1.12)	(1.34)	(1.23)
Log (Science)	-0.049	-0.045	-0.042	-0.043	-0.040
	(-0.48)	(-0.44)	(-0.41)	(-0.42)	(-0.39)
Constant	110.860***	110.872***	110.613***	110.554***	110.560***
	(15.60)	(15.89)	(15.40)	(16.06)	(16.02)
Year FE	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes
Observations	2256	2256	2256	2256	2256
R^2	0.556	0.559	0.558	0.558	0.561
Adjusted R^2	0.553	0.556	0.555	0.555	0.557

Notes: 1) Robust standard errors are clustered at the city level and reported in parentheses; 2) ***, **, * represent significant levels at 0.01, 0.05, and 0.1 levels, respectively.

The control variables provide valuable insights into various factors influencing the employment rate in cities. While economic metrics like GDP per capita and FDI show significant correlations with employment, other variables such as wage levels, firm counts, and science-related indicators present more nuanced relationships that warrant further investigation. Across all models, the logarithm of GDP per capita exhibits a positive and statistically significant relationship with the employment rate. It aligns with intuition and economic literature that cities with a higher GDP per capita tend to have a better employment scenario. The economic rationale can be grounded in the notion that cities with higher economic activity potentially offer more job opportunities, thereby elevating the employment rate. The logarithm of Foreign Direct Investment (FDI) consistently presents a negative and significant relationship with employment rate across all models. It could be inferred that while FDI brings in capital, technology, and expertise, it might also introduce advanced production techniques that could reduce labour demand, hence the observed negative correlation with employment. Population density, when logged, shows a strong and statistically significant negative relationship with employment rate across all models. A possible explanation could be that cities with higher population densities face increased competition for jobs due to the influx of job seekers, leading to a lower employment rate.

5.4.2 Robustness tests

However, using the employment rate as the dependent variable may introduce endogeneity issues, especially given that its value might be influenced by its previous year's level. Thus, it becomes crucial to include its lagged value as an independent variable in the regression. Then, such linear regression may produce biased OLS estimates when the lagged value of a dependent variable is included as an independent variable, in that it may correlate with the error term. To address this potential endogeneity, we will employ a dynamic panel model incorporating the lagged dependent variable and differentiating it as an instrument variable. The difference GMM estimation results are shown in Table 5.3.

The results in Table 5.3 show that the relationship between the impact of robot adoption and employment rate still holds when including the lagged employment rate at the 95% significance level, supporting our **H1**, but the coefficient of Robot exposure decreases to 1.91%. Particularly, Models 7 to 9 reveal the relationships between Robot Exposure and employment rate, taking into consideration various measures of industrial structures and controls over city-specific factors. The coefficients of the interaction terms show the same signs as Models 2 to 4, which confirms that our baseline model is reliable. The insignificance of AR (2) across all models 6 to 9 indicates no autocorrelation for second-order difference residuals, while the insignificance of the Hansen J test implies no over-identification of IVs. These two criteria confirm the effectiveness of our GMM estimation.

Table 5.3 Dynamic panel regression results of robot exposure's local effects

	(6)	(7)	(8)	(9)
Dependent variable:	ER	ER	ER	ER
L.ER	0.106^{***}	0.207^{***}	0.216^{***}	0.213^{***}
	(2.72)	(3.81)	(3.85)	(3.69)
RE	**-1.914****	4.200	-3.358	16.972^{***}
	(-2.18)	(0.97)	(-1.42)	(2.99)
RV		-4.199^{*}		
		(-1.89)		
RE× RV		**-46.454*****		
		(-3.37)		
UV			-8.445^{***}	
			(-3.19)	
RE× UV			**-17.045****	
			(-2.42)	
SPE				0.600^{***}
				(3.38)

RE×SPE				**7.273***** **(3.23)**
Control variables	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	1692	1692	1692	1692
Number of instruments	26	31	34	34
Number of groups/cities	282	282	282	282
AR (2)	0.65	0.45	0.43	1.50
	[0.515]	[0.655]	[0.669]	[0.133]
Hansen test	11.461	18.894	18.922	13.531
	[0.323]	[0.126]	[0.273]	[0.485]

Notes: 1) P-values are reported in brackets; 2) ***, **, * represent significant levels at 0.01, 0.05, and 0.1 levels, respectively.

5.5 Spatial Models

Beyond the static and dynamic fixed-effects panel models, there might exist the inherent spatial dependencies across cities. Such dependencies necessitate a methodological progression to ascertain the validity and robustness of our hypotheses. Accordingly, we would like to further employ spatial econometric models to account for potential spatial effects. Specifically, we estimate a dynamic Spatial Durbin Model (dynamic SDM) to capture the spatial effects:

$$\begin{aligned} ER_{i,t} = {} & \beta_0 ER_{i,t-1} + \beta_1 RE_{i,t-1} + \beta_2 \boldsymbol{W} RE_{i,t-1} + \beta_3 \left(RE_{i,t} \times IndustrialStructure_{i,t}\right) \\ & + \beta_4 IndustrialStructure_{i,t} + \beta_5 \boldsymbol{X_{i,t-1}} + \beta_6 \boldsymbol{W X_{i,t-1}} + \beta_7 \boldsymbol{\chi_i} + \beta_8 \boldsymbol{\xi_t} + \varepsilon_{i,t} \end{aligned} \tag{7}$$

where $\boldsymbol{W}$ denotes the spatial weight matrix that describes the physical/economic proximity between cities; other variables are same as Equation (2). Accordingly, $\boldsymbol{WRE_{i,t-1}}$ signifies the weighted average of robot exposure in neighbouring cities excluding the local city. Stated differently, the coefficient β_2 captures the spillover effects of robot exposure on labour markets in neighbouring cities, if any.

In this study, we deploy two distinct spatial weight matrices to capture the proximal relations between cities. The first matrix is the conventional geographic straight-line distance matrix, in alignment with prevailing literature. By utilising the coordinates of each city's geometric centre, we compute the geographical distance d_{ij} between city pairs. The second matrix, on the other hand, is the reciprocal of this distance, represented as $1/d_{ij}$, which quantifies the geographical proximity of these cities. It is pivotal to note that an augmented weight value, $W_{ij}^{d} = \frac{1}{d_{ij}}$ where $i \neq j$, signifies closer proximity between city pairs, thus a closer spatial relationship. The mathematical calculation for the geographic distance matrix is shown in Equation (8).

$$W_{ij}^{d} = \begin{cases} \dfrac{1}{d_{ij}}, & i \neq j \\ 0, & i = j \end{cases} \tag{8}$$

As discussed previously, the spillover effects of robot exposure are mainly dominated by labour flow between city pairs. Such labour migration, however, cannot be explained solely by geographical proximity, as economic factors also play a significant role (Fan, 2005; Gu et al., 2019). The mathematical formula of the matrix is shown below:

$$W_{ij}^{e} = \begin{cases} \dfrac{1}{\left|pGDP_i - pGDP_j\right|}, & i \neq j \\ 0, \quad i = j \end{cases} \tag{9}$$

where, $pGDP_i$ represents the average annual GDP per capita of city *i* during the study period, collected from the *China Statistical Yearbook*. In such a matrix, GDP per capita in each city is used to characterize economic difference between cities.

To ensure the feasibility of these models, we conduct spatial panel autoregression tests and results can be found at Table 5.4. We find that the statistics of LM-Error and LM-Lag panel tests are significant at the 1% level, rejecting the null hypothesis of “no spatial correlation.” This result indicates the need for a spatial econometric model in empirical analysis. It is worth noting the consistency in the local effects in both models 10 and 14. The coefficients for the local effect in the models are quite proximate. Once again, both models confirm the same direct impact of robot adoption on employment in a city. Employment rate decreases with the increase in robot exposure, even after spatial correlation is taken into consideration. However, when it comes to the spatial effects, the results show opposite signs. Utilizing the inverse distance matrix as the spatial matrix, the estimated coefficient for the spatial effect of RE in model 10 is -6.109, which is significant at the 10% level. This indicates a negative spatial spillover effect, suggesting that an increase in robot adoption in one city may lead to a reduction in the employment rates of neighbouring cities, supporting the **Hypothesis 3a**.

On the other hand, when the economic matrix is adopted as the spatial matrix, evidence shows that one unit increase in robot exposure will induce a 2.63% increase in employment rate in economically tied cities. The positive value suggests that when cities have economic similarities, an increase in robot adoption in one city would boost employment rates in other cities with comparable economic development levels, that is in line with our **Hypothesis 3b**.

Upon integrating interaction terms in the dynamic SDM, notable variations in the estimated parameters emerge, contingent upon the chosen spatial matrix. When utilising the distance matrix, the mediation between RE and RV has a significant negative effect. Similarly, the interaction between RE and UV also has a negative influence, though it is less intense in its coefficient. Contrarily, the interaction between RE and SPE is positive but statistically insignificant.

In contrast, with the adoption of the economic matrix, the model reveals stronger negative effects for the interaction terms for RE and RV, RE and UV pair. The interaction between RE and SPE is significantly positive. Comparatively, the spatial model results illuminate intricate nuances beyond what the linear and dynamic models reveal. The importance of geographical and economic proximities in shaping the relationship between robot exposure and employment rate becomes profoundly evident, especially when these proximities intermingle with the city's industrial structure. The persistent negative interaction effects for both RV and UV across the spatial models suggests a compelling narrative: as cities increasingly adopt robots, especially in locales characterized by industrial variety, there's a palpable downward pressure on employment rates. This finding aligns with the intuitive notion that as automation intensifies, some job roles become obsolete, especially in sectors with diverse or unrelated varieties. The interaction of robot exposure (RE) with specialisation (SPE) presents a distinct dynamic compared to that of RV and UV. Notably, for both the distance and economic matrices, the interaction term RE×SPE is positive, suggesting a potential ameliorating effect of specialisation on the employment impacts of robot adoption, further confirming our **Hypothesis 2a** and **Hypothesis 2b**.

However, the regression results of the spatial effects of the interaction terms do not yield significant results. This means that while local effects are observed, the influence of a city's industrial structure on robot adoption does not extend to neighbouring cities in any measurable or significant way. Despite the lack of statistical significance, the signs of the estimated coefficients for spatial effects remain consistent with those for local effects. This implies that even though the spillover impact is not strong or measurable across city boundaries, the direction of the effect (positive or negative) does not change. The results are in align with our **Hypothesis 4** that moderating effects of a city’s industrial structure—how it influences the relationship between robot adoption and employment—are predominantly localised phenomena. This supports the notion that the industrial structure's ability to amplify or mitigate the impact of automation on employment does not transcend to a broader regional scale but is contained within the city's own economic environment.

Table 5.4 Regression results of dynamic spatial panel model

Dependent variable:	(10) ER	(11) ER	(12) ER	(13) ER	(14) ER	(15) ER	(16) ER	(17) ER
L.ER	0.260**	0.257**	0.256**	0.258**	0.264**	0.261**	0.259**	0.260**
	(2.35)	(2.31)	(2.30)	(2.33)	(2.39)	(2.37)	(2.38)	(2.36)
RE	**-1.217****	**-0.788***	**-1.470****	**-0.671**	**-1.872*****	**-1.244****	**-2.13*****	**-0.802**
	(-2.10)	(-1.73)	(-2.53)	(-1.00)	(-2.68)	(-2.43)	(-3.77)	(-1.05)
W×RE	-6.109*	0.471	-3.372	-3.372	2.630*	3.698**	2.960**	3.359*
	(-1.85)	(0.10)	(-0.67)	(-0.57)	(0.69)	(0.95)	(0.73)	(0.91)
RV		-0.048				-0.046		
		(-0.33)				(-0.30)		
RE× RV		**-2.219***				**-3.273*****		
		(-1.94)				**(-2.80)**		
W×(RE× RV)		-12.301				-4.235		
		(-1.53)				(-1.29)		
UV			-0.054				-0.094	
			(-0.22)				(-0.40)	
RE× UV			**-0.995***				**-1.719*****	
			(-1.73)				**(-3.06)**	
W×(RE× UV)			-3.657				-1.029	
			(-0.86)				(-0.69)	
SPE				0.021				0.032**
				(1.59)				(2.30)
RE×SPE				**0.273**				**0.440****
				(1.45)				**(2.14)**
W×(RE× SPE)				0.301				0.173
				(0.30)				(0.38)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weight matrix type	Inverse distance	Inverse distance	Inverse distance	Inverse distance	Economic distance	Economic distance	Economic distance	Economic distance
Observations	1974	1974	1974	1974	1974	1974	1974	1974
sigma2	1.857***	1.854***	1.849***	1.848***	1.860***	1.852***	1.851***	1.850***
Spatial panel autoregression test								
LM-Error panel test					1624.574***[0.000]			
Robust LM-Error panel test					458.748***[0.000]			
LM-Lag panel test					1324.726***[0.000]			
Robust LM-Lag panel test					158.899***[0.000]			

Notes: 1) all control variables are transformed into log type; 2) Robust standard errors are clustered at the city level and reported in parentheses; 3) P-values are reported in brackets; 4) ***, **, * represent significant levels at 0.01, 0.05, and 0.1 levels, respectively.

