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Explaining High Output Efficiency in Strategic Emerging Industrial Spaces: A Spatial Economic Analysis of 78 Domestic and International Cases

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Abstract

At present, China attaches great importance to the development of new quality productive forces. As the spatial projection carriers of these forces, strategic emerging industrial spaces exhibit high-output efficiency that calls for theoretical explanation. Existing research has largely focused on the internal efficiency of industries, with insufficient attention paid to the mechanisms of spatial attributes — particularly the systematic analysis of spatial economic factors such as intensification, functional mixing, and location−bid rent relations. To address this gap, this study draws upon 78 samples of strategic emerging industrial spaces from China and abroad. By employing quantitative analyses of the density−scale relationship, calculating functional mixing through the information entropy model, and assessing spatial bid rent effects, the study uncovers the underlying causes of the high efficiency observed in new industrial spaces. The results demonstrate that high development intensity and high functional mixing are distinctive characteristics of strategic emerging industrial spaces. Their bid rent capacity in core urban areas exceeds traditional land rent gradients, presenting an empirical challenge to the Alonso model. This high-density, high-mixing spatial pattern fosters reverse industrial clustering in urban cores through mechanisms such as knowledge spillovers, industrial chain collaboration, and innovation network agglomeration, thereby reshaping the theoretical framework of spatial economics. The findings provide a partial explanation for the high-output performance of new industrial spaces and offer a theoretical foundation for optimizing industrial space policies and planning supply strategies.

Keywords: Industrial Space; Industrial City; Urban Spatial Performance; Urban Spatial Organization; Rent Gradient

1. Introduction

The state and relevant departments have attached great importance to the development of new industries, including advanced manufacturing and strategic emerging industries. At the same time, they have explicitly proposed improving the output efficiency of industrial land use (e.g., the policy orientation of "evaluating heroes by output per mu"), which has triggered a series of industrial spatial policy actions such as the redevelopment of inefficient industrial land and the promotion of "industries moving into multi-story buildings." In practice, however, there are significant differences in the output efficiency of industrial land across different cities, closely related to their industrial structures, technological levels, and spatial organization patterns. For instance, in 2022, Shenzhen's industrial added value per unit of industrial land reached approximately 51 billion RMB/km², far exceeding that of Shanghai (12.8 billion RMB/km²), Guangzhou (11.8 billion RMB/km²), Foshan (13 billion RMB/km²), Dongguan (14 billion RMB/km²), and Jiangmen (5.8 billion RMB/km²) during the same period. From an international perspective, some industrially advanced cities also demonstrate high output efficiency of industrial land, such as Tokyo (about 45 billion RMB/km²) and Singapore (about 48 billion RMB/km², converted to RMB).

Multiple factors influence the output efficiency of industrial land and industrial spaces. From the standpoint of classical spatial economic theory, Marshall proposed the theory of external economies to explain the effects of industrial agglomeration (Marshall, 2024). Porter further pointed out that industrial clusters are often accompanied by increased spatial density, which in turn generates scale effects, technological spillovers, and collaborative innovation effects (Porter, 1999). Weber's (1929) industrial location theory emphasized the impact of location factors on production costs and efficiency. Fujita et al. (2021) and Henderson (2024) argued that optimizing the spatial layout of industries can effectively enhance the efficiency and output performance of regional economic activities. Douglass (2000), based on studies of the Asia-Pacific region, highlighted that under globalization, the evolution of "mega-urban regions" reshapes urban economic networks, intertwining processes of industrial agglomeration and diffusion.

With respect to strategic emerging industries and advanced manufacturing, Kincaid et al. (2001), Hoover (1948), Richardson (1969), Greenhut (1956), and Smith (1981) proposed comprehensive analytical theories of industrial spatial layout, emphasizing the combined influence of natural resources, production costs, and market prices on industrial spatial agglomeration (Yue et al., 2022). Furthermore, new economic geography suggests that dominant industries often form regional industrial advantages driven by economies of scale and spillover effects. Domestic research also confirms the positive impact of industrial agglomeration on the output efficiency of industrial spaces (Chen, 2024). However, studies in spatial economics have not sufficiently addressed the role of spatial ontological factors—such as location, density, and spatial organization—on industrial spatial output. Whether spatial factors can explain differences in industrial space output efficiency will directly determine the effectiveness of industrial spatial policies and planning interventions. Therefore, it is necessary to summarize empirical evidence and establish the basic relationship between spatial ontological factors and industrial space output efficiency.

