Front. Econ. China 2025, 20(3): 344–375
DOI 10.3868/s060-020-025-0015-9

RESEARCH ARTICLE

Industrial Spatial Coagglomeration, Knowledge Spillovers, and Innovation Performance: Discussion on the Construction Pathways for Regional Industrial Diversification Clusters*

CHEN Lu[a, b], LIU Xiuyan[a, b]

Abstract

Can the geographical proximity of an industry to the "technological knowledge pool" outside its own sector effectively enhance its innovation performance? Are there differences in the effects brought about by geographical proximity based on different types of linkages? Under the framework of the knowledge production function, this paper empirically examines the innovation performance enhancement effect of differentiated technological knowledge pools formed by directional industrial spatial coagglomeration, using data from the industrial enterprise database and patent database. The findings reveal that the level of industrial innovation is positively influenced by the diverse technological knowledge pools generated through industrial spatial coagglomeration. This conclusion remains valid even after addressing potential endogeneity issues by employing the UK's industrial coagglomeration index as an instrumental variable. In particular, knowledge spillovers serve as the primary mechanism through which industrial coagglomeration is influenced by technological knowledge pools from outside its own sector. The innovation spillover effect of active coagglomeration is significantly greater than that of passive coagglomeration, and the impact of technological knowledge pools on the scale of industrial innovation is slightly stronger than on the quality of innovation. Further research indicates that only active coagglomeration between industries with input-output linkages can significantly enhance the innovation capabilities of both industries, while industrial coagglomeration with technological linkages demonstrates a notable "parasitic effect." The policy implications of this paper suggest that local governments should thoroughly consider the spatial dependency relationships and historical patterns of inter-industry location selection when developing regionally diversified industrial clusters. Simultaneously, they should strengthen intellectual property protection and industry regulation to achieve high-quality development of regional industries.

Keywords industrial spatial coagglomeration; technological knowledge pool; knowledge spillovers; innovation improvement; industrial cluster development

[*] This paper is translated from *Economic Research Journal* 经济研究, 2024, (4), 78–95.

[a] School of Economics & Management, Southeast University, Nanjing 211189, China
[b] National School of Development and Policy, Southeast University, Nanjing 211189, China

1 Introduction

The report to the 20th National Congress of the Communist Party of China emphasizes the need to boost China's strength in strategic science and technology and better allocate innovation resources. And it also highlights the importance of promoting the integrated and clustered development of strategic emerging industries (Xi, 2022). Currently, China's economy has entered a new development stage characterized by a range of significant challenges, including declining economic growth efficiency, the unsustainability of traditional growth models driven by investment and factor inputs, and insufficiency in overall innovation levels of industries and their contributions to economic development. Therefore, China's industrial policy must place greater emphasis on innovation-driven development to address challenges within the Chinese industrial system during this new round of technological revolution and industrial transformation. These challenges include a large but weak manufacturing sector, insufficient independent innovation capabilities, high dependence on foreign technologies and high-end equipment for key technologies, and an incomplete manufacturing innovation system centered on enterprises. Technological innovation is essential for achieving high-quality industrial development, and enhancing innovation capabilities represents a common path for micro-level enterprises and meso-level industries to grow stronger. In the face of various external risk shocks, adjusting the industrial structure, optimizing the spatial layout, promoting the integration of the industrial chain and innovation chain, and improving industrial innovation capabilities are important tasks for current industrial policy in China.

Relevant studies indicate that industries motivated by geographic proximity often originate from different two-digit or three-digit industries (Chen et al., 2020; Ellison et al., 2010). The birth, growth, and evolution of China's regional industrial structure and spatial layout have long been guided by local governments through the construction of industrial parks, investment attraction, and industrial cluster cultivation. In the current context of emphasizing the development of new quality productive forces and strengthening the resilience of the industrial system, local industrial agglomeration or clustering can no longer merely focus on developing single industrial clusters or single industrial parks. Instead, it should rely on the continuous derivation and evolution of diversified industrial structures to enhance overall regional innovation capabilities and economic vitality. For example, in countries like Germany and Japan, the geographic coagglomeration of the automotive manufacturing industry and advanced materials industries (such as advanced metal alloys, plastics, and electronic materials) has collectively driven technological development and innovation in the automotive sector. Driven by local promotion competitions and fiscal incentives, local governments attract investments through land transfers, tax incentives, and resource price discounts, leading to an over-reliance on investment-driven economic growth. This inevitably results in repetitive construction, industrial structural homogenization, and severe overcapacity (Xi et al., 2017). When implementing industrial structure and layout policies, local governments often exhibit significant subjective tendencies in adjusting industrial structures (Xu et al., 2023), lacking objective criteria for rationalizing the existing industrial system and structure. This is often due to their failure to effectively understand the patterns of inter-industry coagglomeration and the externalities they induce. Therefore, clarifying the economic performance externalities of cross-industry spatial coagglomeration and studying its internal mechanisms and impacts on industrial economic growth, particularly on innovation, hold significant practical importance. Such efforts enable local governments to accurately select key industries that align with local advantages, fully leverage agglomeration effects, and effectively implement innovation-driven strategies.

This paper adopts a cross-industry coagglomeration perspective to empirically examine whether the geographical proximity of industries to diversified technology knowledge pools outside their own sectors leads to knowledge spillovers effects that enhance innovation performance. Specifically, by utilizing the directional characteristics of industrial coagglomeration, it bi-directionally tests the differing impacts of “active coagglomeration” versus “passive coagglomeration” in forming technology knowledge pools. This approach reveals the mechanisms of knowledge spillovers resulting from industrial diversification and addresses the limitations of traditional diversification indexes in examining Jacobs externalities. The marginal contributions of this paper are as follows: (1) It is the first study to validate the impact of technology knowledge pools formed by inter-industry coagglomeration on the industrial innovation performance using an industrial coagglomeration index based on geographical proximity; (2) to tackle issues of mutual causality and omitted variables in empirical testing, this paper attempts to use the UK industrial coagglomeration index as an instrumental variable to address endogeneity in causal identification; and (3) from the perspective of inter-industry patent citations, it verifies the micro-mechanisms of knowledge spillovers in inter-industry spatial coagglomeration and examines the differentiated effects of technology knowledge pools formed by industrial coagglomeration on enhancing innovation performance based on input-output and technological linkages, thereby providing empirical evidence for the clustered development path for industrial innovation in China.

The remainder of this paper is organized as follows: Section 2 summarizes relevant concepts and literature, proposing the research hypotheses through a literature review and theoretical framework. Section 3 elaborates on the empirical strategy and the data utilized. Section 4 empirically tests the bidirectional innovation spillovers effects of technology knowledge pools formed by industrial coagglomeration, conducts robustness tests on the main findings, and examines the heterogeneity of bidirectional coagglomeration as well as the heterogeneous spillover effects of technology knowledge pools on innovation scale and quality. Section 5 addresses endogeneity issues using instrumental variable methods. Section 6 validates the micro-mechanisms of innovation enhancement through bidirectional technology knowledge pools formed by industrial coagglomeration from the perspective of patent citations and further explores the differential effects of innovation enhancement based on input-output and technological linkages, discussing pathways to enhance the vitality and capabilities of industrial innovation through clustering. Section 7 proposes policy recommendations for strengthening regional industrial innovation capabilities and developing regional industrial clusters based on the research findings.

2 Literature Review and Research Hypotheses

2.1 Literature Review

Industrial spatial agglomeration is a significant feature in the distribution of industries that has been observed over an extended period. The spatial distribution of industries manifests in two main forms: agglomeration and coagglomeration. Agglomeration occurs within the same industry, while coagglomeration takes place across different industries. In traditional understandings and measurement methods, agglomeration and coagglomeration are essentially equivalent, as both refer to the geographical concentration of micro-level enterprises, with the distinction being whether the geographically proximate enterprises belong to the same industry or to different ones.

Jacobs (1969) argues that the diversification of industries within cities can enhance regional innovation capabilities and economic vitality. The externalities arising from this diversified industrial agglomeration are referred to as Jacobs externalities. This school of thought argues that competition between different industries is minimal, allowing for the exchange of processes and technologies across industries. Consequently, the flourishing of industrial diversification within cities can promote knowledge exchange and diffusion, thereby driving regional innovation and economic vitality. Glaeser et al. (1992) verify the impact of Jacobs externalities on innovation and reach significant conclusions, finding that knowledge spillovers primarily occur between different industries rather than within the same industry. In other words, Jacobs externalities are more effective at explaining innovation than Marshall-Arrow-Romer (MAR) externalities. Numerous international scholars have conducted extensive research, confirming that urban industrial diversification is beneficial for cross-industry knowledge spillovers and innovation. Paci and Usai (1999) find that both Jacobs and MAR externalities can promote regional innovation, but Jacobs externalities have a more significant effect in high-tech industries in medium and large cities. Overall, when discussing innovation enhancement effects of agglomeration economies, the innovation performance enhancement effect of inter-industry Jacobs externalities is generally regarded as positive.

The "tacit knowledge" emphasized by Jacobs externalities refers to knowledge that is ambiguous, incidental, and difficult to codify; and it can only be transmitted within specific spatial limits through direct interaction and communication. This principle forms the theoretical foundation for the knowledge spillovers associated with geographical proximity, which is recognized by both Jacobs and Marshall externalities—namely, that geographical distance is the most significant factor influencing knowledge spillovers. Krugman (1991) notes that knowledge travels more easily through corridors than along highways. Jaffe et al. (1993) empirically test the diminishing effect of knowledge spillovers with distance by comparing the geographical locations of patent citations and the cited patents to demonstrate the geographical limitations of knowledge spillovers. With the continuous development of the internet and information technology, the barriers to sharing explicit and editable knowledge appear to be gradually decreasing. However, for "sticky knowledge" that is prevalent in manufacturing R&D and production activities and characterized by high complexity and uncertainty (von Hippel, 1994), significant updates in process technology or breakthroughs in scientific research require frequent face-to-face interactions among employees for absorption and mastery. From the perspective of patent citations, Kerr and Kominers (2015) demonstrate that knowledge spillovers diminish with increasing geographical distance, arguing that the communication and exchange of tacit knowledge primarily occur within very small spatial scales. Thus, spatial distance significantly constrains the diffusion of such knowledge.