5.6 Chapter Summary

Known as "the world's factory", China continues to thrive as a manufacturing powerhouse. The huge and relatively inexpensive labour pool has been an important source of its international competitiveness in industrial production. The rise in labour wages in recent years, coupled with an increased demand for skilled labour as a response to the need for industrial upgrading, has led many companies to adopt robotics and automation technologies. The introduction of industrial robots in the manufacturing sector has increased efficiency and reduced costs, but it also raises concerns about jobs. However, the systematic and accurate quantitative analysis of industrial robots in employment at the city level remains unexplored due to the limited availability of statistics on industrial robots. Hereby, our study examines the impact of industrial robots on the employment landscape of Chinese cities. Based on employment data from the second *China Enterprise Economic Census* in 2008 and national industrial robot installations data by industry from the IFR, we constructed a Bartik-style indicator as the level of robot exposure for each city, based on which we have proposed several spatial models for estimating the effects of adopting industrial robots. Furthermore, the city's heterogeneity may have differing impacts on the decision of whether to adopt industrial robots for individual enterprises through costs, technologies and markets. We hypothesise that the industrial structure of cities has an impact on the effects of adopting industrial robots on urban labour markets. Based on the framework of evolutionary economic geography, we use the *China Annual Survey of Industrial Firms* to construct indicators of specialisation, related variety and unrelated variety, and use interaction terms between the industrial externality indicators and the robot exposure index to investigate the hypothesis. Then we have crafted a nuanced spatial econometric model to elucidate the potential spatial effects.

Our empirical findings reveal that the integration of industrial robots has a negative influence on local employment rates, echoing the automation-related apprehensions prevalent in current discourse. The results further illuminate the complexities posited in the city's industrial structure emerging as a key mediator in the adoption of robotics. Industrial diversity, rather than uniformly impacting employment, interacts variably with robot adoption: the RV intensifies employment decline more than the UV, suggesting a nuanced interplay between industrial interconnectedness and technological disruption. Conversely, a higher degree of specialization within a city's industries appears to cushion the workforce from the impact of automation. When exploration extends to the spatial dimension of these dynamics, the employment detriments associated with robot adoption do not remain confined to the initiating city but instead cascade through adjacent areas, confirming the spillover effect. Nevertheless, this pattern is not uniform; cities at similar stages of economic development may indeed benefit from their neighbours' robotic advancements, reflecting a positive employment spillover that contradicts the expected trend and adds a layer of complexity to the regional economic landscape. Lastly, the anticipated spatial spillover of industrial structure's mediating effects on employment does not manifest in our findings, reinforcing the idea that the impact of industrial robots is intricately tied to the immediate urban context.

These findings have theoretical implications for our understanding of urban economics and regional science, and for policymaking. Diversification and relatedness are hot-button issues nowadays, not only for academics but also for policymakers (Miguelez & Moreno, 2018). Latecomers in East Asian countries can catch-up with the developed countries technologically through pro-active industrial policies on the development of industries(Liu et al., 2022). Our study advises that policies aimed at technological advancement through automation, such as 'replacing people with machines,' should be intricately tailored to the unique industrial compositions of individual cities. The localisation of the effects observed suggests that a city's distinct industrial fabric can significantly influence the outcome of such policies. This is a critical consideration for policymakers who may overestimate the homogeneity of regional economies and the transferability of outcomes from one urban setting to another. Moreover, our research implies that regional planning strategies require a nuanced approach. Interventions designed for one city are unlikely to propagate as anticipated across adjacent labour markets. This points to the necessity of a unique policy framework that respects the idiosyncrasies of each city, rather than a one-size-fits-all model. As such, policymakers are urged to design region-specific strategies that account for the complex dynamics uncovered by our analysis, avoiding the assumption of uniform economic spillovers between neighbouring urban areas.

CHAPTER6. THE IMPACT OF ROBOTICS ON HOUSING PRICES IN CHINESE CITIES

6.1 Introduction

Despite these flourishing studies focusing on the direct impact of automation, there is still limited discussion on how these economic and labour market consequences spill over into other broader sectors of the economy. Against this backdrop, this study investigates the projected consequences of economic changes induced by automation in the housing market, that is, the relationship between exposure to industrial robots and changes in housing prices and explores the underlying mechanisms of this relationship.

Automation can affect the housing prices by impacting both the demand and supply side of the housing market. On the demand side, automation induces changes in the labour market conditions, which can be linked to changes in housing markets due to changes in housing demand (Reed & Ume, 2016; Zabel, 2012). Specifically, automation can increase the demand for high-skilled workers and decrease the demand for low-skilled workers. This change can affect local employment, which then alters the wage levels and purchasing power of these groups, impacting their housing choices and affordability. On the supply side, land finance serves as a catalyst that further strengthens the relationship between automation progress and a thriving housing market. On the one hand, local governments use cheap industrial land to subsidise automation firms/plants to boom the local economy (Fan et al., 2015), but on the other hand, raise residential land prices by restricting the supply of residential land to capitalise on the economic development brought about by automation. As a result, this dual track strategy of land supply further pushes up the level of local house prices.

This chapter estimates the impact of industrial robot exposure on housing prices from two perspectives: local and spillover effects. First, we constructed a prefecture-city-level robot exposure index to capture the level of predicted robot adoption across cities. Subsequently, we employed dynamic fixed-effect and system-GMM models to estimate the effect of robot exposure on local housing prices. Our findings indicated a statistically significant and positive relationship between robot exposure and local housing prices. This conclusion remains robust after addressing several endogeneity concerns with a well-developed instrumental variable, ensuring the stability of the developed robot exposure index by employing alternative measures and mitigating several potential confounding factors by including additional control variables.

We then examined the mechanisms from both demand and supply perspectives. On the demand side, we found that robot exposure has a positive impact on housing prices in cities with higher manufacturing employment and higher population density, while it diminishes as unemployment rates increase. Additionally, the impact of wage premiums for high-skilled migrants on purchasing power accounts for about one-third of the impact of automation. On the supply side, land financing acts as a catalyst that strengthens the link between automation and housing market booms, especially in cities that are highly dependent on land financing, where automation generates a premium of up to 6.2 per cent.

Then, this chapter estimates the spillover effect of robot exposure on housing prices in neighbouring cities. To achieve this objective, we employed various dynamic spatial panel models. Additionally, an asymmetric geographical–economic weight matrix was developed to improve the asymmetrical spatial relationship of the traditional geographic distance matrix between cities. The dynamic spatial Durbin model used in this study revealed that robot exposure may significantly and negatively impact housing prices in neighbouring cities. The result remained consistent across different spatial panel models, weight matrices, and alternative measures of robot exposure, thus confirming our proposed hypothesis.

6.2 Institutional background and analytical framework

6.2.1 The housing market in China

Since the 1980s, China's housing system has undergone radical changes as an important part of economic reform. Unlike the socialism of the past, when housing was distributed according to work units, China's urban housing system eventually ended with the commercialization and privatization of housing in 1998 (Lee, 2000). Since then, China's housing prices have been on a high-speed train, growing several times over the past 20 years, from 2,170 *yuan* per square meter in 2001 to 9,860 *yuan* in 2020 at the national level (China National Bureau of Statistics). In mega "superstar" cities such as Beijing, Shanghai and Shenzhen, the spike is even more dramatic, with annual appreciation rates of about 12% during the same period.

Unsurprisingly, China's housing market has boomed in tandem with its rapid economic growth, which has created a huge demand for housing. The literature has devoted a great deal of attention to economic development, as well as related policies, as the fundamental factor explaining the continued rise in housing prices in China, including rural-urban migration and urbanization (Wang et al., 2017), increasing income (Wang & Zhang, 2014; Zheng et al., 2009), economic openness (Wang et al., 2011), infrastructure development (Zhou & Zhang, 2021), and some place-based industrial policies (Zheng et al., 2017). However, few scholars have discussed the role of automation in booming the housing market, let alone the installation of industrial robots.

Meanwhile, under the specific system of land finance, the boom in China's housing market is not just an outcome of economic development but also an important path for economic development (Wu et al. 2015; Gyourko et al. 2022). During the reform process of housing marketisation, urban land ownership never changed and remained state-owned, while only land use rights could be sold by the local government. Owing to the shortage of local finances and the need to develop the local economy, land sales revenue has become the most important source of local finance for local governments, supporting (or subsidising) infrastructure development, establishing industrial parks, and introducing manufacturing factories (Fan et al. 2015; Wang and Ye 2016).

In practice, local governments, through the monopolisation of land supply, deliberately increase the supply of industrial land to attract industrial investments and stimulate the economy, but curtail the supply of residential land, thereby raising property prices and increasing land sales revenue, forming a self-reinforcing positive feedback cycle (Gyourko et al. 2022). This is the so-called strategy of ‘low-cost industrialisation and high-cost urbanisation’ (Fan et al. 2015; Tao et al. 2009). Notably, there are significant regional heterogeneity when applying this strategy. Glaeser et al. (2017) reveals that local governments in less developed regions have been the most active in promoting the supply of new housing (a more elastic housing supply), obtaining more land grants to stimulate the economy. In contrast, local governments in more developed regions restrict the housing supply (a less elastic housing supply) to maximising the benefits of land sales. In this land supply mode, the penetration of industrial robots will inevitably trigger a more prosperous housing market. However, this presumption has not been confirmed so far in the literature.

6.2.2 Automation and the housing market

Housing prices are the most visual representation of a city's economic development. According to the Neoclassical inter-urban equilibrium model (Roback 1982), housing prices are determined by a city's wage level and amenities. If amenities are considered exogenous, the equilibrium of housing prices and wage levels across cities is achieved primarily through changes in labour demand and supply within cities, and labour migration between cities. The former can be demonstrated through studies on the relationship between demographic changes and housing prices (Gong and Yao 2022), such as fertility rate (Francke and Korevaar 2021) and population decline and aging (Levin et al. 2009). Conversely, the effects of labour migration on housing prices are reflected in the most direct evidence (Jeanty et al. 2010). Decades of mass labour migration in China have notably increased the demand for housing in coastal cities, contributing to the surge in housing prices (Chen et al. 2011; Wang et al. 2017).

Automation has reshaped the labour market structure, which is the determinant of the housing market. First, automation can directly alter the composition of the local labour force by attracting more high-skilled workers while displacing mid- or low-skilled labour. Following Autor et al.'s (2003) theory, automation primarily replaces jobs with routine-intensive tasks that are mainly performed by low and middle-skilled workers, while reinstating jobs with non-routine-intensive abstract tasks that are performed by high-skilled workers. As a result, automation crowds out low and mid-skilled workers but attracts more high-skilled workers, which leads to 'skill polarisation' in the labour market, as discovered in recent literature (Autor and Dorn 2013; Gallie 1991; Goos and Manning 2007). Second, automation can facilitate economic development in cities by increasing wage levels, particularly in occupations with high skill requirements owing to the skill bias associated with automation. This further translates into wage inequality, as recent empirical studies have found (Hémous and Olsen 2022; Kaltenberg and Foster-McGregor 2020; Prettner and Strulik 2020).

Linking these two literatures together, one primary channel outlines how automation affects housing prices on the demand side of the housing market: the resulting wage inequality ultimately leads to a house price premium. Previous studies have disclosed that wage increases at the high end of the distribution can also raise housing prices paid by those at the low end of the wage distribution (Matlack and Vigdor 2008; Vigdor et al. 2002). The mechanism is straightforward that higher wage workers have more demand for housing and land at the high-end housing market, but housing and land is limited, and it causes prices at the low-end housing market to rise as well. This phenomenon is equally significant in China, where Zhang et al. (2016) revealed that a one-percent rise in income GINI increases the house price/income ratio by 0.026. However, this boom effect may be moderated when mid-skilled workers are crowded into lower-skilled jobs with lower wages, which reduces their ability to purchase homes. In other words, while demand in the high-end housing market is growing, demand at the middle and lower ends of the market is likely to be shrinking.

Additionally, on the supply side of the housing market guided by the strategy of 'low-cost industrialisation and high-cost urbanisation', land finance serves as a catalyst that further strengthens the relationship between automation progress and a thriving housing market. On the one hand, to promote local economic development, local governments may use cheap industrial land to subsidise automation firms/plants (Fan et al. 2015), thereby reducing automation costs. The resulting agglomeration and growth of these firms will prosper the neighbourhood and increase residential housing demand. On the other hand, in order to obtain higher land premium revenues to balance industry subsidy policy expenditures, local governments raise the land prices of residential land by restricting the supply of residential land, thereby capitalising on economic development brought about by automation. This supply restriction is similar to zoning policies in large cities of the United States, which lie at the root of high housing prices in recent years (Glaeser and Gyourko 2003; Gyourko et al., 2013). In such a self-reinforcing positive feedback cycle, we should observe advances in both automation and a thriving housing market.

In summary, these impact channels predicted an increase in housing prices in local cities with the proliferation of automation. Accordingly, we propose the following hypothesis.

H1: ***Automation contributes significantly to the rise in local housing prices.***

The above analysis discusses the impact of automation on the housing market in local cities, emphasising the changes in the labour market within a city. However, it is worth noting that the redistribution of labour is also linked to other neighbouring cities through labour migration. Empirical studies have found that the introduction of new technology in a local city attracts high-skilled labour from other countries/cities through international or internal migration (Beerli et al. 2022). Basso and Rahman (2020) found that more exposed regions with higher

ICT adoption experienced a much larger influx of highly educated immigrants in absolute terms as well as relative to lower educated groups. The same was found to be true in China, where the study by Chen et al. (2022) revealed that the use of industrial robots significantly reduces the regional in-migration rate of labour, a negative effect that comes mainly from low-skilled workers. This mechanism ensures labour supply in local cities, but it causes a loss of highly skilled labour in neighbouring cities. In the meantime, those replaced low and middle-skilled workers may be crowded out from the local city to neighbouring cities. The resulting labour redistribution, therefore, significantly reduces the size of the labour force with house purchasing power and cuts housing demand in neighbouring cities. The decrease in demand is finally captured by a decrease in housing prices.

In the meantime, the neighbouring cities' land supply strategies are also changing in response to regional competition among local governments. As discussed previously, land sales profits are an important financial source for local governments to attract investment and develop the economy. Cities that have advanced economically through automation can afford to constrict residential land supply, maximising land sale revenues due to their pre-existing attractiveness to other investment. Conversely, neighbouring cities lagging behind in economic development may expand their residential land offerings to gain more land sales profits, thus compensating industrial land costs and spurring economic growth. This potentially leads to an oversupply of residential land and housing in the neighbouring market and a subsequent drop in housing prices[1].