2. Research Methods

2.1. Selection of Typical Samples of Emerging Industrial Spaces

This study selected industrial space samples covering the major fields of advanced manufacturing and strategic emerging industries, including electronic information, integrated circuits, new energy, and biomedicine. The sample set includes Shenzhen, China’s largest industrial city and the one with the highest output efficiency; other major industrial cities in China (e.g., Shanghai, Suzhou); as well as industrial parks from overseas countries and regions such as Japan, South Korea, Singapore, Germany, and Switzerland.

The selection followed the principles of representativeness, innovativeness, replicability, and industrial influence, ensuring that the research findings possess broad reference value and academic significance. For each industrial sector, the sample pool includes at least 1-2 typical cases from Shenzhen, 1-2 cases from other Chinese cities, and several overseas cases. In addition, key indicators such as regional characteristics, industrial types, functional layouts, innovation models, and development performance were comprehensively considered to construct a representative sample base.

In total, 78 industrial space samples were selected. Among them, 24 are from Shenzhen, such as the BYD Industrial Park in Pingshan and the Shenzhen Biopharmaceutical Innovation Industrial Park; 36 are from other Chinese cities, including the Tesla Shanghai Gigafactory and the Xiaomi Automobile Gigafactory in Beijing; and 18 are international cases, covering globally representative examples such as the Volkswagen Autostadt in Wolfsburg, Germany, and the Roche Industrial Park in Switzerland.

2.2. Sample Standardization and Selection of Spatial Economic Parameters

To facilitate data analysis and comparison, the selected samples in this study are organized into a unified database format, including the functional layout of the park, industrial types, land-use scale, development intensity, and the functional type of individual buildings. After classifying the functions of different components of industrial space, standardization is conducted based on 50 hectares as the standard unit. This process takes into account the internal functional topological relationships of the industrial space samples, resulting in a standardized industrial space sample database, which will be used for calculations such as spatial mixing degree.

Table 1. Overview of Indicators Included in Land-Use Scale, Development Intensity

Indicator Name	Unit	Data Type
Land Area	Hectares (ha)	Float
Floor Area	10,000 m² (w ㎡)	Float
Floor Area Ratio (FAR)	—	Float
Building Height	Meters (m)	Float
Story Height	Meters (m)	Float

Land Price / Rent	RMB / m² (yuan/㎡)	Int
Distance to City Center	Kilometers (km)	Int

2.3. Spatial Analysis Methods

After completing the baseline data collection and standardization of 78 industrial space samples, this study first groups and classifies the samples according to their geographical distribution (Shenzhen, other domestic cities, and overseas) and industrial attributes, so as to ensure that similar industrial characteristics and planning patterns are better reflected within the same group.

First, two key indicators—land area and floor area ratio (FAR)—are selected. A coordinate fitting approach is applied to conduct regression analyses on each group of samples, thereby deriving the functional relationship between scale expansion and development intensity across different regions or industrial types, which serves to characterize the level of spatial intensification.

Second, the regression parameters of each function—including slope, intercept, and potential inflection points—are estimated using the ordinary least squares (OLS) method. Extreme values are winsorized, and the model parameters are cross-validated through case interviews and literature checks to ensure robustness and explanatory power. These parameters are then compared against the on-site conditions of sample parks and reference data from the literature. Based on this, the information entropy model is employed to calculate the degree of functional mixing of industrial spaces.

Third, by analyzing the relationship between the distance of industrial spaces to city centers and their rental levels, this study evaluates the rent-bidding capacity of new industrial spaces and advanced manufacturing sectors, thereby examining the overall performance relationship of new industrial spaces in contemporary cities.

3. Spatial Economic Analysis of Sample Spaces

3.1. Spatial Intensification Level of New Industrial Spaces

The relationship between land area and development intensity directly reflects the level of intensification in industrial spaces. The smaller the land area and the higher the development intensity, the greater the level of intensification. Whether higher levels of intensification lead to higher output performance constitutes the first sub-question explored in this study.