When studying the innovative capabilities of enterprises in industrial clusters, Baptista and Swann (1998) introduce the concept of "technology knowledge base/pool." This term refers to the types of knowledge that support an enterprise's innovative activities. The proximity of enterprises to a diversified industrial cluster outside their own sector contributes to the creation of an industry technological knowledge pool. Since geographical proximity is a crucial avenue through which Jacobs externalities influence technological innovation, and this influence is only valid in small geographical spaces with significant diminishing effects, it is necessary to further discuss the extent to which current measurement methods of Jacobs externalities reflect micro-level geographical proximity between industries. The mainstream measurement approaches for Jacobs externalities have primarily developed in two directions: One approach is the diversification index, which measures regional industrial diversification using the inverse of the HHI index proposed by Glaeser et al. (1992) and Henderson et al. (1995). Chinese scholars have largely followed this idea in measuring diversification (Fan et al., 2014; He & Chen, 2019). This method can, to some extent, assess the richness of industries within a city or urban agglomeration relative to those in other regions, offering certain measurement advantages. However, its drawbacks are also evident: The mere spatial clustering of multiple industries within a city does not imply they are proximate in micro-level geographical terms, thus failing to reflect that enterprises within a particular industry consider proximity to those in another industry when making location decisions. The measurement provided by this index is too vague, failing to clearly express how industrial diversity promotes technological innovation through knowledge spillovers mechanisms. The other measurement approach is the coagglomeration index between pairs of industries, which quantifies the geographical proximity relationships between industries in a one-to-one manner. The primary measurement methods include the EG index (Ellison & Glaeser, 1997), the DO index (Duranton & Overman, 2008), and the BJ index (Billings & Johnson, 2016). The EG index follows the traditional approach of the spatial Gini coefficient and HHI index, facing similar issues as the diversification index. However, the DO and BJ indices begin to accurately measure the geographical proximity between pairs of industries based on the geographical locations of enterprises. The BJ index, in particular, offers superior measurement. Billings and Johnson (2016) innovatively propose an inter-industry coagglomeration index based on the Wasserstein distance algorithm, which can measure the asymmetric spatial coagglomeration relationship between pairs of industries; that is, Industry A may co-agglomerate with Industry B, while Industry B may not co-agglomerate with Industry A. This directional aspect aligns more closely with the actual characteristics of spatial relationships between industries. Scholars have also noted the asymmetric characteristics of input-output relationships and technological dependencies. Chen et al. (2020) are the first to use the BJ index to measure the industrial coagglomeration index at the level of Chinese urban agglomerations, exploring how input-output and technological linkages drive industrial spatial coagglomeration. However, whether cross-industry coagglomeration from a geographical proximity perspective leads to significant innovation effects remains an area not deeply explored by Chinese scholars, and it remains unclear whether Jacobs externalities play a role in inter-industry coagglomeration under geographical proximity.

Based on existing research, the impact of cross-industry spatial coagglomeration on enhancing innovation performance is a highly dynamic topic. As a competitive hypothesis of MAR externalities, Jacobs externalities are supported by extensive practical evidence and a solid theoretical foundation. However, the key mechanism behind Jacobs externalities is the spillovers of tacit knowledge, which exhibits spatial decay characteristics. Its effects are more pronounced when generated in relatively micro-level geographical spaces, an area where the academic community still lacks specific empirical evidence. Billings and Johnson (2016) and Chen et al. (2020) primarily focus on measuring the new-generation industrial coagglomeration index. In contrast to their research, this paper innovatively utilizes this index to explore the "empirical black box" of how industrial diversification fosters innovation. It investigates how the active and passive geographical proximity of enterprise groups within industries differentially influences innovation performance through knowledge spillovers. Furthermore, building on existing studies of coagglomeration driving factors, this paper examines whether industrial coagglomeration formed by bidirectional industrial linkages and technological connections contributes to enhancing industrial innovation capabilities. This exploration aims to provide valuable theoretical guidance for improving China's new quality productivity and developing industrial clusters.

2.2 Research Hypotheses

Based on the knowledge production function proposed by Audretsch and Feldman (2004) and incorporating the explanation by Hanlon and Miscio (2017) regarding the sources of external industry technology spillovers for enterprises, the enterprise-level knowledge production function can be expressed as:

$$I_{ict} = f(RD_{ict}, HK_{ict}) \cdot g(A_{within}, A_{cross}, A_c, A_t), \tag{1}$$

where I_{ict} represents the innovation output of enterprise i in region c in year t, RD_{ict} denotes the research and development investment of enterprise i, and HK_{ict} represents the human capital input of the enterprise. The function $f(\cdot)$ indicates that the innovation output is a function of innovation inputs, suggesting that internal resources are one of the key sources of innovation output for enterprises. Kerr and kominers (2015) argue that there is a multiplicative relationship between innovation outputs and innovation inputs, meaning that if enterprises aim to achieve multiplied innovation outputs, they need to invest in multiplied innovation resources. The function $g(\cdot)$ represents agglomeration economies that are endogenous to region c and time t but exogenous to enterprise i. In empirical research, $g(\cdot)$ is often treated as a function of regional (or urban) scale or density, serving as the theoretical basis for empirical studies on regional diversification indices. However, Hanlon and Miscio (2017) propose a theoretical framework to unpack this functional "black box," arguing that the knowledge spillovers exogenous to enterprises primarily come from four aspects: (1) knowledge spillovers within the industry, denoted as A_{within}; (2) knowledge spillovers from sectors outside their own sector, denoted as A_{cross}; (3) knowledge spillovers resulting from the overall technological progress in the region, denoted as A_c; and (4) knowledge spillovers stemming from the overall technological progress in the country, denoted as A_t. The first two aspects represent technological spillovers at the meso-industry level, while the latter two represent macro-level technological spillovers. In this slightly modified knowledge production function model, the complexity and diversity of sources for technological advancement at the enterprise level can be observed. Audretsch and Feldman (2004), after summarizing previous research, note that it is challenging for the knowledge production function to manifest at the micro-level of enterprises and suggest conducting empirical estimates at higher aggregation levels (such as at the national level or industrial level).

This study primarily focuses on the impact of geographical proximity of diversified industries on industrial innovation output, specifically emphasizing the effect of A_{cross} in equation (1). Based on the calculation methods and results from Chen et al. (2020), it is found that 12.10% of industries exhibit a spatial coagglomeration pattern in their locations, with only 17.55% of three-digit industries belonging to the same two-digit industry. Over 80% of three-digit industries experience cross-industry coagglomeration across different two-digit sectors, indicating that the cross-sector characteristic of inter-industry spatial coagglomeration is widespread. Cross-industry geographical proximity facilitates the spillovers of "tacit knowledge," and the impact of knowledge spillovers on industrial innovation growth can be understood through two theoretical pathways: The first is based on endogenous growth theory, which posits that knowledge spillovers can promote technological innovation in industries, thereby driving economic growth. This pathway emphasizes the role of spatial factors in endogenous growth. The second is derived from new economic geography, suggesting that knowledge spillovers can promote spatial agglomeration, enhancing geographical proximity during enterprise location decisions and improving economic efficiency. This pathway emphasizes the role of spatial agglomeration in knowledge spillovers.

As described in equation (1), at the meso-level of industries, each industry possesses a technological knowledge pool with its own distinctive characteristics. This knowledge pool primarily originates from two sources: The first is internal knowledge diffusion and spillovers within the industry, which can be accumulated through the knowledge and technology spillovers mechanisms of industrial agglomeration theory. This internal technological diffusion helps to reduce technological disparities within the industry, and the growth of innovation capabilities from this source is endogenously driven within the industry. The second important source is technological spillovers and diffusion from external industries, which can be accumulated through industrial spatial coagglomeration. The innovation capabilities derived from this external source are exogenous to the industry. This paper focuses on the second source of knowledge spillovers from outside the industry. Within the framework of industrial coagglomeration, when enterprises in industry j select their locations, they will choose proximity to enterprises in multiple other industries (q_1, q_2, ..., q_m). Through knowledge matching, learning, and diffusion, a technological knowledge pool for industry j gradually forms through active coagglomeration. Conversely, industry j will also be co-located with a series of industries (p_1, p_2, ..., p_n), creating an external industry technological knowledge pool that is similar to, yet distinct from, the technological knowledge pool formed through active coagglomeration. According to the theories of shared and learning effects in agglomeration economies, when industries are geographically proximate to technological knowledge pools, they can better leverage knowledge spillovers, thereby enhancing their own technological innovation levels. Therefore, the first hypothesis to be tested in this paper is: The cross-industry technological knowledge pool formed by bidirectional industrial spatial coagglomeration enhances the industrial innovation performance.

The essence of industrial agglomeration and coagglomeration lies in the collective patterns that emerge from the location choices of micro-level enterprises in geographical space. Billings & Johnson (2016), in their study of cross-industry spatial coagglomeration, opt not to use the term “coagglomeration,” but instead choose “co-localization,” which refers to the joint location of cross-industry enterprises. Clearly, the latter concept is more nuanced and encompasses the specific meaning of the former.[1] In this paper, a conceptual diagram is used to elaborate on the differences in meaning between industrial coagglomeration and industrial agglomeration, as well as their asymmetric scenarios. As shown in Figure 1, there are two industries in each space: Industry A and Industry B. Due to individual enterprises making location decisions based on their actual needs, different industries exhibit distinct collective characteristics in terms of spatial distribution. For a single industry (A or B), if enterprises are not located close to each other, this manifests as spatial dispersion (1-a); if enterprises are located near each other, this reflects spatial agglomeration (1-b). However, for two industries (A and B), the proximity of enterprises between the industries does not necessarily correlate with the agglomeration of individual enterprises. For instance, even if individual enterprises are agglomerated, if they are clustered in different locations and the two agglomeration

[1] Although Billings and Johnson (2016) employ the term colocalization in their study, considering that their index is developed from the EG index (Ellison & Glaeser, 1997) and the DO index (Duranton & Overman, 2008), and to align with research conventions among Chinese readers (Chen et al., 2020), this paper still uses the term “industrial coagglomeration.”

centers are too far apart (1-b), the industries cannot be considered co-agglomerated. Coagglomeration can only be claimed if the two agglomeration centers are close to or overlapping with each other (2-b and 3-b). Conversely, even if a single industry is entirely dispersed, if enterprises from different industries choose locations together, coagglomeration can still occur (2-a and 3-a). In scenarios 2-a and 3-a, there is also effectively an avoidance of internal competition suppressing external spillovers. Thus, it can be said that industrial coagglomeration is a concept of spatial distribution that shares similarities with industrial agglomeration but is also significantly different. In existing studies that utilize diversity indices or the EG coagglomeration index, all scenarios depicted in Figure 1 may potentially be considered as industrial spatial coagglomeration (relative to other spatial arrangements). However, under the DO coagglomeration index, it is challenging to discern differences between 2-a and 2-b, as well as between 2-a and 3-a. The BJ index effectively circumvents the aforementioned measurement flaws and allows for accurate identification of the various scenarios illustrated in Figure 1.