Combined with changes in supply and demand in the housing market, we can predict that automation progress in one city can deliver negative impacts on housing prices in neighbouring cities. Therefore, we propose the following hypothesis:

H2: ***Automation significantly hampers housing prices in neighbouring cities.***

[1] The oversupply of land driven by land finance can also be found in the literature discussing ghost cities and urban sprawl across Chinese cities, such as Dong et al. (2021), Jiang et al. (2017), Liu et al. (2018), and Zheng et al. (2014).

6.3 Methodology and data

6.3.1 Industrial robots and robot exposure measure

Since the 1960s, the third technological revolution, characterised by IT, has played a significant role in generating economic growth and social progress. With the advent of the new millennium, the momentum of IT has led to the widespread adoption of automation in the manufacturing industry. Automation is not limited to repetitive tasks, as exemplified by industrial robots that do not require manual operations and can perform various tasks through programming, thereby demonstrating high intelligence and versatility. According to ISO 8373:2021, industrial robots are defined as 'automatically controlled, reprogrammable, multipurpose manipulator, programmable in three or more axes, which can be either fixed in place or fixed to a mobile platform for use in automation applications in an industrial environment'. With these advantages, this technology provides a useful case study of the impact of automation on society, and has been widely employed in previous studies to examine the consequences of automation (Acemoglu & Restrepo, 2020; Dauth, Findeisen, & Suedekum, 2021; De Vries et al., 2020; Graetz & Michaels, 2018).

To analyse the impact of robots at the prefectural-city level, we need data on industrial robot installations. Unfortunately, such data is only available at the national level. To overcome this limitation, we adopt a shift-share design that allocates robot adoption across cities based on their industry's share of total employment in that industry. This approach has been used by Acemoglu and Restrepo (2020) and Dauth, Findeisen, Suedekum, et al. (2021)to study other economic phenomena like import competition (Autor et al., 2013) and exposure to information and communication technologies (ICT) (Autor & Dorn, 2013).

We calculate the local robot exposure index by taking a weighted average of robot installations based on each industry's employment share in a local labour market. The formula for calculating this index is as follows:

$$Robot\ Exposure_{ct} = \sum\nolimits_{d=1}^{D} \left(\frac{Emp_{d,c,t=ba}}{Emp_{c,t=base}} \times \frac{Robot_{d,t}}{Emp_{d,t=base}} \right) \quad (1)$$

where $Emp_{d,c,t}$ represents the employment level in industry d, city c, and year t; $Robot_{d,t}$ represents the installation units of industrial robots in industry d and year t from the

International Federation of Robotics (IFR) database (described in Section 6.3.3). Consequently, instead of capturing the actual installation of industrial robots in each city, this measure predicts the level of robot exposure at the city level, assuming that robot adoption per worker in each industry was consistent across cities. To check the validity of this index, we have done a series of robustness tests employing alternative datasets, weights, and initial years (Section 6.4.2).

6.3.2 Empirical Methodology

6.3.2.1 Baseline model

This chapter estimates the effects of robot exposure on housing prices across Chinese cities to test two proposed hypotheses. After developing the robot exposure index, several empirical strategies are introduced to estimate these effects. The baseline model is shown below:

$$HP_{ct} = \tau HP_{ct-1} + \sigma Robot\ Exposure_{ct-1} + \boldsymbol{X_{ct-1}\beta} + \boldsymbol{\chi_c} + \boldsymbol{\xi_t} + \epsilon_{ct} \tag{2}$$

where HP_{ct} denotes the housing price in city c in year *t*, $Robot\ Exposure_{ct-1}$ denotes the exposure level of industrial robots in city c in year *t-1*. $\boldsymbol{X_{ct-1}}$ captures other city-level characteristics in year *t-1* that will be discussed in Section 6.3.3; $\boldsymbol{\chi_c}$ and $\boldsymbol{\xi_t}$ capture city and year fixed effects, respectively; τ, σ, and $\boldsymbol{\beta}$ are the coefficients of estimation; ϵ_{ct} denotes the independent and identically distributed residential error. Notably, because there are significant time-series correlation issues in housing prices, we introduced the one-year lagged housing price HP_{it-1} to eliminate this issue. The other independent variables were also lagged by one year to reflect the impact of lagging on housing prices. This model tests the first hypothesis, while σ is the key coefficient catching the impact of robot exposure on housing prices in local cities. According to H1, σ should be significant or larger than zero.

Two endogeneity issues arise when ordinary least squares (OLS) are used to estimate the model. The first endogeneity issue is the 'dynamic panel bias' caused by the correlation between the lagged dependent variable and the individual specific (i.e., city specific) fixed effects (Nickell, 1981). The traditional fixed-effects dynamic panel data model (dynamic FE), that eliminates all individual specific fixed effect (or time-invariant variables) through within-group transformation, cannot fully solve this issue since the error term is still correlated with the lagged dependent variable in the transformed equation. Instead, an alternative method suggests instrumenting the lagged dependent variable with longer lags of the dependent variable and other effective instrumental variables to mitigate this endogeneity issue. In practice, Arellano and Bover (1995) and Blundell and Bond (1998) developed the dynamic system-GMM method (dynamic S-GMM), which instruments HP_{it-1} with longer lags of HP utilising the generalised method of moment (GMM) estimator to solve the 'dynamic panel bias' while the estimation is still efficient. By applying this method, the empirical model can be estimated efficiently and in an unbiased manner.

The second endogeneity issue arises because local housing prices significantly affect labour costs, which is a consideration for cities/companies adopting industrial robots (Eeckhout et al., 2019). The resulting relationship between housing prices and robot penetration induces reverse causality and biases the estimation results. To mitigate this concern and ensure robustness, this study employs an instrumental variable (IV) approach to address the endogeneity issue, the same IV applied by Acemoglu and Restrepo (2020) and Dauth, Findeisen, Suedekum, et al. (2021). The idea behind this approach is that China's adoption of industrial robots relies heavily on imports from developed countries. This binding relationship allows robot installation in these developed countries to influence robot installation in China, but is intuitively not directly related to the labour market or housing market in Chinese cities. This ensures the validity of the IV. Therefore, we recalculated the local robot exposure index using data from six developed countries – France, Sweden, Denmark, Finland, Italy, and the US– and averaged them for use as an IV.

6.3.2.2 Spatial econometric model

The above model demonstrates how robot installation affects housing prices in local cities, but it does not account for the spillover effects on adjacent cities. Therefore, this section further introduces the dynamic spatial panel model to address this gap, which tests the second hypothesis, **H2**. Specifically, we estimate a dynamic Spatial Durbin Model (dynamic SDM) to capture the spillover effects of robot installation:

$$\begin{aligned} HP_{ct} = \tau HP_{ct-1} + \rho \boldsymbol{W} HP_{ct} + \pi \boldsymbol{W} HP_{ct\;\;\mathbf{1}} + \sigma Robot\ exposure_{ct-1} \\ + \gamma \boldsymbol{W} Robot\ exposure_{ct-1} + \boldsymbol{X_{ct-1}} \boldsymbol{\beta} + \boldsymbol{W} \boldsymbol{X_{ct-1}} \boldsymbol{\theta} + \boldsymbol{\chi_c} + \boldsymbol{\xi_t} + \epsilon_{ct} \end{aligned} \tag{3}$$

where $\boldsymbol{W}$ denotes the spatial weight matrix that describes the physical/economic proximity between cities; other variables are same as Equation (2). Accordingly, $\boldsymbol{W} \cdot Robot\ Exposure_{\boldsymbol{ct-1}}$ signifies the weighted average of robot exposure in neighbouring cities excluding the local city. Stated differently, the coefficient γ captures the spillover effects of robot exposure on housing prices in neighbouring cities. Specifically, if **H2** is correct and there are negative spillover effects of robot exposure on housing prices, then γ should be significant and negative.

This chapter proposes two kinds of spatial weight matrix to characterize the proximity between cities. The first matrix is the traditional geographical straight-line distance matrix, similar to a bunch of previous literature. We first calculate the geographical distance d_{ij} between two cities based on coordinates of city geometric centres. Then, the inverse of the geographic distance $1/d_{ij}$ represents the geographic proximity between two cities, while a larger value of weight ($W_{ij}^{d} = \frac{1}{d_{ij}}, i \neq j$) marks the closer proximity of the two cities and thus a stronger spatial effect. The mathematical formula for the geographic distance matrix is shown below:

$$W_{ij}^{d} = \begin{cases} \dfrac{1}{d_{ij}}, & i \neq j \\ 0, & i = j \end{cases} \tag{4}$$

As discussed previously, the spillover effects of robot exposure are mainly dominated by labour flow between city pairs. However, such labour migration, however, cannot be explained solely by geographical proximity, as economic factors also play a significant role (Fan, 2005; Gu et al., 2019). Additionally, labour migration is asymmetric, with more migrants moving to developed cities than leaving for less developed ones. To model this asymmetric pattern, this chapter leverages an asymmetric geography-economy weight matrix, considering both geographical distance and spatial economic linkages (Parent & LeSage, 2008; Shao et al., 2020). The mathematical formula of the matrix is shown below:

$$W_{ij}^{e} = \begin{cases} \dfrac{pGDP_j}{d_{ij} \times pGDP_i}, & i \neq j \\ 0, & i = j \end{cases} \tag{5}$$

where, $pGDP_i$ represents the average annual GDP per capita of city *i* during the study period, collected from the *China Statistical Yearbook*. In this matrix, GDP per capita in each city is used to characterize economic difference among cities, while the physic proximity is captured by geographic distance. By incorporating both factors, the spatial model provided a more accurate representation of the spillover effects of robot exposure on housing prices.

6.3.3 Data source

This chapter used two databases to construct the key variable, *Robot exposure*. Firstly, we collect robot installation data from the IFR. So far, the IFR database on industrial robots is the only reliable source of long-term information regarding robot installations and stock amounts by country, industry, and year, as it is collected from nearly all industrial robot suppliers worldwide (Jurkat et al., 2022). In other words, this database can trace almost all robot installations domestically and overseas. Using the IFR dataset since 1993, academics have studied the impact of industrial robots on the labour market and firm-level implementation in France, Germany, the US, etc (Acemoglu & Restrepo, 2017, 2020; Aghion et al., 2020; Dauth et al., 2017; Jurkat et al., 2022). This dataset allows us to calculate the annual number of robot installation units across industries in China.

Second, employment data were obtained from the second wave of the China Enterprise Economic Census (CEEC) in 2008. This database records the detailed number of workers by industry and city. A challenge encountered when linking these two databases is the use of different industrial classifications. To address this issue, we grouped them into 19 sectors linking two databases together (please find more details in Appendix of Chapter 6, in subsection B1.) Using Equation (1), we calculated the annual installation units of industrial robots and employment shares for each sector in 2008. Table 1 presents the descriptive statistics of the developed robot exposure index.

This chapter analyses annual average housing prices at the prefecture-city level in China from 2009 to 2017 using data from the *China Statistical Yearbook*. Housing prices are defined as 'the annual average commercial housing selling price'. However, this information is not available for nearly 30 of the least-developed cities, which affects the panel data balance and model estimation[2]. Thus, we excluded these cities, leaving a sample of 261 cities and 2349 observations.

We also include other city-level variables collected from *the China Statistical Yearbook* between 2008-2016. First, as discussed in Section 6.2.2, economic development and population are the most significant factors affecting house prices (Gong & Yao, 2022; Roback, 1982). Thus, we employed *GDP per capita* and *Population* to capture these two factors. Second, higher urban density implies limited land supply and higher demand for housing, thereby increasing housing prices (Fesselmeyer & Seah, 2018). This chapter controls for *Employment density* (employment-to-urban area ratio) to control this factor. Third, we also consider industry investment and development factors using the *Fixed investment ratio* (fixed investment-to-GDP ratio) and *Industry structure* (proportion of tertiary industry GDP to secondary industry GDP), given that industry investment and development significantly facilitate local economic development, thus booming the housing market (Wan & Qiu, 2023; Zhou & Zhang, 2021). Finally, different levels of urban amenities can be capitalised into housing prices across cities (H. Li et al., 2019; Roback, 1982; Rosen, 1979). Therefore, this chapter employed *Teacher per capita*, *Doctor per capita, and Green area per capita* to measure urban amenity levels. Missing values were replaced with moving averages to ensure a balanced panel data[3]. Table 6.1 presents descriptive statistics for all variables.

Table 6.1 The descriptive statistics of variables

Variables	Observations	Mean	Std. Dev	Min	Max
Housing prices (HP)	2,349	4849.797	3239.437	1296.000	47935.760

[2] According to *China Statistical Yearbook*, these cities are predominantly small and medium-sized cities, with an average population of around 771,632 in 2009, and are concentrated in Central and Western less developed regions (especially in Tibet and Xinjiang provinces). On the one hand, the real estate market itself is underdeveloped because the cities are too small. On the other hand, government statistics may be inadequate. These all contribute to the lack of records of local housing prices. As a result, readers need to be mindful of the particularities of the sample on which this paper focuses when considering our findings, in particular the difference in the general size of cities in China as compared to cities abroad. We thank the reviewer for suggesting this boundary condition of our paper.

[3] The number of missing values is very small (less than 0.1%) and all are missing in only a few years. Therefore, the use of the moving average method does not have an impact on the model estimates.

Robot exposure	2,349	1.208	1.344	0.089	10.788
Population	2,349	149.102	190.366	18.600	2449.000
GDP per capita	2,349	54748.590	36570.380	4134.000	467749.000
Employment density	2,349	0.022	0.027	0.0002	0.251
Fixed investment ratio	2,349	0.736	0.314	0.024	5.595
Industry structure	2,349	0.993	0.603	0.128	5.051
Teacher per capita	2,349	86.765	22.085	8.019	254.662
Doctor per capita	2,349	33.518	16.008	4.504	146.598
Green area per capita	2,349	43.248	52.751	0.414	1179.137

6.4 Local impact of robot exposure

6.4.1 Baseline results

According to our hypothesis **H1** proposed in Section 6.2, we expect that cities with higher levels of robot exposure will experience higher housing price premiums. This section tests this hypothesis using several estimation strategies. Table 2 presents the baseline results of Equation (2). Column (1) reports the naïve pooled OLS regression, which controls for city-level characteristics, year fixed effects, and city fixed effects. The model explains 95.5% of housing prices. It is clear in the results that *Robot exposure* is statistically strongly significant at the 10% level, demonstrating that for each additional unit of predicted robot deployment per 10,000 workers, the housing price increases by 0.9%, which confirms our hypothesis. However, this estimation does not consider time-series correlations or endogeneity issues with the key variables in the model. To address these concerns, we subsequently explored alternative methods.

Lagged housing prices must be included in the model to account for the time-series correlation of housing prices. However, as discussed in Section 6.3.2, this may lead to a 'dynamic panel bias' that can affect the coefficient estimation. Therefore, we use the dynamic fixed-effect panel data model to address this problem initially, as shown in Column 2. Our results show that *Robot exposure* still exerts a significant positive effect on housing prices, with an improved significance level from 10% to 1% as well as increased intensity of economic effects. To ensure the robustness of our results, we employ another estimator, the dynamic system-GMM estimator, and report the results in Column (3). The insignificance of AR (2) indicates no autocorrelation for the second-order difference residuals, whereas the insignificance of the Hansen J test implies no overidentification of IVs. These two criteria confirm the effectiveness of the GMM estimation system. With this new estimator, the significance level of *Robot exposure* remains at 1%, but the coefficient of *Robot exposure* increases to 0.031, indicating that for each additional unit of predicted robot deployment per 10,000 workers, the housing price increases by 3.1%.

Regarding the second endogeneity issue mentioned above, we used the IV strategy. We leveraged a developed IV, to predicted robot exposure, using robot installation data from six developed countries (France, Sweden, Denmark, Finland, Italy, and the US). As mentioned in Section 6.3.2, the installation of industrial robots in these developed countries will affect the installation of industrial robots in China, which relies heavily on imports. In the meantime, the former intuitively does not affect China's real estate market, thus ensuring the effectiveness of the developed IV.

As shown in Appendix B2, the first-stage regression results show that the developed IV has significant positive effects on *Robot exposure* at the 1% significance level, primarily confirming the feasibility of the IV. We have also done several IV tests reported in Column (4) of Table 2: (1) the significance of Kleibergen-Paap rk LM statistic at 1% level reveals that the null hypothesis of underidentification test is rejected, and (2) both Cragg-Donald Wald F statistic (682.145) and Kleibergen-Paap rk Wald F statistic (24.868) are larger than the 10% Stock-Yogo weak ID test critical values (16.38), proving that the proposed IV is not a weak instrumental variable. Regarding the result shown in Column (4), the second stage regression demonstrates that the significance level of *Robot exposure* remains at 1%, while the economic impact of *Robot exposure* still remained at a high level with a coefficient of 0.027, implying that one more unit of predicted robot deployment per 10,000 workers increases local housing prices by 2.7%.

Finally, we combine all strategies with the dynamic system-GMM estimator, longer lags of HP, other controlling variables, and an additional exogenous IV. The final results are reported in column (5) and are highly robust and consistent with those in columns (3) and (4). Therefore, we are confident to infer that the economic impact of *Robot exposure* on housing prices is statistically significant, suggesting that one more unit of predicted robot deployment per 10,000 workers increases local housing prices by approximately 3%, or one standard deviation (1.344) increase in robot exposure pushes up local housing prices by 4.032%. This robust finding undoubtedly supports our first hypothesis **H1**, that automation contributes significantly to the rise in local housing prices. We also conducted a series of robustness tests considering potential effects from alternative robot exposure indices, industrial upgrading, other technologies, international trade and high-speed railways, as reported in Appendix B3.

Table 6.2 Regression results of robot exposure's local effects

Dependent variable:	(1)	(2)	(3)	(4)	(5)
	Log (HP)	*Log (HP)*	*Log (HP)*	*Log (HP)*	*Log (HP)*
L. Log (HP)		0.447***	0.492***	0.450***	0.503***
		(0.032)	(0.127)	(0.031)	(0.131)
Robot exposure	**0.009***	**0.015*****	**0.031*****	**0.027*****	**0.032*****
	(0.005)	**(0.005)**	**(0.007)**	**(0.009)**	**(0.007)**
Log (population)	0.042**	0.010	0.114***	0.003	0.111***
	(0.021)	(0.022)	(0.030)	(0.017)	(0.031)
Log (GDP per capita)	0.059***	0.016	0.113**	0.019	0.107**
	(0.022)	(0.020)	(0.048)	(0.018)	(0.048)
Employment density	0.055	0.007	0.740	-0.142	0.672
	(0.309)	(0.386)	(0.472)	(0.262)	(0.472)
Log (Fixed direct	0.018	0.014	0.000	0.017	0.000
investment)	(0.012)	(0.010)	(0.026)	(0.011)	(0.025)
Industry structure	0.012	0.008	0.078**	0.011	0.077**
	(0.012)	(0.011)	(0.036)	(0.012)	(0.036)
Log (teacher per	-0.013	-0.011	0.071*	-0.020	0.062
capita)	(0.023)	(0.020)	(0.040)	(0.019)	(0.038)
Log (doctor per	-0.033**	-0.023*	-0.027	-0.023*	-0.022
capita)	(0.013)	(0.012)	(0.022)	(0.012)	(0.021)
Log (green area per	-0.005	-0.011	0.027**	-0.009	0.025**
capita)	(0.008)	(0.008)	(0.013)	(0.008)	(0.013)
Constant	8.704***	4.496***	2.076***	4.502***	2.093***
	(0.356)	(0.347)	(0.434)	(0.354)	(0.446)
Year FE	Yes	Yes	Yes	Yes	Yes
City FE	Yes	-	-	-	-
Method	Pooled OLS	Dynamic FE	Dynamic S-GMM	Dynamic FE	Dynamic S-GMM

Observations	2,349	2,088	2,088	2,088	2,088
Adjusted R^2	0.955	0.759		0.760	
Kleibergen-Paap rk				45.470	
LM statistic				[0.000]	
Cragg-Donald Wald F statistic				682.145	
Kleibergen-Paap rk Wald F statistic				24.868	
Number of instruments			20		21
Number of groups/cities			261		261
AR (2)			-0.13		-0.07
			[0.893]		[0.945]
Hansen test			2.96		3.66
			[0.228]		[0.300]

*Notes: 1) The key variable in columns (3) and (5) are instrumented by the developed IV variable; 2) Robust standard errors (with Windmeijer's finite-sample correction when employing system-GMM estimator) are clustered at the city level and reported in parentheses; 3) P-values are reported in brackets; 4) ***, **, * represent significant levels at 0.01, 0.05, and 0.1 levels, respectively..*

Our controlling variables have high explanatory power for housing prices, in addition to the key variable. While some of these variables are significant in the pooled OLS estimation results, their significance disappears when the Dynamic FE model is used. A possible reason for this is that the fundamental economic variables changed very little during the chosen period, resulting in the removal of time-invariant effects by the dynamic FE model. However, as shown in Columns (3) and (5), this problem is sidestepped by the dynamic system GMM estimation, allowing the controlling variables to become significant again. Specifically, we find that: 1) large population size and high GDP per capita predict high housing prices; 2) cities with a higher ratio of tertiary industries also have higher housing prices; and 3) cities with better amenities, such as teachers and green areas, tend to have higher housing prices.

6.4.2 Mechanism analysis

In this chapter, we have already identified a significant positive effect of *Robot exposure* on local housing prices, but the underlying mechanisms remain unclear. This subsection provides direct or indirect evidence to connect with previous studies, thus revealing the underlying mechanisms. The first possible channel argues that automation may create more high-skilled jobs and replace low-skilled jobs, attracting more high-skilled labour from other cities/regions and crowd out low-skilled labour, as discussed by Beerli et al. (2023). This change in the skill composition of the local labour market can reshape the demand structure of the housing market, thus contributing to higher local house prices. Unfortunately, data regarding the annual skill composition of the labour market (or internal migrants) are not accessible in China, which hinders direct empirical evidence on this mechanism. Instead, we attempt to provide indirect evidence that relies on a heterogeneity analysis.

First, manufacturing industries typically have higher robot penetration rates, leading to a more vulnerable labour market in the face of industrial robots, especially in China, where the manufacturing workforce is dominated by low-skilled labour. As such, if the aforementioned mechanism holds, we should observe a larger economic impact of *Robot exposure* on housing prices in cities with a higher share of manufacturing employment. To confirm this idea, we introduce the interaction terms between *Robot exposure* and *Manufacturing employment share*, which capture the changing effects of robot exposure along with cities with different manufacturing employment shares, as shown in Column (1) of Table 6.3. This interaction term was significantly positive with large impact magnitude, while the *Robot exposure* turns to non-significant. This implies a larger impact of robot exposure on housing prices in cities with higher manufacturing employment shares. Thus, our hypothesis was confirmed.

Second, we consider that the larger impact of *Robot exposure* may also hold in cities with higher employment densities because of the direct impact on the labour market. Thus, we introduced an interaction term between *Robot exposure* and *Employment density*. This idea is also confirmed by the results reported in Column (2) of Table 6.3, which demonstrate the larger impact of robot exposure on housing prices in cities with higher population density. This analysis provides indirect evidence of the first impact of *Robot exposure* on housing prices. However, this mechanism needs to be supported by more direct evidence from rich labour market data.

In contrast, we further consider an opposing viewpoint that, because of the displacement effect, robot exposure may lead to a higher level of unemployment rate (Acemoglu & Restrepo, 2020; Dauth, Findeisen, & Suedekum, 2021) and thus hamper housing prices at local levels. As discussed by Du and Wei (2022), this negative impact on unemployment is pronounced in

China. We calculated the yearly *unemployment rate* (data collected from the *China Statistical Yearbook*) and interacted it with *Robot exposure* to examine the moderating effect of unemployment on the impact of robot exposure. Column (3) of Table 6.3 reports these results. Given the significantly negative interaction coefficient, this result confirms that the impact of robot exposure decreases as the urban unemployment rate increases (and even fades when the unemployment rate is larger than 0.08). Stated differently, robot exposure has a negative impact on housing prices, which manifests itself through the unemployment rate, and partly offsets the positive impact. This implies that the positive effects of *Robot exposure* will be more significant if their negative effects are isolated, calling for in-depth studies supported by more detailed data in the future.

Table 6.3 Heterogeneity in the local effects of robot exposure across cities

Dependent variable:	(1) *Log (HP)*	(2) *Log (HP)*	(3) *Log (HP)*
L. Log (HP)	0.589*** (0.175)	0.603*** (0.117)	0.637*** (0.138)
Robot exposure	0.014 (0.010)	0.012** (0.006)	0.038*** (0.009)
Robot exposure × Manufacturing employment share	0.031** (0.014)		
Robot exposure × Employment density		0.433*** (0.146)	
Robot exposure × Unemployment rate			-0.312*** (0.104)
Control variables	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Estimator	Dynamic S-GMM	Dynamic S-GMM	Dynamic S-GMM
Observations	2,088	2,088	2,088
Number of instruments	28	30	30
Number of groups/cities	261	261	261
AR (2)	0.10 [0.920]	0.10 [0.922]	0.16 [0.873]
Hansen test	11.88 [0.156]	14.20 [0.222]	16.93 [0.110]

Notes: 1) The key variable in all columns are instrumented by the developed IV variable; 2) Robust standard errors (with Windmeijer's finite-sample correction when employing system-GMM estimator) are clustered at the city level and reported in parentheses; 3) P-values are reported in brackets; 4) ***, **, * represent significant levels at 0.01, 0.05, and 0.1 levels, respectively.

The second possible mechanism argues that automation can induce wage premiums for high-skilled labour and, thus, greater purchasing power in housing, contributing to higher housing prices. In other words, the wage level plays a mediating role in the local effects of robot exposure. To verify this conjecture, we conduct an intermediary analysis of the wage level of urban residents using wage data from *the China City Statistical Yearbook*. Table 6.4 reports all the related results.

In the first step we attempt to capture the effects of robot exposure on the average urban wage level, as shown in Column (1) of Table 6.4. However, the coefficient of robot exposure was not statistically significant, implying that robot exposure had no significant effect on the *average urban wage level*. This aligns with previous results on the negative effects of robot exposure on the wages of workers, in China (Giuntella & Wang, 2019) and the US (Acemoglu & Restrepo, 2020). This is because industrial robots are replacing low-skilled labour, resulting in lower wage levels. These two opposing directions of wage changes between high- and low-skilled workers lead to uncertainty regarding the change in average wages.