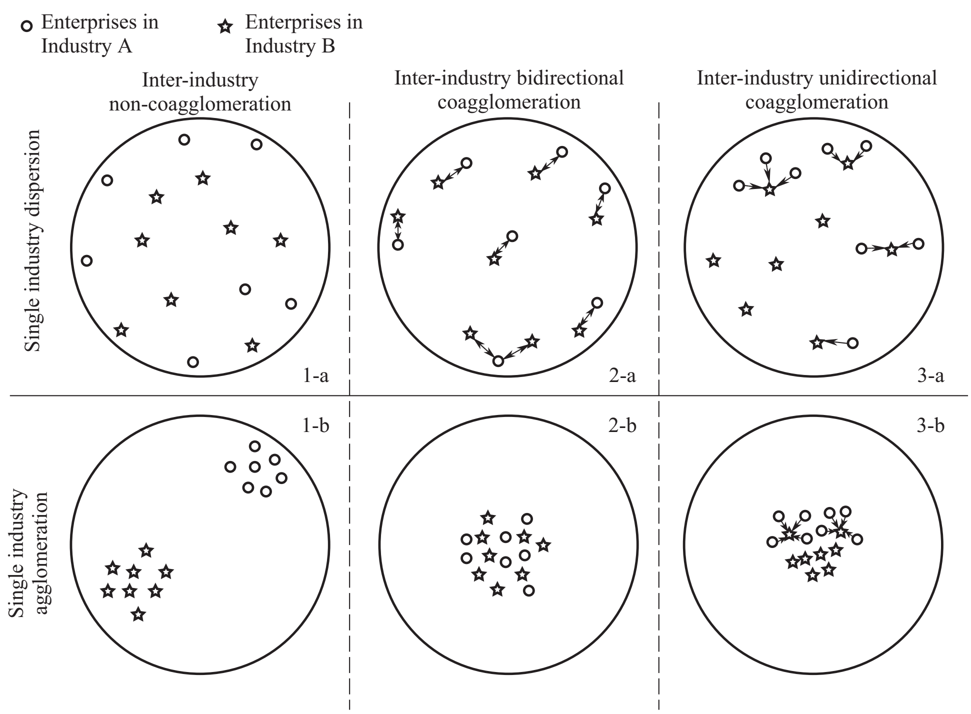

Figure 1 Concept Differences between Industrial Spatial Coagglomeration and Industrial Agglomeration, and Direction of Industrial Coagglomeration

Simultaneously, spatial coagglomeration between industries also exhibits a directional attribute (Billings & Johnson, 2016; Chen et al., 2020), manifested as unidirectional coagglomeration. In scenarios 2-a and 2-b of Figure 1, there are enterprises from Industry B near enterprises from Industry A, and likewise, there are enterprises from Industry A near enterprises from Industry B—this indicates a case of bidirectional coagglomeration.

However, in scenarios 3-a and 3-b, there may be enterprises from Industry B near enterprises from Industry A, while it is not guaranteed that there are enterprises from Industry A near enterprises from Industry B. In other words, enterprises within Industry A will consider the proximity of enterprises from Industry B when making location choices, whereas enterprises within Industry B do not necessarily take into account the proximity of enterprises from Industry A in their location decisions. This paper finds, through measurement, that industries with bidirectional coagglomeration comprise only 35.6% of all coagglomerating pairs, implying that nearly 70% of industrial coagglomeration is unidirectional. The knowledge pools pursued through unidirectional active coagglomeration tend to match better with the industry itself, and the purpose of technological learning is stronger. In contrast, industries that experience passive coagglomeration primarily acquire knowledge spillovers through unintentional knowledge exchanges, leading to a weaker purpose of technological learning. Therefore, it can be inferred that there may be significant differences in the enhancement of the industry's innovation capability resulting from these two different spatial coagglomeration modes. Hence, the second hypothesis proposed for testing in this paper is that there are significant differences in the innovation spillovers effects between active coagglomeration technology knowledge pools and passive coagglomeration technology knowledge pools on industries.

In the theory of agglomeration economies, the MAR externalities of a single industry are trinitarian, meaning that the three types of externalities pursued by enterprises within the same industry are homogeneous. However, in the context of cross-industry spatial coagglomeration, there are certain differences among industries in terms of benefiting from knowledge spillovers, input-output markets, and labor pools. These differences are determined by the degree of inter-industry connectivity. For instance, the same knowledge spillovers may attract enterprises from two industries that seem to be unrelated in terms of classification but are closely related in technology to coagglomerate spatially. The emphasis on the heterogeneity of Marshall's three externalities in industrial spatial coagglomeration lies in the fact that the technological, input-output, and labor skill linkages between pairs of industries are often inconsistent. As stated by Ellison et al. (2010) in their analysis of the driving forces behind cross-industry spatial coagglomeration in the US, some industries exchange goods with one another but employ entirely different types of workers, while others employ similar workers but never engage in trade with one another. Relevant studies have demonstrated that industrial spatial coagglomeration is driven by the heterogeneity of cross-industry Marshall externalities (Chen et al., 2020; Diodato et al., 2018). There are certain technological barriers to innovation imitation between different industries, and labor mobility is not as fluid as within the same industry. Jacobs (1969) argues that industries with strong input-output linkages exhibit significant innovation spillovers, while Peng and Jiang (2011) find that the stronger the technological complementarity among diversified industries, the greater the innovation-promoting effect. Based on the empirical fact that over 80% of three-digit industries in China coagglomerate spatially without belonging to the same two-digit sector (Chen et al., 2020), compared to cases where only input-output or technological linkages exist between two industries, if industries with input-output or technological linkages also exhibit spatial proximity, the combination of spatial coagglomeration and input-output or technological linkages can, in theory, significantly enhance inter-industry technological exchange and knowledge spillovers, thereby improving industrial innovation performance. Accordingly, the third hypothesis to be tested in this paper is proposed: Industrial spatial coagglomeration based on input-output and technological linkages has positive effects on the industrial innovation performance, but with certain differences in the magnitude of these effects.

3 Empirical Model Design, Identification Strategy, and Variable Description

3.1 Empirical Model Design

Based on the theoretical analysis and research hypotheses presented earlier, this paper focuses on empirically identifying whether a single industry can acquire knowledge spillovers externalities by accessing the technological knowledge pool from industrial agglomerations outside its own sector through geographic proximity, thereby enhancing its innovation performance. The directional industrial spatial coagglomeration will create two types of technological knowledge pools: One is the "active" technological knowledge pool formed through active spatial coagglomeration, and the other is the "passive" technological knowledge pool formed through passive spatial coagglomeration. This paper will discuss the extent of improvement in the industrial innovation performance from the perspectives of these two types of technological knowledge pools. Guided by the theoretical model in equation (1), equation (2) is formulated to investigate the impact of the technological knowledge pool of industry j formed through active coagglomeration on its own innovation performance.

$$\begin{cases} Inno_{jct} = \alpha + \beta_1 KP\_outward_{jct} + \beta_2 X\_outward_{jct} + \beta_3 agg_{jct} + \beta_4 X_{jct} + u_j + \upsilon_t + \delta_c + \varepsilon_{jct}, \\ KP\_outward_{jct} = \sum patent_{kct}\phi_{j\to k}, \quad \phi_{j\to k} = \begin{cases} 1, & Coagg_{j\to k} \geqslant 0.95, \\ 0, & Coagg_{j\to k} < 0.95. \end{cases} \end{cases} \tag{2}$$

$Inno_{jct}$ represents the level of innovation capability of industry j in region c at time t; $KP\_outward_{jct}$ denotes the level of the technological knowledge pool formed by industry clusters that are actively and significantly spatially coagglomerated by industry j in region c at time t. From the perspective of industry j, it represents an active coagglomeration with other industries, and for clarity, this is referred to as "outward coagglomeration." $Coagg_{j\to k}$ indicates the likelihood of industry j coagglomerating with industry k, and $\Phi_{j\to k}$ represents whether industry j is coagglomerating with industry k at a 95% confidence level,[2] corresponding to the knowledge spillovers from industries outside its own sector as shown in equation (1),

[2] The innovation of this paper, lies in its novel exploration of the innovation spillovers effects resulting from industrial spatial agglomeration, approached from the perspective of geographic proximity. As the measurement method is not the primary focus of this paper, it will not be discussed in detail. For more information on the measurement method, please refer to Chen et al. (2020) and Appendix 1 available on the website of *Economic Research Journal*.

denoted as A_{cross}; agg_{jct} represents the agglomeration level of industry j itself, corresponding to the knowledge spillovers from the respective industry in the theoretical model, denoted as A_{within}; $X\_outward_{jct}$ represents a control variable for the characteristics of economies of scale and labor pools formed by multiple industries coagglomerating with industry j. X_{jct} represents a control variable for the scale and employment levels of industry j, while controlling for industry fixed effects, jointly corresponding to the impact of the industry's own input-output level on innovation in the theoretical model; furthermore, the time fixed effects υ_t represents knowledge spillovers resulting from overall technological advancement in the country, denoted as A_t, while the regional fixed effects δ_c indicates knowledge spillovers arising from overall technological advancement in the region , denoted as A_c.