To address the issue, we proposed that wage levels of low-skilled migrants may be less uncertain as they can easily relocate to other cities in response to lower wages. As suggested by Zheng et al. (2009), internal migrants in China only take destination cities as workplaces rather than places of residence. As such, the wage premium is more revealing in the wage level of migrants since low-skilled migrants have continued to flow. Following this idea, we estimate the effects of robot exposure on the wage level of migrants[4], which is reported in Column (2). By contrast, we found a significant positive effect of robot exposure on the average wage level of migrants, denoting that one more unit of predicted robot deployment per 10,000 workers increases 1.3% wage levels of migrants. Subsequently, we estimated the effects of robot exposure on housing prices after introducing the average wage level of migrants using the baseline results as a reference in Column (3). The results in Column (4) show that both *Robot exposure* and *Log (average wage level of migrants)* are statistically positive, implying a

[4] The data for calculating the average wage level of migrants comes from *China Migrant Dynamic Survey*, which is typically used to study the "floating population" in China. Please find more details at https://www.chinaldrk.org.cn/.

positive impact on housing prices. However, compared with Column (3), both the significance level and coefficient size of *Robot exposure* dropped significantly. This change demonstrates that nearly one third (31.25%) of robot's impact can be attributed to the change in migrants' wage levels, confirming its mediating role. In other words, the impact of robot exposure on housing prices is partly through its effect on migrants' wage levels, which is the second impact mechanism proposed above. Similarly, we need to acknowledge that these results capture only a portion of the labour market (migrants), which can be improved with more adequate data on the wage levels of the labour force at different skill levels in each city.

Table 6.4 The mediating role of average wage level in local effects of robot exposure

	(1)	(2)	(3)	(4)
Dependent variable:	*Log (average urban wage level)*	*Log (average wage level of migrants)*	*Log (HP)*	*Log (HP)*
L. Dependent variable	0.901***	0.802**	0.503***	0.675***
	(0.077)	(0.337)	(0.131)	(0.205)
Robot exposure	-0.001	0.013***	0.032***	0.022**
	(0.003)	(0.005)	(0.007)	(0.010)
Log (average wage level of migrants)				0.206*
				(0.112)
Control variables	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Estimator	Dynamic S-GMM	Dynamic S-GMM	Dynamic S-GMM	Dynamic S-GMM
Observations	2,088	1,228	2,088	1,503
Number of instruments	21	18	21	21
Number of groups/cities	261	257	261	261
AR (2)	0.68	1.03	-0.070	0.45
	[0.500]	[0.304]	[0.945]	[0.653]
Hansen test	2.13	5.08	3.660	5.47
	[0.351]	[0.166]	[0.300]	[0.140]

Notes: 1) The key variable in all columns are instrumented by the developed IV variable; 2) Robust standard errors (with Windmeijer's finite-sample correction when employing system-GMM estimator) are clustered at the city level and reported in parentheses; 3) P-values are reported in brackets; 4) ***, **, * represent significant levels at 0.01, 0.05, and 0.1 levels, respectively.

Finally, we focus on the impact mechanism from the supply side of the housing market. In section 6.2.2, we argue that the land finance acts as a catalyst to strengthen the relationship between automation progress and a thriving housing market. The important cornerstone of land finance is the revenue from state-owned land sales to balance local fiscal revenues and expenditures. As such, we collected prefectural-city level land sale revenue from the *China Urban Construction Statistical Yearbook* and local public budgetary revenue from local government budgetary documents.

Table 6.5 reports the final results regarding the moderating role of land finance in local effects of robot exposure. First, we directly interact *Robot exposure* with *Land sale revenue* in logarithmic form, which captures the changing effects of robot exposure along with cities with different scales of land sales, as shown in Column (1). The coefficient of the interaction is significantly positive at 5% level, implying that the effects of robot exposure on housing prices are more pronounced in cities with higher level of land sales. This result initially supports the catalyst role of land finance. Yet, the scale of land sale revenue may be a result of city size, rather than the city's dependence on land finance. As such, we instead employ the indicator *Land sale revenue per capita* to eliminate this concern. As shown in Column (2), the final results remain consistent, with a similar impact magnitude.

To ensure robustness, we finally introduce a new indicator *Land finance* (the ratio of land sale revenue to local public budgetary revenue) following Wang et al. (2020), which can directly capture the degree of dependence of local finances on land sales. As shown in Column (3), the key variable *Robot exposure* remains significant and positive, indicating that, even if local finances are totally independent of land sales, the housing price still increases by 1.8% for each additional unit of predicted robot per 10,000 workers. This effect comes mainly from the impact of automation on the demand side of the housing market. Moreover, the interaction term between *Robot exposure* and *Land finance* is also significant and positive, consistent with previous results. This effect captures the impact of automation on the supply side of the housing market. Statistically, the house price premium generated by automation would reach upon 6.2% in cities with the highest dependence on land finance. In summary, land finance further stimulates the booming impact of automation on the housing market, effectively confirming our proposed impact mechanism.

Table 6.5 The catalytic role of land finance in local effects of robot exposure

Dependent variable:	(1) Log (HP)	(2) Log (HP)	(3) Log (HP)
L. Dependent variable	0.786***	0.797***	0.772***
	(0.065)	(0.072)	(0.076)
Robot exposure	-0.022	-0.010	0.018***
	(0.016)	(0.011)	(0.005)
Robot exposure ×Log (Land sale revenue)	0.003**		
	(0.001)		
Robot exposure × Log (Land sale revenue per capita)		0.003**	
		(0.002)	
Robot exposure × Land finance			0.022*
			(0.012)
Control variables	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Estimator	Dynamic S-GMM	Dynamic S-GMM	Dynamic S-GMM
Observations	1,918	1,918	1,918
Number of instruments	24	24	27
Number of groups/cities	253	253	253
AR (2)	0.89	0.89	0.86
	[0.373]	[0.371]	[0.391]
Hansen test	6.33	7.32	9.10
	[0.276]	[0.198]	[0.334]

Notes: 1) The key variable in all columns are instrumented by the developed IV variable; 2) Robust standard errors (with Windmeijer's finite-sample correction when employing system-GMM estimator) are clustered at the city level and reported in parentheses; 3) P-values are reported in brackets; 4) ***, **, * represent significant levels at 0.01, 0.05, and 0.1 levels, respectively.

6.5 Spillover impact of robot exposure

6.5.1 Baseline results

Beyond the local impact of robot exposure, this chapter also discusses the spillover impact on housing prices in adjacent cities. As argued by our hypothesis H2, the redistribution of labour is linked to other neighbouring cities through labour migration, which thus influences their labour markets (Basso et al., 2020; Beerli et al., 2023; Y. Chen et al., 2022), and finally induces spillover effects on housing prices in adjacent cities. The following empirical works attempt to validate this idea.

The use of dynamic spatial panel models enabled us to explore the above hypotheses. Our main results are presented in Table 6.6. To ensure the feasibility of these models, we conduct spatial panel autoregression tests and find that the statistics of LM-Error and LM-Lag panel tests are significant at a 1% level, rejecting the null hypothesis of 'no spatial correlation'. This result indicates the need for a spatial econometric model in the empirical analysis[5]. For comparison, we present the results of the dynamic S-GMM estimation in Column (1). In Column (2), we estimate a dynamic panel spatial autoregressive (SAR) model using an asymmetric geography-economy weight matrix (W_{ij}^{e}). The model introduced both year-lagged and spatially lagged housing prices and confirmed their significant effects on the dependent variable. Not surprisingly, *Robot exposure* remained significant at the 1% level with even a slightly larger impact magnitude. This confirms the positive local effects of robot exposure on housing prices, even after considering the spatial correlation. However, this model does not portray the spillover effects.

Table 6.6 Regression results of robot exposure's spillover effects

Dependent variable:	(1) *Log (HP)*	(2) *Log (HP)*	(3) *Log (HP)*	(4) *Log (HP)*	(5) *Log (HP)*	(6) *Log (HP)*
L. Log (HP)	0.492***	0.576***		0.624***		0.611***
	(0.127)	(0.025)		(0.028)		(0.030)
W × Log (HP)		0.358***	1.544***	4.618***	1.335***	3.470***
		(0.068)	(0.148)	(0.158)	(0.200)	(0.184)
L. (W × Log (HP))					0.927***	0.571***
					(0.201)	(0.191)
Robot exposure	0.031***	0.024***	0.048***	0.024***	0.050***	0.025***
	(0.007)	(0.004)	(0.007)	(0.005)	(0.007)	(0.005)
W × Robot exposure			-0.069**	-0.110***	-0.089***	-0.163***
			(0.028)	(0.021)	(0.030)	(0.021)

[5] In addition to these tests, we also conduct a series of spatial correlation tests, which are discussed in detail in online Appendix A4.

Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	-	-	-	-	-
Method	Dynamic S-GMM	Dynamic SAR	Static SDM	Dynamic SDM	Dynamic SDM	Dynamic SDM
Weight matrix type	-	Asymmetric Geography-economy	Asymmetric Geography-economy	Asymmetric Geography-economy	Asymmetric Geography-economy	Asymmetric Geography-economy
Observations	2,088	2,088	2,088	2,088	2,088	2,088
Sigma2	-	0.008***	0.011***	0.007***	0.010***	0.007***
	-	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
Spatial panel autoregression test						
LM-Error panel test	3181.978***[0.000]					
Robust LM-Error panel test	2385.723***[0.000]					
LM-Lag panel test	923.592***[0.000]					
Robust LM-Lag panel test	127.337***[0.000]					

Notes: 1) all control variables are transformed into log type; 2) Robust standard errors are clustered at the city level and reported in parentheses; 3) P-values are reported in brackets; 4) ***, **, * represent significant levels at 0.01, 0.05, and 0.1 levels, respectively.

A spatial Durbin model (SDM) is employed to investigate the potential spillover effects of robot exposure on housing prices. The findings are presented in column (3), where a static SDM is estimated considering spatially lagged housing prices (*W* × *Log (HP)*), *Robot exposure*, spatially lagged robot exposure (*W* × *Robot exposure*), and all other control variables. First, the results reveal that spatially lagged housing prices maintain considerable explanatory power, indicating significant spatial dependence on housing prices across local cities. Second, the direct and statistically significant effects of robot exposure on housing prices within local cities were observed, which is consistent with previous results. Finally, it is worth noting that spatially lagged robot exposure exhibits significant negative effects on housing prices at a 1% significance level. This suggests that housing prices are negatively influenced by robot exposure in neighbouring cities, which lends initial support to our second hypothesis H2.

To address concerns regarding time-series correlation in the housing price data, we extend our analysis to include a dynamic SDM model in Columns (4), (5), and (6). In column (4), we added lagged housing prices from the previous year (*L. Log (HP)*) to the spatially lagged housing prices and control variables. The results show that the key variables, including robot exposure and spatially lagged robot exposure, maintain high significance levels, with only slight changes in their coefficient values after controlling for year-lagged housing prices. In column (5), we included space-time lagged housing prices (*L. (W × Log (HP))*) in the model. The coefficients of robot exposure and spatially lagged robot exposure remain robust, indicating that the negative spillover effects of robot exposure on housing prices in neighbouring cities still hold. Finally, in Column (6), we introduce both year-lagged and space-time-lagged housing prices into the model. The results demonstrate that these additions have no effect on the significance or sign of the coefficients of robot exposure or spatially lagged robot exposure. These robust findings provide further evidence supporting our second hypothesis, namely, that robot exposure has a negative spillover effect on housing prices in neighbouring cities. We also conducted a series of robustness tests considering alternative weight matrix and robot exposure indices, as shown in Appendix B5.

6.5.2 Marginal effect analysis

This subsection discusses the marginal effects of robot exposure on housing prices in neighbouring cities. Empirically, we decompose these effects into direct and indirect effects following (Elhorst & Elhorst, 2014; LeSage & Pace, 2009). The former embodies the average direct impact of *Robot exposure* on housing prices in local cities and the feedback effect of *Robot exposure* on housing prices in local cities through neighbouring cities. In the meantime, the latter embodies the local spillover effect of robot exposure on housing prices in neighbouring cities and the global spillover effects of robot exposure on housing prices in neighbouring cities through the spatial dependence between house prices in different cities (please see Elhorst and Elhorst (2014) for detailed discussions). Moreover, these effects can be further decomposed into short-term and long-term effects. The short-term effects only consider effects from the current period neglecting effects passed on from other periods, while the long-term effects consider effects from all periods.

The decomposition results are presented in Table 6.7[6]. As shown in Column (1), the marginal effects estimated by the static SDM suggest significant negative spillover effects, implying that one more unit of predicted robot deployment per 10,000 workers decreases housing prices by an average of 5.5% in neighbouring cities, consistent with our hypothesis. Yet, the dynamic SDM shows a slightly different picture. Column (2) indicates that this negative effect occurs mainly in the current period with a slightly smaller impact magnitude, while the global spillover effects will offset this negative impact after considering all previous periods. This result is mainly due to the existence of two different impact mechanisms captured by local and global spillover effects, respectively. On the one hand, as we proposed in the analytical framework, robot exposure can exert negative effects on housing prices in neighbouring cities through labour migration and land finance. This has been identified in the previous subsection. On the other hand, the calculated marginal effects also consider the positive spillover effects of housing prices premium in local cities (induced by robot exposure) on housing prices in neighbouring cities, given the positive spillovers of housing prices between regions (Meen, 1999; Zhang et al., 2017). The two impact mechanisms act simultaneously and in opposite directions, ultimately leading to insignificant impact spillovers of robot exposure in the long term.

Table 6.7 Decomposition of robot exposure's marginal effects

Marginal effect types	Static SDM	Dynamic SDM
Short-run direct effects		0.024***
		(0.005)
Short-run indirect effects		-0.031*
		(0.019)
Short-run total effects		-0.007
		(0.021)
Long-run direct effects	0.050***	0.062***

[6] To avoid model overfitting or covariance problems, we have adjusted the model setting when estimating. In detail, in addition to considering the spatial and temporal lag terms of the dependent variable Log *(HP)*, we only include the spatial lag term of the key coefficient *Robot exposure* instead of all controlling variables, which does not affect the interpretation of the model results.