Corresponding to equation (2), equation (3) is further constructed to investigate the impact of the technological knowledge pool for industry j formed through passive coagglomeration on its innovation performance. From the perspective of industry j, it is passively and spatially coagglomerated with other industries. For clarity, this is collectively referred to as "passive coagglomeration" (inward) below. Unlike equation (2), the core explanatory variable in equation (3) is KP_inward_{jct}, which represents the level of technological knowledge pool formed by industrial clusters that are significantly and spatially coagglomerated toward industry j at time t, and X_inward_{jct} represents the control variable for the characteristics of economies of scale and labor pools resulting from multiple industries coagglomerating with industry j.

$$\begin{cases} Inno_{jct} = \alpha + \beta_1 KP\_inward_{jct} + \beta_2 X\_inward_{jct} + \beta_3 agg_{jct} + \beta_4 X_{jct} + u_j + \upsilon_t + \delta_c + \varepsilon_{jct}, \\ KP\_inward_{jct} = \sum patent_{kct}\phi_{k\to j}, \qquad \phi_{k\to j} = \begin{cases} 1, & Coagg_{k\to j} \geqslant 0.95, \\ 0, & Coagg_{k\to j} < 0.95. \end{cases} \end{cases} \tag{3}$$

In the empirical process, to enhance the depth of discussion and examine heterogeneity, we decompose the innovation levels of industry j to separately investigate innovation scale and innovation quality. Accordingly, the technological knowledge pools formed through active and passive coagglomeration are evaluated in terms of "size and quality of the technological knowledge pool."

3.2 Variable Description

The data foundation for calculating the industrial coagglomeration index is spatial geographical information at the micro-level of enterprises, representing the smallest units of industry spatial distribution. The data used in this paper is sourced from the China Industrial Enterprise Database, covering the years 1998 to 2013. This database includes samples from all state-owned industrial enterprises as well as relatively large non-state-owned industrial enterprises. Following the approach of Chen et al. (2020), this paper excludes abnormal samples from the enterprise longitude and latitude data. When local governments set industrial development goals, they must transcend the spatial limitations of their own cities and focus on the coordinated development of industries across urban agglomerations (Fan et al., 2021).

Therefore, the spatial scale selected for this paper is urban agglomeration. Considering the relative stability of industrial spatial coagglomeration, we measure results for 3,327,494 pairs of industries across 21 urban agglomerations for the years 1998, 2001, 2004, 2007, 2010, and 2013 and then calculate the core explanatory variables according to equations (2) and (3).

This paper measures the industrial innovation performance within urban agglomerations from the perspective of innovation output. Two common indicators for measuring innovation output are the number of patent applications granted and the value or sales revenue of new products. Since data on the value or sales revenue of new products in the China Industrial Enterprise Database—which is the primary focus of this paper—is difficult to compile into a complete panel data set, the variable measuring innovation capacity relies on patent-related indicators. This paper collects all patent applications submitted to the China Patent Database from 1998 to 2020, matching enterprise names and codes with those in the China Industrial Enterprise Database from 1998 to 2013 to obtain each enterprise's patent information. These patents are then summed to calculate the innovation performance levels of each region and each three-digit industry. The innovation level in this paper is evaluated from two perspectives: innovation scale and innovation quality. Innovation scale is measured by the total number of patents granted to the industry during the year. Innovation quality is measured using patent value, as provided by the Patent Management Department of the China National Intellectual Property Administration. This indicator evaluates each patent based on legal, technical, and economic dimensions in accordance with the Operation Manual for Patent Value Analysis Indicator System. Following the research of Su et al. (2020), this paper employs location entropy to measure the agglomeration level of the industry itself. Additionally, it uses the total industrial output value to assess the scale of the industry and the economies of scale outside its sector formed through spatial coagglomeration, and utilizes year-end employment numbers to reflect the employment levels of the industry and the labor pool outside its sector formed through spatial coagglomeration. All indicators entering the regression are processed by taking the natural logarithm after adding 1.[3]

4 Test of the Spillover Effect of the Technological Knowledge Pool Formed through Industrial Spatial Agglomeration

4.1 Benchmark Regression

Based on the research design outlined earlier, this paper first employs a fixed effects model to estimate equations (2) and (3), controlling for fixed effects related to urban agglomerations, time, and industries, while clustering at the industry level. Table 1 presents the benchmark regression results for the innovation spillover effects of the technological knowledge pool formed through active coagglomeration. The results indicate that the technological knowledge

[3] Due to space limitations, the descriptive statistics of the explained variable, explanatory variables, and control variables primarily discussed in this paper are detailed in Appendix 1 available on the website of *Economic Research Journal*.

pool generated by active coagglomeration has a significant positive impact on both the scale and quality of innovation within the industry. Specifically, for every 1% increase in the size of the knowledge pool formed through active coagglomeration, the industry's innovation scale and quality increase by approximately 0.288% and 0.374%, respectively. Similarly, for every 1% increase in the quality of the knowledge pool formed through active coagglomeration, the industry's innovation scale and quality rise by about 0.174% and 0.235%, respectively. Regarding control variables, contrary to the findings of Glaeser et al. (1992), we find that the level of industry agglomeration at the urban agglomeration level has a significant positive effect on the industry's innovation scale, and this effect is notably greater than the spillover effects of the cross-industry technological knowledge pool formed through coagglomeration. This suggests that the technological knowledge pool created by industry agglomeration remains one of the key sources for enhancing industrial innovation capabilities. It should be noted that the economies of scale generated from active coagglomeration have a significant negative impact on industrial innovation. Baptista and Swann (1998) characterize this negative effect of intra-cluster scale diversity as the "congestion effect." This paper supports that view by indicating that a larger industrial cluster size formed through active coagglomeration is increasingly detrimental to innovation growth within the industry. Additionally, the labor pool formed through active coagglomeration, along with the industry's own scale and employment levels, also exerts a significant positive influence on industrial innovation.

Table 1 OLS Regression of Innovation Spillover Effects of the Technological Knowledge Pool Formed through Active Industrial Coagglomeration

Variable	Industrial innovation scale		Industrial innovation quality	
Size of technological knowledge pool	0.288*** (0.0110)		0.374*** (0.0142)	
Quality of technological knowledge pool formed through active coagglomeration		0.174*** (0.00801)		0.235*** (0.0108)
Economies of scale formed through active coagglomeration	−0.131*** (0.0140)	−0.137*** (0.0142)	−0.168*** (0.0184)	−0.177*** (0.0188)
Labor pool formed through active coagglomeration	0.060*** (0.0164)	0.103*** (0.0174)	0.071*** (0.0224)	0.123*** (0.0234)
Industry agglomeration level	0.331*** (0.0441)	0.326*** (0.0446)	0.448*** (0.0583)	0.441*** (0.0589)
Enterprise size	0.0286** (0.0124)	0.0305** (0.0128)	0.0421** (0.0166)	0.0444** (0.0172)
Number of employees in the industry	0.0332* (0.0174)	0.0314* (0.0177)	0.0401* (0.0229)	0.0381 (0.0232)
Constant term	0.815*** (0.188)	0.575*** (0.183)	1.271*** (0.246)	0.978*** (0.241)

(*To be continued*)

(*Continued*)

Variable	Industrial innovation scale		Industrial innovation quality	
Observed value	20,281	20,281	20,281	20,281
R^2	0.632	0.615	0.650	0.636
Industry fixed effects	Control	Control	Control	Control
Year fixed effects	Control	Control	Control	Control
Urban agglomeration fixed effects	Control	Control	Control	Control

Note. The values in parentheses represent robust cluster standard errors; *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$; the regression controls for industry, year, and urban agglomeration fixed effects, with clustering at the three-digit industry level; the same applies to the following tables.

Table 2 presents the benchmark regression results for the innovation spillover effects of the technological knowledge pool formed by a single industry through passive coagglomeration. The findings indicate that the technological knowledge pool created by passive coagglomeration has a significant positive impact on both the scale and quality of innovation within the industry. Specifically, for every 1% increase in the scale of knowledge formed through passive coagglomeration, the industry's innovation scale and quality increase by approximately 0.230% and 0.294%, respectively. Similarly, for every 1% increase in the quality of the knowledge pool formed by passive coagglomeration, the industry's innovation scale and quality rise by about 0.151% and 0.199%, respectively. Regarding control variables, in addition to the industry's own level of agglomeration and employment numbers, which significantly and positively influence the scale and quality of innovation, the economies of scale generated by passive coagglomeration have a significant negative impact on the scale of industrial innovation but do not significantly affect the quality of innovation. Furthermore, the labor pool resulting from passive coagglomeration also negatively impacts both the scale and quality of industrial innovation, indicating that, compared to active coagglomeration, the economies of scale associated with passive coagglomeration and the "congestion effect" generated by the labor pool are more pronounced.

The benchmark regression results in Tables 1 and 2 provide preliminary validation of the first hypothesis of this paper. Industries located in geographic proximity to multiple other sectors can acquire diversified knowledge spillovers through sharing, learning, and matching, which significantly enhance both their innovation scale and quality. This finding is one of the core conclusions of this paper and serves as empirical evidence for Jacobs' innovation externalities from the perspective of geographic proximity, utilizing data from China. Industries acquire "sticky knowledge" of innovations from external sectors through spatial agglomeration, which they subsequently internalize into their own knowledge pools. Through industry clustering, this knowledge is further shared and diffused within the industry, resulting in an overall enhancement of its innovative capabilities. This explanatory pathway facilitates the integration of Jacobs externalities and Marshall externalities theories.