	(0.007)	(0.012)
Long-run indirect effects	-0.055***	-0.080
	(0.011)	(0.626)
Long-run total effects	-0.006	-0.017
	(0.015)	(0.63)
L. Log (HP)	No	Yes
W × Log (HP)	Yes	Yes
L. (W × Log (HP))	No	Yes

Notes: 1) Robust standard errors are clustered at the city level and reported in parentheses; 2) P-values are reported in brackets; 3) ***, **, * represent significant levels at 0.01, 0.05, and 0.1 levels, respectively.

6.6 Chapter Summary

This chapter fills a gap in the literature by examining how industrial robots influence housing prices at the prefecture-city level through their impact on the labour market on one hand and land supply on the other. It investigates the effects of robot exposure on local housing prices and their spillover effects on housing prices in neighbouring cities based on a city-level predicted robot exposure index and multiple estimation methods. Based on our estimates, one more unit of predicted robot deployment per 10,000 workers leads to a 3% increase in local housing prices, and in cities with high manufacturing employment and high population density, this effect is stronger; however, as unemployment rates increase, this effect weakens; meanwhile, 31.25% of the impact of automation is caused by wage premiums that affect purchasing power for highly skilled migrants. Land finance, especially in cities with high reliance on this policy, strengthens the link between automation and housing price increases by up to 6.2 per cent. Based on the spatial econometric models, we confirm that for every additional industrial robot predicted per 10,000 workers in neighbouring cities, the housing price in neighbouring cities decreases by 5.5%, suggesting a potential brain drain effect and hampering housing prices in these neighbouring cities.

The spread of robotics, artificial intelligence and other automation technologies has increased productivity and boosted the economy while simultaneously raising concerns about their dark side affecting jobs and wages. Our study further extends these discussions and argues that automation is not just a threat to jobs, it also increases the cost of living, specifically in the form of increased housing costs. This also means that the income/wage inequality induced by the direct labour impact of automation will be even greater when housing costs are further considered. This result is particularly important for the government's policy response. While considering the most direct security policies (e.g., unemployment insurance, manpower training, etc.) to cope with automation (as discussed in previous studies), the government also needs to synchronise and follow up some indirect social security measures (e.g., housing subsidies, land and property taxes, etc.) to reduce the cost of living and thus ameliorate social inequality.

This point is particularly pronounced and imperative in China, both because of the country's massive installation of industrial robots and its unique land finance policy. In fact, the above-mentioned automation impacts are just a snapshot of China's economic development strategy. Land finance is used as a fulcrum to pry industrial development, while the cost of development is transferred to the public, which is manifested in high housing prices and a high degree of social inequality (Zhou and Song 2016; Gyourko et al. 2022). These valuable lessons are equally vital for a number of developing countries at a similar stage of development when adopting a development path similar to China's (e.g., similar industrial and land policies). In detail, the development of productivity through automation technologies needs to be accompanied by consideration of a range of social issues such as rising housing prices and inequality.

Moreover, our study also confirms that although automation initially affects a localised area, its effects spread to neighbouring areas as well. This outcome is comparable to the siphoning effects observed in large cities on neighbouring smaller cities regarding economic growth and production factors, as demonstrated in prior studies (Burger et al. 2015; Partridge et al. 2009). In our case, regional automation likewise creates this siphoning effect, primarily through brain gain and brain drain, and manifests itself in the housing market. This effect will be further reinforced by the regional competition feature of the land finance policy in China. Correspondingly, cities should cooperate through regional planning and policy design to mitigate the negative impacts of inter-city competition. This aspect will ensure balanced development across regions.

CHAPTER7.   CONCLUSIONS

7.1 Summary of Major Findings and contribution

7.1.1 The development of Industry 4.0 technologies in China

The thesis first presented findings highlighting the complexity and varied influences on the development of I4.0 technologies in China, emphasising the significance of both technological and geographical proximity. Cities with knowledge bases closely related to I4.0 technologies or in close geographical proximity to cities specialising in these technologies are more likely to foster I4.0 developments, indicating the applicability of the relatedness framework in this context. Moreover, the development trajectory of I4.0 technologies in China predominantly exhibits path dependence on the ICT industry, rather than automated business equipment, aligning with the findings of Laffi and Boschma (2022). The path dependence, however, varies across different technological subcategories. While the influence of technological proximity remains consistently significant across various I4.0 categories, the role of geographical proximity and the relevance of 3.0 technologies differ. Notably, AI and big data development are less constrained by geographical factors, and there exists a competitive dynamic linkage between automated business devices and other I4.0 technologies, such as big data, IoT, 3D printing, and robotics.

This study makes advancements in the ongoing debate about the transformative impact of Industry 4.0. By focusing on China as a case study and applying a novel relatedness framework, we have uncovered fresh perspectives in this field. Unlike previous research efforts, such as those by Laffi & Boschma (2022), which primarily investigated whether regions specializing in Industry 3.0 technologies are poised to contribute to the development of Industry 4.0, our study takes a distinctive approach. This study improves the measurement of Industry 3.0 technologies, introducing a more robust and comprehensive indicator. This involves leveraging the average relatedness between two key components - ICT technology and automated business equipment technology - to better understand and quantify a city's accumulated technological knowledge.

7.1.2 Impact of imports, R&D, and FDI on innovation

The research focuses on understanding how countries, particularly developing economies like China, can leverage imports to foster innovation in the context of rapidly evolving automation technologies. The key findings from the study are: Firstly, at the city-industry level, importing automation technologies provides an immediate boost to innovation. This effect is attributed to the diffusion of ideas and competitive dynamics. However, at the enterprise level, the impact of imports on innovation depends on a firm's capacity to absorb and integrate external knowledge, which varies based on the firm's existing capabilities, resources, and strategic orientation; Secondly, across both city-industry and enterprise levels, R&D investment consistently emerges as a critical driver of innovation. This underlines the importance of internal efforts in developing and enhancing innovation capabilities; Thirdly, the impact of FDI on innovation shows variation. Its influence differs over time and across different levels of analysis, reflecting the complex nature of FDI's role in fostering innovation.

In this chapter, we present robust empirical evidence demonstrating the influence of robot imports on local innovation capabilities within a significant developing economy like China. Our research reveals that the impact of imports on innovation varies across macro (city-industry) and micro (enterprise) levels, offering insights into the adaptation and learning processes that underlie this relationship. Moreover, this study extends the existing literature by offering a detailed understanding of innovation dynamics within the rapidly evolving context of China. The findings highlight the importance of both external trade linkages and internal factors like R&D and FDI in shaping innovation trajectories, even in strategic sectors such as robotics.

7.1.3 Robotic and employment: the interplay of robotics

The study's empirical research sheds light on the relationship between the adoption of industrial robots and local employment rates, revealing that robot adoption generally leads to a decrease in employment, a finding that aligns with widespread concerns about automation's impact on jobs. This negative effect, however, is mediated by the city’s industrial structure. Notably, the research uncovers that industrial diversity influences how robot adoption impacts employment. In cities with a higher RV, the decline in employment is more pronounced compared to cities with a higher UV, indicating a complex interaction between the diverse industrial landscape and technological advancements. On the other hand, cities with a greater degree of industry specialisation seem to be more resilient to the job-displacing effects of automation.

The study also explores the spatial dynamics of these effects, revealing that the employment challenges posed by robotic adoption are not limited to the cities where they occur but also spill over into neighbouring areas. This demonstrates the interconnected nature of urban economies and the far-reaching impact of automation. Interestingly, the findings also suggest that cities at similar economic development stages might experience positive employment spillovers from neighbouring cities' robotic advancements, challenging the conventional narrative of automation-related job losses. Contrary to expectations, the study does not find a significant spatial spillover of the industrial structure's mediating effects on employment, underscoring that the impact of industrial robots is local.

This study enriches the theoretical framework at the intersection of automation and urban labour markets in several key aspects: First, in contrast to previous studies that have focused on national impacts or types of occupations, this study explores city-level impacts. Although the penetration of automation into manufacturing has changed the dynamics of urbanisation (Li et al., 2020), cities play an important role in promoting economic development and encouraging industrial upgrading - such as by encouraging the introduction of industrial robots. By providing robust evidence from the adoption of industrial robots across Chinese cities, it empirically validates the often-presumed inverse relationship between automation and employment. Beyond that, this study expands the current knowledge by demonstrating how the industrial externality of a city moderates the impacts of automation on employment, addressing the call by Frank et al. (2018) by answering the question that "are the forces of diversity and, specialisation shaping a city's ability to accommodate automation?" This research provides the first empirical study connecting the two forces of industrial externalities and automation's impact on employment, adding to the lively debate on automation and to the discourse on economic geography and labour economics. Third, this research identifies the spatial spillover effects of robot adoption and the mediating effects of industrial structure on employment. It uncovers both the ripple of negative consequences and the conditions under which positive employment spillovers occur, thus contributing to regional science and inter-city economic studies. By establishing that the moderating effects of industrial structure on robot adoption are localised, this study contributes to the literature on local economic ecosystems and their unique capacities to respond to technological disruptions.

7.1.4 Impact of automations on housing markets

The study uncovers notable effects of industrial robot installation on local housing markets. It reveals that the adoption of one robot per 10,000 workers corresponds with a significant increase in local housing prices, approximately 3%. This correlation is robust, consistently observed across different estimation methods, including an IV approach, and remains valid even when incorporating various additional control variables into the analysis. Furthermore, the research extends to understanding the impact of robot adoption on the housing markets of neighbouring cities. Here, the study finds that the presence of robots in one city negatively influences housing prices in adjacent cities. This trend is consistently observed across different spatial econometric models and weighting matrices. This finding suggests that the introduction of robots may be attracting high-skilled labour away from neighbouring cities, contributing to a 'brain drain' effect. As a result, these neighbouring cities experience a downturn in their housing markets.

This chapter expands the current understanding of the impact of automation, moving beyond labour markets to shed light on its effects on housing markets. Traditionally, the focus has revolved around how automation affects employment patterns, skill polarization, and income disparity, with compelling findings that highlight the skill-biased nature of automation (Goos & Manning, 2007; Hémous & Olsen, 2022; Kaltenberg & Foster-McGregor, 2020). However, this study unveils another dimension, suggesting that automation might inadvertently push up living expenses for displaced workers beyond the employment challenges. The second contribution of this chapter delves into the often-overlooked arena of inter-city linkages stemming from the automation process. Rather than limiting its examination to the immediate impact on a single locality, this research pioneers an exploration into how the ripples of automation's benefits and drawbacks resonate with the real estate markets beyond the local area. By doing so, it underscores the interconnected nature of regions and highlights the potential for automation-induced changes in one area to cascade into neighbouring cities through labour mobility. This study offers a comprehensive framework for understanding the multi-dimensional effects of automation on regional economies.

7.2 Policy implications from major findings

In this section, the thesis tries to provide policy suggestions on the practical application of the major findings of this thesis, specifically focusing on how to translate the research findings into feasible policy suggestions that can be used as references by city managers and policy makers. The emergence of Industry 4.0 technologies brings challenges and opportunities for urban development. This study has revealed the factors that drive the development of Industry 4.0 technologies and also highlighted the possible socio-economic impacts of Industry 4.0 technologies, and we aim to provide a roadmap for policy makers to promote technological growth, economic development, and a sustainable urban future towards Industry 4.0.

The thesis has evaluated the impact of cities' technological framework and knowledge infrastructure, the local government can conduct a thorough and systematic assessment of technological endowment according to the research outcome of this thesis. A comprehensive assessment of the current technological endowment, including technological capabilities and their external linkages, is crucial. Such an assessment serves as a critical diagnostic tool, providing urban planners and policymakers with a clear picture of the city's current technological status. Through diagnostics, local governments can make better decisions about the areas of strength that the city can develop in the future, as well as the gaps that need to be filled. If the city's own resource endowment and technological base are not excellent, the content of Chapter 5 reveals that it is possible to bridge the base of latecomers by importing products with embedded advanced technologies or attracting FDI. These assessments inform the integration of advanced technologies and the development of smarter, more strategic approaches. The governments can formulate differentiated policy measures according to the characteristics and needs of different industries. For example, in the case of traditional manufacturing industries, more emphasis could be placed on the transformation and upgrading of basic technologies, while in the case of high-technology industries, more support for research and development and protection of intellectual property rights could be provided. By accurately quantifying their readiness, cities can tailor-make their Industry 4.0 strategies to their specific advantageous contexts, ensuring more effective and efficient implementation.

Moreover, our research suggests that neighbouring cities could have impacts in the context of advancing towards Industry 4.0. The recommendation is particularly crucial for cities that find themselves lagging in technological advancements. In an era that interconnectivity and knowledge sharing are vital, the potential for technological spillover from technologically advanced neighbourhoods or other inter-connected cities presents a significant opportunity. Chapter 3 reveals that cities in close geographical proximity to those specialising in specific Industry 4.0 technologies are more likely to develop similar technologies. Chapter 5 reveals that the negative effects of robot exposure on employment will spill over to nearby cities. Additionally, Chapter 6 sheds light on the influence of technological advancements on housing markets, revealing that such influence likewise will ripple out to adjacent cities. Therefore, it becomes imperative that policymakers should not only focus on their city's internal technological development, but also to actively engage in regional networks. This engagement can facilitate shared learning experiences, mitigate negative spillovers, and harness the positive impacts of technology adoption across city borders.

However, in navigating the diverse landscape of Industry 4.0, it is crucial to recognise that the heterogeneity in these fields. Industry 4.0 is characterised by a wide array of technologies, each with unique requirements, potential impacts, and development paths. Technologies such as artificial intelligence, the IoT, robotics, and big data analytics, while all under the umbrella of Industry 4.0, differ significantly in their applications, infrastructure needs, and skill requirements. Recognizing and embracing this diversity is crucial for effective policy formulation. Policies tailored to the specific nuances and demands of each technology are essential. This means that strategies effective for the advancement of AI may not be directly applicable or beneficial for the development of, say, robotics or additive manufacturing. Such tailored policies should take into account the specific resource requirements, regulatory frameworks, and skillsets needed for each technology. The research findings from Chapters 4 to 6, while providing in-depth insights into the field of robotics, may have limited applicability to other Industry 4.0 technologies due to the distinct characteristics and implementation contexts of these technologies.

7.3 Suggestions for Future Studies

As we draw the thesis to an end, it becomes imperative that to look beyond the current scope of this study and to contemplate the paths that future research might take. While the research has yielded significant insights into the intricacies of Industry 4.0 technologies, there is a rich landscape of opportunities for further investigation.

The first thing that future studies can address is the limitations with our current database. This study used patent data to offer information on Industry 4.0 development in Chapters 3 and 4. A more complementary perspective is essential to show how the integration of advanced technologies into the industrial manufacturing process and to explore further innovations resulting from the implementation of Industry 4.0 in manufacturing settings (Corradini et al., 2021; Szalavetz, 2019). In examining the impacts of industrial robots in Chapters 5 and 6, we allocated national level data across cities based on industry employment shares. While this method, inspired by previous studies (Acemoglu & Restrepo, 2020; Dauth, Findeisen, & Suedekum, 2021; De Vries et al., 2020; Graetz & Michaels, 2018), offers a pragmatic approach to overcoming the lack of city-level data, there are potential limitations and areas for improvement. We suggest that future studies incorporate more detailed, city-specific data, when available.

Secondly, the research extensively focuses on robotics in Chapters 4 to 6, which has a great impact on the socio-economic landscape. However, 3D printing (or additive manufacturing) is also a comparatively new and evolving form of Industry 4.0 technology that has the potential to transform the geographies of manufacturing (Gress & Kalafsky, 2015). The potential transformation indicates a wealth of research opportunities, particularly in examining how 3D printing could affect production spaces, trade patterns, geographies of labour, global production networks and so on. Such research could provide valuable insights into the sustainable development of manufacturing industries and contribute to a deeper understanding of Industry 4.0's overall impact on global economic structures and spatial configurations.

APPENDICES: SUPPLEMENTARY INFORMATION

Appendix of Chapter 3

A1- Sampling strategy

Table A1 Sampling Strategy for Chapter 2

Technology and references	IPC classes	Keywords (In Chinese)
AI **Source: Martinelli et al. (2021)**	A61B, B29C, F02D, F03D, F05B, F16H, G05B, G06F, G06K, G06N, G06Q, G06T, G10K, G10L, H04L, H04N	Artificial Intelligence, AI, 3computational intelligence, neural networks, Bayesian networks, data mining, decision models, deep learning, genetic algorithms, logical programs, machine learning, natural language generation, natural language processing, reinforcement learning, supervised learning, supervised training, swarm intelligence, expert systems, fuzzy logic, migration learning, learning algorithms, learning models, support vector machines, random forests, decision trees, gradient model boosting, xgboost, adaboost, rankboost, logistic regression, stochastic gradient descent, multi-layer perceptron, potential semantic analysis, multi-agent systems, hidden Markow models
Big Data **Source: UK IP Office (2014a); Martinelli et al. (2021); Corradini et al. (2021)**	G06F11, G06F12, G06F17, G06F19, G06Q10, G06Q30, G06Q40	Big Data
3D printing **Source: UK IP Office (2013); Martinelli et al.**	B22F, B23K, B29C, B41J, G03F, G06F, B28B, H05K, B22C, A61F, C04B, B28B,	3D Printing, Additive Manufacturing

(2021); Corradini et al. (2021)	A01G, A61L, C08L	
Internet of Things (IoT) **Source: UK IP Office (2014c); Ardito et al. (2018)**	G06K, H01Q, G07C, G08B, G05B19/418, G06F15/16, G08C17/02, H04B7/26, H04L12/28, H04L29/06, H04L29/08, H04W4/00, H04W72/04, H04W84/18	Internet of Things, RFID, Radio Frequency Identification, Sensor, Wireless Access, M2M, NFC, Cloud Computing, Intelligent Control, cloud computing, Proximity Wireless Communication
Robotics **Source: UK IP Office (2014b)**	B23K, B23Q, B25J, B65G, B60R, B60W, F15B, F16H, H02K, H02N, H04N, G01B, G02D, G01L, G01S, G05B, G05D, G06F, G06N, G06T, G09B, G08G	(robot, industrial robot, manipulator, manipulator arm, grip claw) and (joint, linkage, palletising, assembly, welding, handling, processing, cutting, polishing, stamping, molding, warehousing, injection, assembly, coordination, parallel, sorting, packing, unpacking, packing, unloading, , loading, unloading, spraying, coating, painting, bonding, encapsulation, processing, identification, surfacing, testing, measuring, arc welding, spot welding, cutting machine tool, fixing, forging, casting, polishing, sewing sheet, sewing plate, gripping, picking, gluing, cutting, sewing, warp, weft, washing, printing, scribing, baking, plating, lithography, laser, inspection, clamping)

Appendix of Chapter 4

Table A2 Eight types of industrial robots and their custom codes

HS Code	Product Name
84795010	Multi-functional industrial robots
84795090	Other industrial robots (excluding multi-functional industrial robots)
84864031	Automated material handling machines solely or principally of a kind used in the electronic integrated circuits factories
84248920	Spraying robot
84289040	Carrying robot
85153120	Robot for (including plasma arc) welding of metals
85152120	Robot for resistance welding of metals
85158010	Robot for laser welding of metals

Appendix of Chapter 6

B1. Industry classification matching

The IFR industry classes are related to and derived from the International Standard Industrial Classification of All Economic Activities (ISIC) revision of the four schemes, with some minor adjustments. However, the second wave of *China Enterprise Economic Census* (CEEC) in 2008 used a different industry classification according to *China National Economic Classification and Codes* (GB/T 47542002). Therefore, we manually matched the two classifications and grouped all industries into 19 sectors. Specifically, we have seven broad industries, and the manufacturing industry is further classified into 13 disaggregated industries. The matching results are listed in Table A3.

Table A3 Industry matching table

Industries	Sector codes in IFR	4-digit code range in CEEC
Agriculture, Forestry, and Fishing	A-B	0111-0540
Mining and quarrying	C	0610-1100
Manufacturing		
Food and beverages	D (10-12)	1310-1690
Textiles	D (13-15)	1711-1942
Wood and furniture	D (16)	2011-2190
Paper and printing	D (17-18)	2210-2452
Plastic and chemical products	D (19-22)	2511-3090
Minerals	D (23)	3111-3199
Basic metals	D (24)	3210-3353
Metal products	D (25)	3411-3499
Electrical and electronics	D (26-27)	3911-4190
Industrial machinery	D (28)	3511-3699
Automotive	D (29)	3721-3726
Other vehicles	D (30)	3711-3719, 3731-3799
Other manufacturing production	D (91)	4211-4320
Electricity, gas, water supply	E	4411-4690
Construction	F	4710-5090
Education, research, and development	P	7510-7830, 8410-8499
Other services	G	5110-7499, 7910-8390, 8511-9720

B2. First stage results of IV estimation

Table A4 First stage regression results

Dependent variable: ***Robot exposure***	(1) *Coefficients*	(2) Robust standard errors
L. Log (HP)	-0.326*	(0.179)
IV (Robot exposure)	**0.349*****	(**0.070**)
Log (population)	0.295***	(0.101)
Log (GDP per capita)	-0.215***	(0.080)
Employment density	10.829***	(2.160)
Log (Fixed direct investment)	-0.184**	(0.088)
Industry structure	-0.215***	(0.058)
Log (teacher per capita)	0.422***	(0.110)
Log (doctor per capita)	-0.031	(0.072)
Log (green area per capita)	-0.122**	(0.048)
Year FE	Yes	
Observations	2,088	

Notes: 1) Robust standard errors are clustered at the city level and reported in parentheses; 2) ***, **, * represent significant levels at 0.01, 0.05, and 0.1 levels, respectively.

B3. Robustness tests of robot exposure's local impact

To further ensure the robustness of our empirical results, we conducted a series of tests to address these concerns. First, the basic assumption of our proposed robot exposure index is that robot adoption per worker in each industry is consistent across cities. However, this assumption may not hold because capital availability may also influence whether a company installs industrial robots. Instead of using employment share as the weight, we recalculated the robot exposure index based on two new weights: industrial output share and total industrial asset share. We use a new database, the 2008 Micro-database of Chinese Industrial Enterprises[7],

[7] Differing from the CEES, this database focuses on industrial firms, including Mining and quarrying industries, manufacturing industries, and Electricity, gas, and water supply industries. These industries happen to be the most automated, and therefore the calculated indices are able to predict robot adoption to a large extent.

which contains national census data with sufficient information on industrial output and total capital at the firm level. Three new indices were calculated with three different weights based on the new database, according to Equation (1).

Columns (1), (2), and (3) of Table A5 report the regression results. New indices still have significant positive effects on housing prices at the 1% significance level, which confirms that the way the robot penetration degree is weighted does not affect the reliability of the results. It is worth noting that there is a significant difference in the impact magnitude between *Robot exposure (employment)* and *Robot exposure (output/asset)*, since they have different scales. The results of Columns (2) and (3) suggest that adding one robot per one million yuan of industrial output or total industrial asset increases local housing prices by approximately 4%.

Another concern related to the index calculation is that the baseline employment shares are calculated based only on 2008 data. This is consistent with one of the main assumptions of the shift-share design: changes in robot installations in a city are mainly driven by nationwide robot installations rather than by city-specific labour markets, ensuring that our estimates of robot exposure are not affected by labour market fluctuations from 2009 to 2016. This estimation has limitations: it assumes that there are no changes in the labour structure of cities or labour market mobility throughout the periods. To address this concern and test its stability, we recalculated the robot exposure for the latter half of the research period using a new baseline labour share. Practically, the index from 2008 to 2012 was calculated based on the industry conditions in 2008, while the index from 2013 to 2016 was recalculated based on the industry conditions in 2013, leveraging the same new database. Therefore, we attempted to capture trends more accurately for robot use across cities.

Column (4) of Table A3 reports the final results, showing that the key variable, *Robot exposure* (weighted by employment share), is still statistically significant, with an even larger coefficient. Columns (5) and (6) of Table A4 further report the results of *Robot exposure* weighted by industrial output share and industry asset share, respectively. These results are robust and confirm the reliability of the impact of robot exposure on housing prices. Regarding the impact magnitude of new indices, our coefficients of all three indices nearly tripled after adjusting the baseline labour share. One potential explanation is that as the penetration of industrial robots increases year after year, the scale effect of industrial robots in automated industries gradually becomes apparent, accompanied by the emergence of skill complementary resulting from the adaptation of associated industrial workers. These lead to a greater impact of industrial robots on housing prices.

Table A5 Robustness tests of robot exposure's local effects: alternative index

Dependent variable:	(1) *Log (HP)*	(2) *Log (HP)*	(3) *Log (HP)*	(4) *Log (HP)*	(5) *Log (HP)*	(6) *Log (HP)*
L. Log (HP)	0.567***	0.638***	0.576***	0.507***	0.582***	0.519***
	(0.143)	(0.072)	(0.151)	(0.117)	(0.130)	(0.110)
Robot exposure (employment)	0.009***			0.022***		
	(0.003)			(0.006)		
Robot exposure (output)		0.041***			0.115**	
		(0.011)			(0.045)	
Robot exposure (asset)			0.040***			0.121***
			(0.010)			(0.032)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Estimator	Dynamic S-GMM	Dynamic S-GMM	Dynamic S-GMM	Dynamic S-GMM	Dynamic S-GMM	Dynamic S-GMM
Observations	2,088	2,088	2,088	2,088	2,088	2,088
Number of instruments	21	21	23	21	25	21
Number of groups/cities	261	261	261	261	261	261
AR (2)	-0.11	0.07	-0.12	-0.30	-0.18	-0.40
	[0.912]	[0.941]	[0.908]	[0.761]	[0.860]	[0.690]
Hansen test	5.51	6.08	8.04	3.31	10.48	4.12
	[0.138]	[0.108]	[0.154]	[0.347]	[0.163]	[0.249]

Notes: 1) All robot exposure indices are calculated based on the new database, the 2008 Micro database of Chinese Industrial Enterprises; 2) In columns (1) to (3), robot exposure is weighted based on the industry condition in 2008, while robot exposure in columns (4) to (6) is weighted based on the industry condition in 2008 and 2013 in different periods; 3) The key variable in all columns are instrumented by the developed IV variable; 4) Robust standard errors with Windmeijer's finite-sample correction are clustered at the city level and reported in parentheses; 5) P-values are reported in brackets; 6) ***, **, * represent significant levels at 0.01, 0.05, and 0.1 levels, respectively.

Second, industrial upgrading (from secondary to tertiary industries) and spatial transfer (from coastal to inland cities) has been ongoing in China for decades, which may have induced changes in the composition and outcomes of local labour markets (Cai and Wang 2010), and consequently affected the housing market, similar to automation. If these two trends overlap, then the factors influencing housing prices are unclear. We have already included industrial structure as a control variable to address this question. Moreover, we considered the *Manufacturing employment share*, which is the employment share of the manufacturing sector in all sectors, as an additional controlling variable. Manufacturing is the sector in which the impact of industrial robots is most direct and significant. Column (1) of Table A6 reports the regression results after controlling *Manufacturing employment share*. This control had little effect on the key variable, *Robot exposure,* which remained significant at the 1% level without any significant changes in the coefficient size.