Table 2 OLS Regression of Innovation Spillover Effects of the Technological Knowledge Pool Formed through Passive Industrial Coagglomeration

Variable	Industrial innovation scale		Industrial innovation quality	
Size of technological knowledge pool formed through passive coagglomeration	0.230*** (0.00883)		0.294*** (0.0111)	
Quality of technological knowledge pool formed through passive coagglomeration		0.151*** (0.00667)		0.199*** (0.00872)
Economies of scale formed through passive coagglomeration	−0.00705 (0.00667)	−0.0227*** (0.00695)	−0.00501 (0.00921)	−0.0244** (0.00953)
Labor pool formed through passive coagglomeration	−0.0452*** (0.00967)	−0.0148 (0.0100)	−0.0626*** (0.0133)	−0.0269* (0.0138)
Industry agglomeration level	0.305*** (0.0426)	0.305*** (0.0435)	0.415*** (0.0565)	0.416*** (0.0577)
Enterprise size	0.00144 (0.0114)	0.00338 (0.0116)	0.00677 (0.0153)	0.00899 (0.0156)
Number of employees in the industry	0.0477*** (0.0154)	0.0485*** (0.0157)	0.0594*** (0.0204)	0.0605*** (0.0207)
Constant term	0.427*** (0.136)	0.383*** (0.138)	0.699*** (0.180)	0.648*** (0.183)
Observed value	20,281	20,281	20,281	20,281
R^2	0.635	0.620	0.652	0.641

Note. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

4.2 Robustness Tests

4.2.1 Standard Conversion of Confidence Level for Key Indicators

The measurement of indicators for industrial agglomeration is based on statistical hypothesis testing. In the benchmark regression, this paper adopts a 95% confidence level to measure the industrial coagglomeration index and calculates the scale and quality of technological knowledge pools formed by both active and passive coagglomeration of industries. To test the robustness of the results, this paper recalculates the industrial coagglomeration index using 90% and 99% confidence levels to construct the scale and quality indicators for the technological knowledge pools formed by coagglomeration. The results[4] indicate that, regardless of whether the statistical thresholds for the industrial coagglomeration index are relaxed or tightened, the impacts on the scale and quality of the technological knowledge pools formed through industrial coagglomeration, in both active and passive directions, remain consistent with those of the benchmark regression. Furthermore, these benchmark results fall within the range of the two robustness test indicators. This suggests that the core conclusions of this paper are resilient to adjustments in the measurement standards of the

[4] Due to space limitations, the regression results are detailed in Schedules 2 and 3 of Appendix 3 available on the website of *Economic Research Journal*.

industrial coagglomeration index, indicating robust findings.

4.2.2 Exclusion of Industry Pairs Exhibiting Bidirectional Coagglomeration

In measuring active and passive coagglomeration across industries, certain industry pairs may exhibit bidirectional coagglomeration scenarios. To mitigate the excessive influence of bidirectional coagglomeration on the technological knowledge pools formed by both active and passive coagglomeration, which could affect the benchmark regression conclusions of this paper, the bidirectional coagglomeration segments within the technological knowledge pools, economies of scale, and labor pools are removed. The test is then conducted according to the benchmark regression settings. The results[5] clearly indicate that the core conclusions of this paper remain valid even after excluding the industry pairs exhibiting bidirectional coagglomeration.

4.3 Examination of the Heterogeneity of Innovation Spillover Effects from the Technological Knowledge Pool Formed by Spatial Industrial Agglomeration

4.3.1 Industrial Innovation Characterized by Asymmetric Spatial Coagglomeration Enhances Heterogeneity

To verify Hypothesis 2, this paper further investigates the heterogeneous innovation effects arising from the directionality of industrial coagglomeration. The results[6] indicate that there are significant differences in the impact of technological knowledge pools formed by active and passive agglomeration on the industrial innovation performance. From the perspective of the standardized coefficients of each regression, whether considering the influence of the scale of technological knowledge pools on the scale and quality of industrial innovation, or the impact of the quality of technological knowledge pools on the scale and quality of industrial innovation, the promotional effect of technological knowledge pools formed by active agglomeration is significantly greater than that formed by passive agglomeration. On the one hand, industries are better positioned to acquire externalities through active geographical proximity to other industries, leading to a higher spillover effect of the knowledge pool resulting from active coagglomeration. On the other hand, while industries that are passively geographically proximate to others can achieve a certain degree of knowledge spillovers, factors such as knowledge matching and asymmetries in knowledge levels lead to a spillover effect that is significantly weaker than that from technological knowledge pools formed by active agglomeration.

---

[5] Due to space limitations, the regression results are detailed in Schedule 4 of Appendix 3 posted on the website of *Economic Research Journal*.

[6] Due to space limitations, the regression results can be found in Schedule 5 of Appendix 4 available on the website of *Economic Research Journal*.

4.3.2 Knowledge Pool Formed through Industrial Spatial Coaggregation Affects the Heterogeneity of Innovation Scale and Innovation Quality

The technological knowledge pool formed by industrial spatial agglomeration positively influences the industrial innovation performance. However, it is crucial to further explore whether there are differences in its effects on the scale and quality of industrial innovation. In the benchmark regression, due to overlapping confidence intervals of coefficients for the same explanatory variable, comparing coefficient magnitudes is not feasible. Consequently, this paper expands the sample size to twice its original size, generating dummy variables (*Industrial Innovation Scale_Dummy* = 0, and *Industrial Innovation Quality_Dummy* = 1) and tests for significant differences between the two sets of coefficients using interaction terms. The results [7]reveal that there are significant differences in the influences of the four explanatory variables from the benchmark regression on the industrial innovation scale and quality. Based on the results from Tables 1 and 2, it can be calculated that a 1% increase in the scale of active agglomeration knowledge pools leads to approximately a 0.514% increase in industrial innovation scale[8] and a 0.482% increase in industrial innovation quality; a 1% increase in the quality of active agglomeration knowledge pools results in approximately 0.377% and 0.368% increases in industrial innovation scale and quality, respectively; a 1% increase in the scale of passive agglomeration knowledge pools leads to approximately 0.386% and 0.357% increases in industrial innovation scale and quality, respectively; and a 1% increase in the quality of passive agglomeration knowledge pools results in approximately 0.315% and 0.300% increases in industrial innovation scale and quality, respectively. The scale effect from technological knowledge pools formed by industrial agglomeration is slightly higher than the quality effect, although both levels of impact are roughly comparable.

5 Endogeneity Test: Instrumental Variable for the UK Coagglomeration Index

There is a significant issue of reverse causality between geographic location choices in industries and the exchange and diffusion of knowledge. Resolving this issue is essential for the validity of the conclusions drawn in this paper. This study references the relevant work by Ellison et al. (2010), which discusses the measurement of the inter-industry coagglomeration index in the US and its driving factors. Their research explores the effects of Marshall's three major externalities on inter-industry coagglomeration in the US. To address endogeneity issues, the authors uses the UK's input-output coefficients and labor similarity index as instrumental variables for the corresponding U.S. metrics. Inspired by this approach, this paper utilizes micro-level enterprise survey data from the UK to measure the inter-industry

[7] Due to space limitations, the regression results can be found in Schedule 6 of Appendix 4 available on the website of *Economic Research Journal.*

[8] The standardized coefficient is calculated as 0.514 = 0.288 × 3.067 (standard deviation of explanatory variable) ÷ 1.719 (standard deviation of the explained variable). The same applies to subsequent calculations.

coagglomeration index in the UK based on the aforementioned method and employs it as an instrumental variable for China's inter-industry coagglomeration index. The reasons for selecting this instrumental variable are as follows: First, previous research indicates that industrial coagglomeration between countries is related through factors such as international input-output relationships and labor (Ellison et al., 2010). Therefore, there is a theoretical connection between China's industrial coagglomeration and that of the UK. Second, the UK, as the first country to undergo the Industrial Revolution, has a long history of industrial development. The agglomeration arising from location decisions of enterprises within industries and coagglomeration from inter-industry location decisions has evolved over hundreds of years. China began its comprehensive industrial development after reform and opening up, absorbing many experiences in industrial system construction from developed Western countries, including the UK. Thus, the spatial layout of industries in the UK has practically influenced the spatial layout of industries in China. Moreover, there is no correlation between the level of inter-industry coagglomeration in the UK and the innovation level in China, suggesting that using the UK's industrial coagglomeration index as an instrumental variable for China's industrial coagglomeration index is a reasonable choice.

The inter-industry coagglomeration index levels in the UK are calculated using the latitude and longitude coordinates of nearly 100,000 enterprises across 270 three-digit industries, as provided by the Fame database of Bureau van Dijk, applying the same coagglomeration index algorithm mentioned earlier. The UK national industry classification is then mapped to China's national industry classification. Based on the UK's industrial coagglomeration index, the scale and quality of the technological knowledge pools resulting from both active and passive agglomeration are calculated and used as instrumental variables in the benchmark regression. Tables 3 and 4 present the two-stage least squares (2SLS) estimation results for the innovation enhancement effects of active and passive industrial agglomeration, respectively. In these tables, the Kleibergen-Paap rk LM tests reject the null hypothesis of underidentification of the instrumental variable at a 1% significance level, and the Kleibergen-Paap F statistic exceeds the critical value at the 10% level for the Stock-Yogo test, rejecting the null hypothesis of weak instruments. This indicates a strong correlation between the instrumental variable and the potential endogenous variable. In summary, the instrumental variables selected in this paper are appropriate, and the estimation results from the various models in the benchmark results are satisfactory. Even when considering potential endogeneity issues, the scale and quality of the technological knowledge pools formed through active and passive spatial agglomeration have positive technological enhancement effects on the scale and quality of industrial innovation, reinforcing the core conclusions of this paper.

Table 3 Two-stage Instrumental Variable Regression Results for the Innovation Enhancement Effects of Technological Knowledge Pool Formed by Active Industrial Coagglomeration

Variable	Stage I		Stage II			
	Size of technological knowledge pool	Quality of technological knowledge pool formed through active coagglomeration	Scale of industrial innovation		Quality of industrial innovation	
Size of technological knowledge pool formed by active coagglomeration			0.606*** (0.0347)		0.808*** (0.0461)	
Size of technological knowledge pool by active coagglomeration (UK)	0.473*** (0.0108)					
Quality of technological knowledge pool by active coagglomeration				0.410*** (0.0314)		0.577*** (0.0431)
Quality of technological knowledge pool by active coagglomeration		0.358*** (0.0101)				
Control variable	Control	Control	Control	Control	Control	Control
Underidentification test	184.71***	169.85***				
Weak identification test	1929.93***	1252.18***				
Observed value	20,281	20,281				

Note. The underidentification test and weak identification test provide the statistics of Kleibergen-Paap rk LM and Kleibergen-Paap rk Wald F tests, respectively; values in parentheses are robust cluster standard errors; *** $p < 0.01$; and the same applies below.

Table 4 Regression Results of Two-Stage Instrumental Variables on the Innovation Promotion Effect of Technological Knowledge Pool Formed through Passive Industrial Coagglomeration

Variable	Stage I		Stage II			
	Size of technological knowledge pool formed through passive coagglomeration	Quality of technological knowledge pool formed through passive coagglomeration	Scale of industrial innovation		Quality of industrial innovation	
Size of technological knowledge pool by passive coagglomeration			0.621*** (0.0203)		0.817*** (0.0269)	
Size of technological knowledge pool by passive coagglomeration (UK)	0.600*** (0.0149)					
Quality of technological knowledge pool by passive coagglomeration				0.418*** (0.0206)		0.571*** (0.0287)
Quality of technological knowledge pool by passive coagglomeration (UK)		0.408*** (0.0146)				
Control variable	Control	Control	Control	Control	Control	Control
Underidentification test	177.57***	152.78***				
Weak identification test	1615.62***	782.97***				
Observed value	20,281	20,281				

Note. *** $p < 0.01$.

6 Micro-Mechanism Test and Further Discussion

6.1 Micro-Mechanism Test

This paper investigates the impact of innovation externalities on a single industry resulting from a spatial coagglomeration network within an industrial context. It can be observed that the coagglomeration of an industry with other industries in geographic space can lead to positive cross-industry enhancements in innovation performance. From a bidirectional coagglomeration perspective, whether an industry is coagglomerated by others or actively co-agglomerates toward them, the innovation enhancement effect is present in both scenarios. To explain the positive external innovation enhancement effect generated by such a network as a whole, this paper references the gravity model of patent citations proposed by Kerr & Kominers (2015). This model expresses the relationship between citations between two industries and the distance between them through equation (4):

$$citation_{j \to k} = e^{\beta \times \phi_{j,k}}(patent_j \times patent_k)^{\gamma}. \tag{4}$$

In equation (4), citation $j \to k$ represents the level of patent citations from industry j to industry k, $\phi_{j,k}$ represents the level of agglomeration between industries j and k, and *patent* represents the patent level of the industry. The equation captures that the citation of patents between two industries is jointly influenced by the distance of coagglomeration and the patent stock of both industries. A higher level of coagglomeration indicates a smaller spatial proximity between the industries. If knowledge spillovers decrease with increasing distance between the two industries, it means that knowledge spillovers increase with a higher level of inter-industry coagglomeration. Therefore, it is empirically reasonable to surmise that $\beta > 0$. If the number of patents in both industries grows, the number of citations between the two industries will also increase, suggesting that $g > 0$. Consequently, the empirical judgment of $\gamma > 0$ leads to taking the logarithm of both sides of equation (4), resulting in equation (5):

$$\ln citation_{j \to k} = \beta\phi_{j,k} + \gamma_1 \ln patent_j + \gamma_2 \ln patent_k. \tag{5}$$

$\Phi_{j,k}$ is the spatial coagglomeration relationship between industries. Equation (5) is further decomposed and refined into equations (6) and (7).

$$\ln citation_{j \to k,c,t} = \alpha + \beta_1\phi_{j \to k,c,t} + \beta_2 \ln patent_{jct} + \beta_3 \ln patent_{kct} + u_j + \upsilon_t + \delta_c + \varepsilon_{jct}, \tag{6}$$

$$\ln citation_{j \leftarrow k,c,t} = \alpha + \beta_1\phi_{j \to k,c,t} + \beta_2 \ln patent_{jct} + \beta_3 \ln patent_{kct} + u_j + \upsilon_t + \delta_c + \varepsilon_{jct}, \tag{7}$$

where $citation_{j \to k,c,t}$ represents the patent citation level of industry j to industry k in region c at time t; $citation_{j \leftarrow k,c,t}$ represents the patent citation level of industry j by industry k in region c at time t;[9] $\Phi_{j \to k,c,t}$ represents the coagglomeration level of industry j to industry k in region c at time t; $patent_{jct}$ represents the patent level of industry j in region c at time t; and $patent_{kct}$ represents the patent level of industry k in region c at time t.

This paper employs a fixed effects model to estimate equations (6) and (7) separately.

[9] The citations and cited frequency of patents in this paper are the citations of various patents from the China National Intellectual Property Administration spanning from 1998 to the first quarter of 2020. Objectively, the number of citations for earlier patents is significantly greater than that for more recently applied patents. However, considering that the focus of this paper is on patents from 1998 to 2013, this impact will be diminished.

Column (1) of Table 5 illustrates the relationship between patent citations from industry j to industry k and the influence of coagglomeration from industry j to industry k. It can be observed that active coagglomeration between industries significantly and positively affects patent citations among them. This indicates that active geographical proximity between industries facilitates knowledge spillovers through matching learning, which is reflected in the increase in patent citations among these industries. Column (2) of Table 5 employs the UK industrial coagglomeration index as an instrumental variable to address the endogeneity issue in equation (6). Even within the instrumental variable framework, the effect remains identifiable. Column (3) of Table 5 presents the relationship between patent citations of industry j from industry k and its influence from the coagglomeration of industry j toward industry k. Similarly, a significant positive relationship can also be observed. This further suggests that the proximity of inter-industry spatial clusters increases the citations of patents within the industry, facilitating passive coagglomeration with other industries. Column (4) of Table 5 uses the same endogeneity identification method, and this positive effect remains significant.

Table 5 Test Results of the Influence of Inter-Industry Bidirectional Coagglomeration on Inter-Industry Citation

Variable	Patent Citations from Industry j to Industry k		Patent Citations of Industry j by Industry k	
	(1) Benchmark regression	(2) UK Industrial coagglomeration as instrumental variable	(3) Benchmark regression	(4) UK Industrial coagglomeration as instrumental variable
Coagglomeration of industry j towards industry k $\Phi_{j \to k}$	0.00899** (0.000218)	0.138*** (0.0463)	0.00106*** (0.000226)	0.108*** (0.041)
ln $patent_j$	0.00237*** (0.000178)	0.00292*** (0.000291)	0.00240*** (0.000185)	0.00285*** (0.000294)
ln $patent_k$	0.00242*** (0.000233)	0.000828 (0.00603)	0.00246*** (0.000238)	0.00117** (0.000522)
Observed value	3327494	3327494	3327494	3327494
R^2	0.0246		0.0237	
Underidentification test		11.48***		11.48***
Weak identification test		12.34**		12.34**

Note. *** $p < 0.01$ and ** $p < 0.05$.

The micro-mechanism test results of bidirectional industrial coagglomeration and patent citation illustrate the innovation effects of industrial coagglomeration from the perspective of knowledge spillovers. Inter-industry spatial coagglomeration represents the general pattern of collective location choices across industries. Enterprises within an industry tend to cluster geographically near those from another industry, leveraging this spatial proximity to access knowledge spillovers, thereby enhancing the overall innovation performance of the industry. Additionally, geographical proximity facilitates passive knowledge spillover from the industry, consequently elevating the innovation performance levels of the co-agglomerated industries.

6.2 Further Discussion

The empirical research presented in this paper has preliminarily confirmed the significant positive role of the technological knowledge pool formed by industrial spatial coagglomeration in enhancing both the scale and quality of industrial innovation. This positive effect primarily arises from knowledge spillovers facilitated by geographical proximity. For an extended period, the construction of industrial parks and the development of regional clusters have been crucial strategies in China's industrial policy. If regional industrial policies adopt a single-industry strategy, it will increase the concentration of regional industries, whereas a diversified industry strategy will promote regional industrial coagglomeration. How can we further stimulate the innovative output of this policy tool to achieve the goal of high-quality clustered development of Chinese industries? Continuing along a path of singular and homogeneous development is unsustainable. The real-world development of industrial clusters largely relies on strategies such as constructing industrial parks and incubating innovative industries. However, this approach faces a critical choice of model: Should diversification in industrial clusters be built around upstream and downstream relationships of industries, or should it be centered on the technological linkages between industries? This section will further investigate the heterogeneous impacts of input-output linkages and technological linkages in industrial coagglomeration, focusing on whether geographic proximity between industries with input-output linkages or technological linkages can significantly enhance technological innovation. Due to the asymmetric characteristics of industrial spatial coagglomeration, industrial input-output linkages, and industrial technological linkages, this paper aims to verify the cross-influence between industrial spatial coagglomeration and industrial linkage. The main validation regression model is presented in equations (8) and (9):

$$\begin{aligned} Inno_{jct} = {} & \alpha + \beta_1 inno_{kct} + \beta_2 \phi_{j,k} + \beta_3 \phi_{j,k}\, inno_{kct} + \beta_4 IO_{j,k} + \beta_5 IO_{j,k}\, inno_{kct} \\ & + \beta_6 IO_{j,k} \times \phi_{j,k}\, inno_{jct} + \beta_7 X_{jct} + u_j + \upsilon_t + \delta_c + \varepsilon_{jkct}, \end{aligned} \tag{8}$$

$$\begin{aligned} Inno_{jct} = {} & \alpha + \beta_1 inno_{kct} + \beta_2 \phi_{j,k} + \beta_3 \phi_{j,k}\, inno_{kct} + \beta_4 Tech_{j,k} + \beta_5 Tech_{j,k}\, inno_{kct} \\ & + \beta_6 Tech_{j,k} \times \phi_{j,k}\, inno_{kct} + \beta_7 X_{jct} + u_j + \upsilon_t + \delta_c + \varepsilon_{jkct}, \end{aligned} \tag{9}$$

where $IO_{j,k}$ represents the input-output relationship between industries. The input-output relationship between industries is one of the important indicators for measuring industrial linkages. This indicator shows the upstream and downstream relationship between industries and possesses directionality. Verifying the impact of the inter-industry input-output relationship on industrial spatial coagglomeration can further elucidate the causes of active industrial spatial coagglomeration analyzed qualitatively above. Following the practices of Billings and Johnson (2016) and Ellison et al. (2010), this paper utilizes the inter-industry input-output table to determine the inter-industry input-output relationship. $IO_{j \to k}$ represents the proportion of industry j's output contributed by industry k's input, which indicates the degree of dependence of industry j on industry k in production relations; conversely, $IO_{j \leftarrow k}$ represents the proportion of industry k's output contributed by industry j's input. This paper employs the 2012 China 139 Industry Input-Output Table to construct this indicator through industry matching. This indicator illustrates the bidirectional input-output relationship of industry j to industry k.