Table A6 Robustness tests of robot exposure's local effects: other economic changes

Dependent variable:	(1) *Log (HP)*	(2) *Log (HP)*	(3) *Log (HP)*	(4) *Log (HP)*	(5) *Log (HP)*
L. Log (HP)	0.513***	0.558***	0.760***	0.524***	0.800***
	(0.132)	(0.108)	(0.101)	(0.144)	(0.086)
Robot exposure	0.031***	0.023***	0.032***	0.033***	0.022***
	(0.007)	(0.005)	(0.009)	(0.007)	(0.006)
Manufacturing employment share	0.038				0.049
	(0.032)				(0.047)
Telecom business		0.300**			0.198**
		(0.126			(0.088)
Mobile users		-0.017			-0.014
		(0.013)			(0.011)
Internet users		0.267***			0.102*
		(0.071)			(0.056)
IT employment share		1.837**			1.133
		(0.824)			(0.800)
Import amount			-0.005		-0.001
			(0.016)		(0.011)
Export amount			-0.003		-0.003
			(0.011)		(0.015)

High speed rail				-0.043**	-0.039**
				(0.019)	(0.016)
Control variables	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Estimator	Dynamic S-GMM	Dynamic S-GMM	Dynamic S-GMM	Dynamic S-GMM	Dynamic S-GMM
Observations	2,088	1,566	1,771	2,088	1,264
Number of instruments	22	23	40	23	43
Number of groups/cities	261	261	257	261	257
AR (2)	-0.05	-0.46	-0.22	-0.04	-0.41
	[0.961]	[0.646]	[0.825]	[0.967]	[0.681]
Hansen test	4.06	4.01	27.50	5.10	24.52
	[0.255]	[0.260]	[0.155]	[0.277]	[0.220]

Notes: 1) The key variable in all columns are instrumented by the developed IV variable; 2) Robust standard errors with Windmeijer's finite-sample correction are clustered at the city level and reported in parentheses; 3) P-values are reported in brackets; 4) ***, **, * represent significant levels at 0.01, 0.05, and 0.1 levels, respectively.

Third, industrial robots are not the only technology that impacts society, such as the spread of ITs during the same period (Zhang et al. 2021). Accordingly, we employ several indicators derived from the *China Statistical Yearbook* as proxies for information technologies, including *Mobile users* (number of cell phone subscribers per 100 people), *Internet users* (number of Internet broadband access subscribers per 100 people), *Telecom business* (total telecom services per capita), and *IT employment share* (the proportion of employees in the computer services and software industry). We introduce these four controls into the empirical model, as Column (2) of Table A4 shows. Our results show that *Telecom business*, *Internet users*, and *IT employment share* exert significant influence on housing prices, demonstrating that information technologies can also induce technological advances and affect the housing market. These ITs do result in a nearly 28% reduction in the impact magnitude of *Robot exposure*, but still maintain a 1% level of significance. After addressing this issue, our key variable is still economically significant enough that adopting one robot per 10,000 workers increases local housing prices by approximately 2.3%.

Fourth, we consider that international trade (imports and exports) may influence the demand for labour in local cities and thus affect the housing market, as discussed by Autor et al. (2013). To capture the local effects of international trade, we collect import and export amounts by city and year from the China *Customs Import and Export Statistics Database.* The regression results are reported in Column (3) of Table A6. Again, our results confirm that international trade itself has no significant effect on housing prices, and that our key variable, *Robot exposure,* has a significantly positive effect on housing prices.

Fifth, the large-scale construction of high-speed railway (HSR), another key economic feature influencing local housing markets in China, is coincided with the time industrial robots matching into China' labour market. To eliminate this concern, we introduce a dummy variable *High speed rail* to indicate whether this city has opened the high-speed railway in that year. Final results are reported in Column (4) of Table A6, suggesting a significant negative relationship between HSR operation and local housing prices on average. This result seems unexpected, but makes sense when considering the heterogeneity between cities. For example, Dong et al. (2021) found that without a good location, regions with high-speed rail also fail to prosper and become 'ghost cities', which may further hamper the local housing market. Similarly, Yu and Jin (2023) found a significant negative impact of the operation of HSR on service industry output of non-core cities because of the siphoning effect of HSR. Of course, this negative correlation needs to be discussed and tested in more studies, beyond the scope of this paper. In contrast, and most importantly, our estimates of the key variable remain virtually unchanged with the same significance level and impact magnitude after accounting for HSR. In summary, the robustness tests comprehensively address the concerns raised and confirm the validity of the first hypothesis.

B4. Spatial correlation test

To determine if spatial econometric models are necessary, we conduct several spatial correlation tests before the analysis. In accordance with Elhorst (2014), traditional Global and Local Moran's I tests are conducted in this paper, while their mathematical formulas are shown below:

$$Moran'I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}(Y_i - \bar{Y})(Y_j - \bar{Y})}{S^2 \sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}} \tag{A1}$$

$$Moran'I_i = \frac{(Y_i - \bar{Y})}{S^2} \sum_{j=1}^{n} W_{ij}(Y_j - \bar{Y}) \qquad \text{(A2)}$$

where, Y_i is the variable value in city *i* we aim to test; $S^2 = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \bar{Y})^2$ denotes the sample variance. Equation (A1) explains Global Moran's I index, which indicates the average spatial correlation of all cities. A positive Moran's I means a positive spatial correlation, and *vice versa*. In contrast, Equation (A2) gives the mathematical procedure of Local Moran's I index that signifies the spatial correlation locally. $Moran'I_i > 0$ means that city i with high (low) value of the variable is surrounded by cities with high (low) values, and *vice versa*.

Following the above methods, we test the Global Moran's I index of housing prices and robot exposure index each year to verify the existence of spatial autocorrelation. The results in Table A7 demonstrate that most indices are significant at the 1% level, regardless of the spatial weight matrix on which the results are based. In addition, all coefficients are larger than zero, indicating a positive spatial correlation.

Table A7 Global Moran'I index

Year	2009	2010	2011	2012	2013	2014	2015	2016	2017
Weight matrix: W_{ij}^{d}									
Log (HP)	0.127***	0.129***	0.132***	0.135***	0.134***	0.121***	0.108***	0.119***	0.136***
Robot exposure	0.061***	0.014***	0.033***	0.037***	0.039***	0.052***	0.095***	0.089***	0.122***
Weight matrix: W_{ij}^{e}									
Log (HP)	0.149***	0.153***	0.158***	0.160***	0.160***	0.145***	0.130***	0.149***	0.169***
Robot exposure	0.067***	0.015**	0.035***	0.040***	0.042***	0.059***	0.116***	0.106***	0.155***

Notes: 1) ***, **, * represent significant levels at 0.01, 0.05, and 0.1 levels, respectively.

We then use the local Moran's I index to test the local spatial correlation based on an asymmetric geography-economy weight matrix. Figure A1 shows scatter plots of the local Moran's I index for Log (HP) and Robot exposure in three periods. The chart indicates that most observations are in the first and second quadrants, indicating high-high and high-low agglomeration. This result suggests that positive spatial correlation is not always present among cities; negative spatial correlation can also occur. These results highlight the importance of using spatial econometric models to explain these correlations.

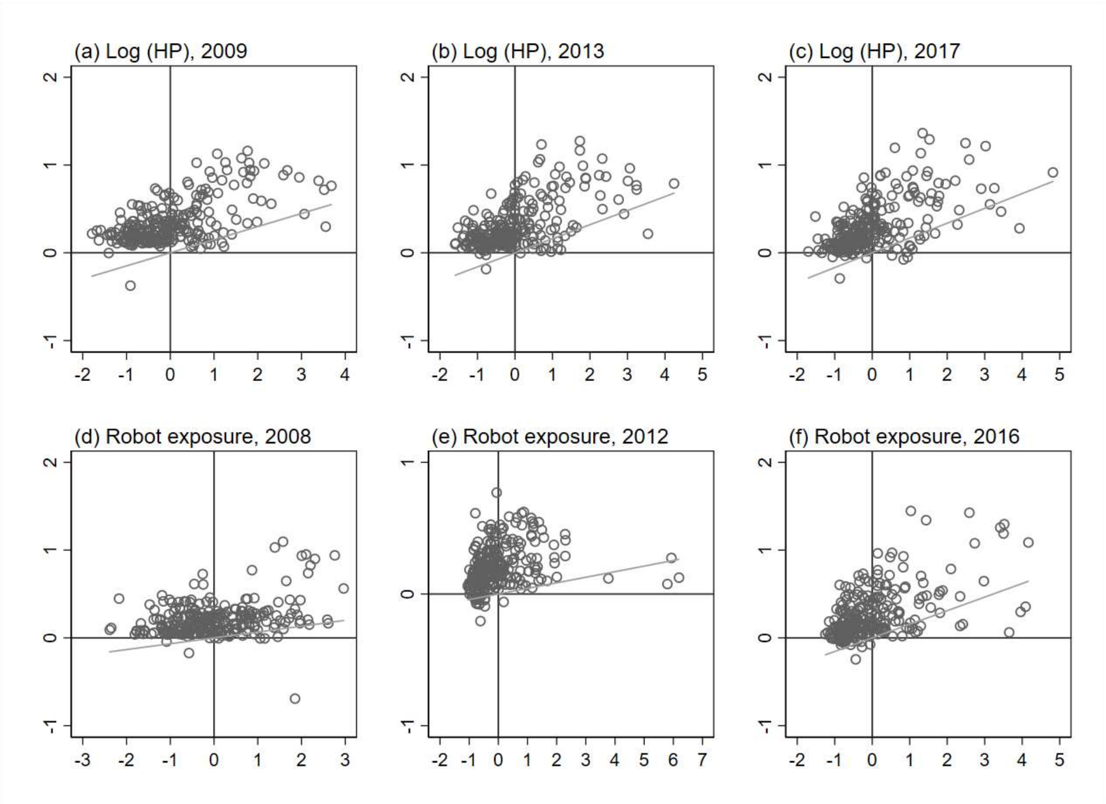


Figure A1. Scatter plots of the local Moran's index of key variable Log (HP) and Robot exposure with asymmetric geography-economy weight matrix (W_{ij}^{e})

B5. Robustness tests of robot exposure's spillover impact

To further ensure the robustness of robot exposure's spillover impact, we checked the use of an alternative weight matrix in Column (1) of Table A8 by employing the traditional geographical distance weight matrix (W_{ij}^{e}). We found that all the variables remain stable, with slight changes in their coefficient sizes. In Column (2), we examined the use of a geographical distance matrix with a distance attenuation coefficient ranging from 1 to 2. However, we found that the negative effects of spatially lagged robot exposure quickly faded. As discussed previously, the spillover effects of robot exposure are driven mainly by labour flows between pairs of cities. However, geographic proximity is not the only factor that determines labour migration between cities. Economic and industrial proximity also play a role in workers' migration decisions. In other words, the spatial reallocation of workers involves a wide range of cities beyond geographically contiguous cities. Therefore, an excessively large distance attenuation coefficient fails to adequately consider the affected cities, which explains the insignificance of the results in Column (2). These findings support our theoretical inferences and the use of an asymmetric geography-economy weight matrix.

Additionally, traditional geographical distance measures the Euclidean distance without considering the geographical barriers to mountains or rivers. As such, we further measured the travel distance (minimum driving distance) using the *Baidu Map* to recalculate the Asymmetric Geography-Economy matrix. The final result in Column (3) shows that spatially lagged *Robot exposure* exerts significant effects on housing prices, with an even larger coefficient, implying that the way the distance is calculated does not affect the stability of the estimation results.

Finally, we also employed alternative robot exposure indices with different weights (as discussed in Section 4.2) to test the reliability of the indices in the spatial models, and the final results are reported in Columns (4), (5), and (6) of Table A8. It is clear that the positive impact of *Robot exposure* on housing prices in local cities and the negative impact on housing prices in neighbouring cities remain significant, even with different weights

Table A8 Regression results of robot exposure's spillover effects: alternative weight matrix and index

Dependent variable:	(1) *Log (HP)*	(2) *Log (HP)*	(3) *Log (HP)*	(4) *Log (HP)*	(5) *Log (HP)*	(6) *Log (HP)*
Robot exposure	0.016***	0.014**	0.022***	0.015***	0.055**	0.054***
	(0.006)	(0.006)	(0.005)	(0.002)	(0.014)	(0.010)
W × Robot exposure	-0.267***	-0.001	-0.374***	-0.439***	-1.048***	-1.468***
	(0.014)	(0.007)	(0.035)	(0.010)	(0.061)	(0.047)
Time & spatial lags of *Log (HP)*	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Method	Dynamic SDM	Dynamic SDM	Dynamic SDM	Dynamic SDM	Dynamic SDM	Dynamic SDM
Robot exposure index type	-	-	-	New index (employment)	New index (output)	New index (asset)
Weight matrix type	Geographic Distance	Squared Geographic Distance	Asymmetric Geography-economy &	Asymmetric Geography-economy	Asymmetric Geography-economy	Asymmetric Geography-economy

			Driving distance			
Observations	2,088	2,088	2,088	2,088	2,088	2,088
Sigma2	0.007***	0.007***	0.007***	0.007***	0.008***	0.007***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Notes: 1) all control variables are transformed into log type; 2) Robust standard errors are clustered at the city level and reported in parentheses; 3) ***, **, * represent significant levels at 0.01, 0.05, and 0.1 levels, respectively

In summary, the above results strongly support our second proposed hypothesis: in addition to the local housing market, the impact of automation can spill over to the housing markets in (economically) neighbouring cities through labour migration. This result is consistent with those of studies that focused on the spatial diffusion of housing prices across different regions (Brady 2014; Fingleton 2008; Gong et al. 2020). In their narrative, the regional housing price can spillover to other regions through a ‘ripple of fundamental factors’ and information spillover. Conversely, our results emphasise the role of labour migration in connecting the labour and housing markets across cities.

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