$Tech_{j \to k}$ represents inter-industry technological linkages. In this paper, technological linkages serve as an indicator to measure inter-industry technological dependence, which possesses directionality. The internal driver of inter-industry technological linkages arises from knowledge spillovers, meaning that proximate enterprises can benefit from each other's technological externalities. Technological externalities are manifested not only at the R&D level but also through education and training. Building on the creation and definition of this indicator by Hidalgo et al. (2007), this paper employs it as a measure of inter-industry technological linkages, which can be understood as "product proximity" resulting from inter-industry technological linkages. This paper adopts the concepts and methods of the aforementioned studies and further endows this indicator with directional properties to measure the level of technological dependency between industries.[10]

Traditionally, input-output linkages and technological linkages between industries are not distinctly differentiated. Ellison et al. (2010) identify significant differences among MAR's three major externalities while analyzing the drivers of cross-industry spatial coagglomeration in the US. Diodato et al. (2018) empirically test the heterogeneous impacts of technological linkages, input-output linkages, and skill linkages across industries on spatial coagglomeration from a cross-sectional perspective. This paper calculates the correlation between the bidirectional input-output linkage indicator and the bidirectional technological linkage indicator, finding that the correlation between inter-industry input-output linkages and technological linkages is weak. This suggests that industries with input-output relationships do not necessarily possess strong technological linkage relationships, thereby laying the empirical foundation for our subsequent study on the differences in innovative outputs of spatial coagglomeration among different industrial relationships.

6.2.1 The Spatial Coagglomeration Innovation Spillover Effect of Input-Output Linkages

Table 6 shows the estimation results of equation (8). In particular, columns (1) and (3)

[10] Due to space limitations, the calculation method is detailed in Appendix 5 available on the website of *Economic Research Journal*.

present the innovation impact effects of active and passive coagglomeration of industry j toward industry k under the condition that industry j is an upstream industry in the production chain of industry k; columns (2) and (4) present the innovation impact effects of active and passive coagglomeration of industry j towards industry k under the condition that industry j is a downstream industry in the production chain of industry k. It can be observed that only when industry j has an input-output relationship with industry k can significant innovation enhancement effects arise from the spatial coagglomeration of industry j towards industry k. Conversely, when industry j is passively co-agglomerated by industry k, the existence of an input-output relationship does not lead to a significant improvement in innovation performance. This somewhat contradicts Hypothesis 3, indicating that the innovation performance enhancement effects from spatial coagglomeration among industries with input-output linkages are conditional. This provides insights for localities that aim to build industrial clusters around the upstream and downstream chains of industries, suggesting that the demand for geographical proximity among industries should be considered. If two industries with production linkages tend to select locations that support mutual synergy based on historical development patterns, then constructing diversified industrial clusters according to these patterns will benefit the innovation levels of industries, parks, and even the entire region. Conversely, if industries that could have addressed transportation costs of the production chain through transportation convenience are geographically concentrated through an “arranged marriage” approach, this will merely reduce transportation costs without generating sufficient knowledge spillovers effects to enhance the innovation levels of the related industries.

Table 6 Test of the Innovation Enhancement Effect of Industrial Spatial Coagglomeration and Input-Output Linkages

Variable	(1) Active-upstream	(2) Active-downstream	(3) Passive-upstream	(4) Passive-downstream
$\Phi_{j\to k} \times IO_{j\to k} \times innovation_{kct}$	0.132*** (0.0395)			
$\Phi_{j\to k} \times IO_{j\leftarrow k} \times innovation_{kct}$		0.133** (0.0531)		
$\Phi_{j\leftarrow k} \times IO_{j\to k} \times innovation_{kct}$			−0.0569 (0.0692)	
$\Phi_{j\leftarrow k} \times IO_{j\leftarrow k} \times innovation_{kct}$				−0.0378 (0.0405)
Observed value	3,327,494	3,327,494	3,327,494	3,327,494
R^2	0.625	0.625	0.626	0.626

Note. *** $p < 0.01$ and ** $p < 0.05$.

6.2.2 The Innovation Spillovers Effect of Spatial Coagglomeration of Technological Linkages

Table 7 shows the estimation results for equation (9). In particular, columns (1) and (3) present the innovation impact effects of active and passive coagglomeration of industry *j* towards industry *k* under the condition that industry *j* technologically depends on industry *k*; columns (2) and (4) present the innovation impact effects of active and passive coagglomeration of industry *j* toward industry *k* under the condition that industry *j* is technologically dependent on industry *k*. From the results, it is evident that under these four conditions, the innovation performance of industries is significantly influenced by these differences. Similar to input-output linkages, spatial active coagglomeration based on technological linkages can generate a certain positive effect, while spatial passive coagglomeration based on technological linkages shows significant negative effects. This reaffirms Hypothesis 2, indicating that there is an asymmetric innovation spillovers effect in industrial spatial coagglomeration. However, it also somewhat contradicts Hypothesis 3, as the technological innovation effects of spatial coagglomeration between industries with technological linkages do not yield a purely positive enhancement effect. Specifically, when industry *j* has a technological dependence on industry *k* and actively seeks to spatially coagglomerate with it, a strong enhancement in innovation performance can be achieved. Conversely, if this technological dependence is reversed, it could weaken the technological innovation enhancement effects. Moreover, we must confront the result that, based on the current empirical examination of technological linkages in China’s industrial coagglomeration, a zero-sum game has emerged. Knowledge within the knowledge pool of the passively co-agglomerated party flows to the actively co-agglomerating party, resulting in negative innovation enhancement effects. This aligns with the concept of parasitism in ecology (Odum, 2004). From a practical perspective, we speculate that the active spatial agglomeration of industries may intensify competition for technical talent or lead to unethical practices such as technological “plagiarism.” Of course, this hypothesis requires further evidence for validation. This offers valuable insights for localities seeking to develop diversified industrial clusters based on technological linkages. If industries with mutual collaborative location strategies possess technological linkages, the overall innovation capacity of these diverse parks is likely to be stronger. Conversely, if the relationship between industries is primarily one of unilateral technological dependence, geographical proximity will not enhance the overall innovation capacity of the cluster. Therefore, when local governments are establishing industrial innovation clusters, it is essential to clearly define the technological relationships between industries and the patterns of spatial location selection, while also strengthening intellectual property protection and industry operational standards.

Table 7 Test of the Innovation Enhancement Effect of Industrial Spatial Coagglomeration and Technological Linkages

Variable	(1) Active-technological dependence	(2) Active-subject of technological dependence	(3) Passive-technological dependence	(4) Passive-subject of technological dependence
$\Phi_{j\to k} \times Tech_{j\to k} \times innovation_{kct}$	0.0177 (0.0168)			
$\Phi_{j\to k} \times Tech_{j\leftarrow k} \times innovation_{kct}$		0.0683*** (0.0195)		
$\Phi_{j\leftarrow k} \times Tech_{j\to k} \times innovation_{kct}$			−0.102*** (0.0241)	
$\Phi_{j\leftarrow k} \times Tech_{j\leftarrow k} \times innovation_{kct}$				−0.0442** (0.0222)
Observed value	3,327,494	3,327,494	3,327,494	3,327,494
R^2	0.625	0.627	0.628	0.627
Control variable	Control	Control	Control	Control

Note. *** $p < 0.01$ and ** $p < 0.05$.

7 Conclusion and Policy Implications

Innovation is the core driving force behind the emergence of new quality productive forces and is essential for implementing new development concepts. The findings of this paper provide a theoretical foundation for local governments to move away from traditional economic growth modes and productivity development paths, enabling adjustments in industrial structure and optimization of industrial layout to cultivate. This paper validates the innovation performance enhancement effect of differentiated technological knowledge pools formed through spatial bidirectional coagglomeration among industries. The research indicates that industries benefit positively from the diverse technological knowledge pools formed through spatial coagglomeration, with both the scale and quality of these knowledge pools significantly enhancing the innovation scale and quality of regional industries. This conclusion has been confirmed through robustness and endogeneity tests. Furthermore, there are notable differences in innovation spillovers effects between “active coagglomeration” and “passive coagglomeration,” with the technological enhancement effects of active coagglomeration surpassing those of passive coagglomeration. The improvements in innovation performance resulting from the size of the technological knowledge pool are slightly greater than those arising from its quality. Additionally, this paper finds that only active coagglomeration can significantly enhance the innovative capabilities of industries with input-output linkages, while coagglomeration among industries with technological linkages demonstrates significant “parasitic effects,” leading to negative innovation spillovers effects for industries with passive coagglomeration. However, the innovation performance of industries coagglomerating toward nearby technologically related sectors can experience notable improvements. This provides a new explanatory perspective on Jacobs' externalities and serves as a reference for decision-making in the high-quality innovative development of industrial clusters in China. The policy implications of this paper are as follows:

First, industrial spatial multi-ecosystem complexes serve as crucial mechanisms for fostering regional new quality productive forces and promoting high-quality industrial development. China's current developmental practices reveal that local governments typically adopt the development model illustrated as 1-b in Figure 1 when establishing industrial clusters. However, this paper demonstrates that geographical proximity across industries significantly enhances innovation performance. Therefore, moving away from traditional single-industry industrial parks or incubators toward either the "diversified decentralization" approach (Models 2-a and 3-a) or the "diversified clustering" strategy (Models 2-b and 3-b) represents viable pathways for innovative and clustered development of industries. Building a diversified technological knowledge pool that aligns with local development foundations and potential, along with scientifically grounded planning of industrial parks based on regional characteristics, can cultivate a resilient and innovation-driven industrial system. This approach accelerates the dissemination of tacit knowledge across industries, thereby enhancing the overall innovation capability of the region's industries.

Second, it is vital to balance the coordinated development of both the quantity and quality of regional diversified industrial technological knowledge pools. According to the findings of this paper, both the scale and quality of local diversified technological knowledge pools can significantly enhance the innovation drive and vitality of regional industries. When evaluating the performance of multi-industry innovation clusters, local governments should adopt a dialectical perspective on the relationship between innovation scale and quality. Pursuing either "low-quality, high quantity" or "high-quality without scale" in industrial innovation is unadvisable. Instead, it is crucial to adhere to the innovation principle that "quantitative change promotes qualitative change" and "qualitative change leads to quantitative change," aligning with local innovation endowments and advantages to pursue sustainable innovation development.

Third, it is essential to understand the patterns of regional industrial coagglomeration, implement scientific industrial planning, and create a favorable business environment to facilitate positive active industrial spatial coagglomeration. Active coagglomeration is driven by intrinsic market behaviors. Local governments should identify the core industries within the regional industrial system and concentrate on attracting investment for these sectors. They should create a diversified industrial layout incorporating core industries and those with active spatial coagglomeration linkages, based on local resource endowments, to effectively promote high-quality innovative development of local industrial clusters. Two key points should be considered. Firstly, it is imperative to break away from the traditional thinking of supply chain dictating innovation chain. This paper indicates that the technological linkages between upstream and downstream industries in the industrial chain are relatively weak. In today's context of well-developed transportation infrastructure, utilizing urban agglomerations as a spatial scale for the division of labor in industrial chains is a relatively rational approach to industrial spatial layout. Secondly, when building a multi-industry innovation ecosystem around the innovation chain, it is crucial to strengthen the protection of intellectual property rights and coordinate the management of high-tech talent flow. It is also necessary to safeguard the innovation output of local pillar industries while fostering positive spillovers of tacit knowledge between industries through the establishment of effective technology collaboration and knowledge exchange platforms.

Fourth, it is important to strengthen institutional and mechanism construction to explore the development of diversified new industrial cluster complexes. Policymakers should reassess the distinctions and connections between industrial chains and innovation chains. The innovation potential of industrial cluster complexes built on industrial chains is waning in the face of current external challenges of "decoupling and disruption." With the rapid advancement of a new generation of technological revolutions represented by artificial intelligence, cross-disciplinary, cross-industry, and cross-technology integrated development has become an inevitable trend. Therefore, it is essential to further explore and understand the hidden technological linkages between industries, creating diverse regional "technological knowledge pool," "talent pools," and "innovation capital pools" in terms of talent, capital, and system. This approach will fully leverage the overall advantages of innovation clusters formed by multi-industry coagglomeration during the innovation and upgrading of industries, thereby enhancing the overall innovation capacity and resilience of the regional industrial system.

Of course, what defines a reasonable innovation ecosystem for industrial coagglomeration necessitates further research. Through multidimensional comparisons from international horizontal and historical vertical perspectives, summarizing the objective patterns of historical development and current needs and deriving a practical guiding system for multi-industry coagglomeration will be a key topic that this study will explore further.

Acknowledgments This paper is supported by the major project of the National Social Science Fund of China (No. 22&ZD066); the youth program of the National Natural Science Foundation of China (No. 72303026); and the general program of the China Postdoctoral Science Foundation (No. 2022M710693).

References

Audretsch, D. B. (1996). R&D spillovers and the geography of innovation and production. *American Economic Review*, (3), 630–639.

Audretsch, D. B., & Feldman, M. P. (2004). Knowledge spillovers and the geography of innovation. In J. V. Henderson & J-F. Thisse (Eds.), *Handbook of regional and urban economics* (pp. 2713–2739). Elsevier.

Baptista, R., & Swann, P. (1998). Do firms in clusters innovate more? *Research Policy*, (5), 525–540.

Billings, S. B., & Johnson, E. B. (2016). Agglomeration within an urban area. *Journal of Urban Economics*, *91*, 13–25.

Boschma, R. (2005). Proximity and innovation: A critical assessment. *Regional Studies*, (1), 61–74.

Buzard, K., Carlino, G. A., Hunt, R. M., Carr, J. K., & Smith, T. E. (2020). Localized knowledge spillovers:

Evidence from the spatial clustering of R&D labs and patent citations. *Regional Science and Urban Economics*, *81*, 103490.

Chen, L., Liu, X., Ye, X., & Hu, H. (2020). Industrial coagglomeration and industrial space governance from the perspective of urban clusters: Measurement of machine learning algorithm. *China Industrial Economics*, (5), 99–117 (陈露, 刘修岩, 叶信岳, 胡汉辉 (2020). 城市群视角下的产业共聚与产业空间治理:机器学习算法的测度. 中国工业经济, (5), 99–117).

Das, S., & Finne, H. (2008). Innovation and Co-location. *Spatial Economic Analysis*, (2), 159–194.

Diodato, D., Neffke, F., & O' Clery, N. (2018). Why do industries coagglomerate? How Marshallian externalities differ by industry and have evolved over time. *Journal of Urban Economics*, *106*, 1–26.

Du, R., & Zheng, S. (2020). Agglomeration, housing affordability, and new firm formation: The role of subway network. *Journal of Housing Economics*, *48*, 101668.

Duranton, G., & Overman, H. G. (2008). Exploring the detailed location patterns of UK manufacturing industries using microgeographic data. *Journal of Regional Science*, (1), 213–243.

Ellison, G., & Glaeser, E. L. (1997). Geographic concentration in US manufacturing industries: A dartboard approach. *Journal of Political Economy*, (5), 889–927.

Ellison, G., Glaeser, E. L., & Kerr, W. R. (2010). What causes industry agglomeration? Evidence from coagglomeration patterns. *American Economic Review*, (3), 1195–1213.

Fan, J., Feng, M., & Li, F. (2014). Industrial agglomeration and total factor productivity of enterprises. *World Economy*, (5), 51–73 (范剑勇, 冯猛, 李方文 (2014). 产业集聚与企业全要素生产率. 世界经济, (5), 51–73).

Fan, J., Liu, N., & Liu, Y. (2021). Geographic distances, input-output linkages, and agglomeration. *Economic Research Journal*, (10), 138–154 (范剑勇, 刘念, 刘莹莹 (2021). 地理距离、投入产出关系与产业集聚. 经济研究, (10), 138–154).

Feldman, M. P., & Audretsch, D. B. (1999). Innovation in cities: Science-based diversity, specialization and localized competition. *European Economic Review*, (2), 409–429.

Glaeser, E. L., Kallal, H. D., Scheinkman, J. A., & Shleifer, A. (1992). Growth in cities. *Journal of Political Economy*, (6), 1126–1152.

Hanlon, W. W., & Miscio, A. (2017). Agglomeration: A long-run panel data approach. *Journal of Urban Economics*, *99*, 1–14.

He, C., & Chen, T. (2019). External demand shocks, related variety, and resilience of export. *China Industrial Economics*, (7), 61–80 (贺灿飞, 陈韬 (2019). 外部需求冲击、相关多样化与出口韧性. 中国工业经济, (7), 61–80).

Henderson, V., Kuncoro, A., & Turner, M. (1995). Industrial development in cities. *Journal of Political Economy*, (5), 1067–1090.

Hidalgo, C. A., Klinger, B., Barabási, A. L., & Hausmann, R. (2007). The product space conditions the development of nations. *Science*, (5837), 482–487.

Jacobs, J. (1969). *The economy of cities*. Random House.

Jaffe, A. B., Trajtenberg, M., & Henderson, R. (1993). Geographic localization of knowledge spillovers as evidenced by patent citations. *Quarterly Journal of Economics*, (3), 577–598.

Kerr, W. R., & Kominers, S. D. (2015). Agglomerative forces and cluster shapes. *Review of Economics and Statistics*, (4), 877–899.

Krugman, P. (1991). Increasing returns and economic geography. *Journal of Political Economy*, (3), 483–499.

Odum, E. P. (2004). *Fundamentals of ecology*. Cengage Learning.

Paci, R., & Usai, S. (1999). Externalities, knowledge spillovers and the spatial distribution of innovation. *GeoJournal*, (4), 381–390.

Peng, X., & Jiang, C. (2011). Industrial agglomeration, knowledge spillovers, and regional innovation: Evidence from China. *China Economic Quarterly*, (3), 913–934 (彭向, 蒋传海 (2011). 产业集聚、知识溢出与地区创新——基于中国工业行业的实证检验. 经济学(季刊), (3), 913–934).

Su, D., Sheng, B., Shao, C., & Chen, S. (2020). Global value chain, industry agglomeration and firm productivity's interactive effect. *Economic Research Journal*, (3), 100–115 (苏丹妮, 盛斌, 邵朝对, 陈帅 (2020). 全球价值链、本地化产业集聚与企业生产率的互动效应. 经济研究, (3), 100–115).

von Hippel, E. (1994). Sticky information and the locus of problem solving: Implications for innovation. *Management Science*, (4), 429–439.

Xi, J. (2022). *Hold high the great banner of socialism with Chinese characteristics and strive in unity to build a modern socialist country in all respects—Report to the 20th National Congress of the Communist Party of China (October 16, 2022)*. People's Publishing House (习近平 (2022). 高举中国特色社会主义伟大旗帜 为全面建设社会主义现代化国家而团结奋斗——在中国共产党第二十次全国代表大会上的报告 (2022-10-16). 人民出版社).

Xi, P., Liang, R., Xie, Z., & Su, G. (2017). Fiscal stress, excess capacity, and supply-side reform. *Economic Research Journal*, (9), 86–102 (席鹏辉, 梁若冰, 谢贞发, 苏国灿 (2017). 财政压力、产能过剩与供给侧改革. 经济研究, (9), 86–102).

Xu, W., Chen, D., Liu, L., & Liang, S. (2023). How local governments guide the industrial structure adjustment. *World Economy*, (11), 79–102 (徐巍, 陈冬华, 刘磊, 梁上坤 (2023). 地区产业结构调整中的经验借鉴: 基于官员异地调任的证据. 世界经济, (11), 79–102).