For all overseas industrial samples, except for a few specialized or highly advanced industrial types (such as semiconductors and integrated circuits, safety and environmental protection, and precision instruments and equipment), most industrial spaces exhibit a relatively convergent trend in their demand for land area and FAR. In contrast, industrial spaces in Chinese cities other than Shenzhen generally show lower FARs and larger land areas. This phenomenon may be associated with relatively abundant land resources, historical path dependence in urban planning and industrial layout, and insufficient anticipation of space demand for industrial development. Model analyses conducted using the same approach indicate that new industrial spaces and advanced manufacturing sectors in Chinese cities (excluding Shenzhen) also demonstrate a certain gradient relationship between land use and development intensity. However, their level of intensification is still lower than that of the overseas samples.

Overall, it is evident that the spatial intensification level of Shenzhen's industrial spaces is higher than that of other domestic cities, and even exceeds that of overseas countries and regions. Specifically, when the land area is less than 80 hectares, the floor area ratio (FAR) of Shenzhen's industrial spaces is approximately 1.5 times that of the international samples and 1.2 times that of other domestic cities. When the land area exceeds 80 hectares, its FAR even reaches twice that of other domestic cities. Considering that Shenzhen's industrial output per unit of land is comparable to that of developed countries and regions overseas, yet several times higher than that of other domestic cities, the degree of spatial intensification can partly explain the differences in industrial space performance between Shenzhen and other Chinese industrial cities. However, it does not fully account for the phenomenon of Shenzhen achieving output performance levels similar to those of overseas countries and regions. In addition, among the overseas samples, the data points reflecting the relationship between land area and FAR tend to converge, indicating that the morphological patterns of advanced industrial spaces overseas are becoming more uniform. Medium-intensity industrial spaces built on relatively small plots have become the mainstream overseas, whereas in China, the morphological differences in new industrial and advanced manufacturing spaces remain relatively significant.

3.2. Functional Organization of New Industrial Spaces

The functional organization of new industrial spaces plays a crucial role in determining their overall effectiveness (Zhu, 2023). A layout characterized by high spatial mixing within industrial parks enhances spatial vitality and functional synergies (Wang & Meng, 2020). Such a configuration tightly integrates functions of R&D, production, and living services within the park, not only increasing its attractiveness to high-end talent and investment but also providing strong support for strengthening upstream–downstream collaboration in industrial chains and enhancing innovation capacity. Given the increasingly critical role of functions beyond production and manufacturing—such as R&D, innovation, and social interaction—this study's second sub-question examines the functional organization and performance of industrial spaces from the perspective of functional mixing. Spatial mixing degree is a quantitative indicator used to measure the diversity and balance of functional zoning within a given area. Its core idea is to evaluate the relative proportions and distribution characteristics of different functional types, thereby reflecting the coordination and integration of spatial layouts. A higher level of spatial mixing indicates that functional zones are more diverse and balanced, potentially generating stronger synergies between functions. The development of new quality productive forces imposes higher requirements on the spatial organization of cities, with key features such as knowledge spillover effects, industrial chain collaboration, and the spatial agglomeration of innovation networks, driving industrial spaces toward higher density and higher degrees of mixing (Yang, 2020). At present, the calculation of spatial mixing degree typically relies on information entropy or related indices, which provide an intuitive means of quantifying the diversity and balance of functional distributions (Zagorskas, 2016). The calculation formula is as follows:

$$H =- \Sigma_{i=1}^{n} P_i \cdot \ln(P_i)$$

Where: H denotes the spatial mixing degree, with a value range of [0, 1];

P_i represents the proportion of the i-th functional zone;

n is the total number of functional zones.

A value closer to 1 indicates a more diverse and balanced functional distribution.

To further investigate the differences in spatial organization patterns among Shenzhen, other domestic industrial cities, and overseas countries and regions, this study selected six representative types of industrial parks — intelligent connected vehicles, intelligent robotics, biomedicine, synthetic biology, marine industry, and semiconductor integrated circuits — and calculated and compared their spatial mixing degrees of functional zoning. The analysis results show that industrial park samples in Shenzhen generally exhibit higher spatial mixing degrees than those in comparable domestic and overseas parks. Shenzhen’s parks tend to integrate more diverse functional zones — such as R&D, production, office, commercial, and residential facilities—within limited spaces, thereby achieving tightly nested and synergistically coexisting multifunctional layouts. Such high-mixing spatial configurations not only improve land-use efficiency but also enhance the coupling between industrial activities and the effects of innovation linkages.

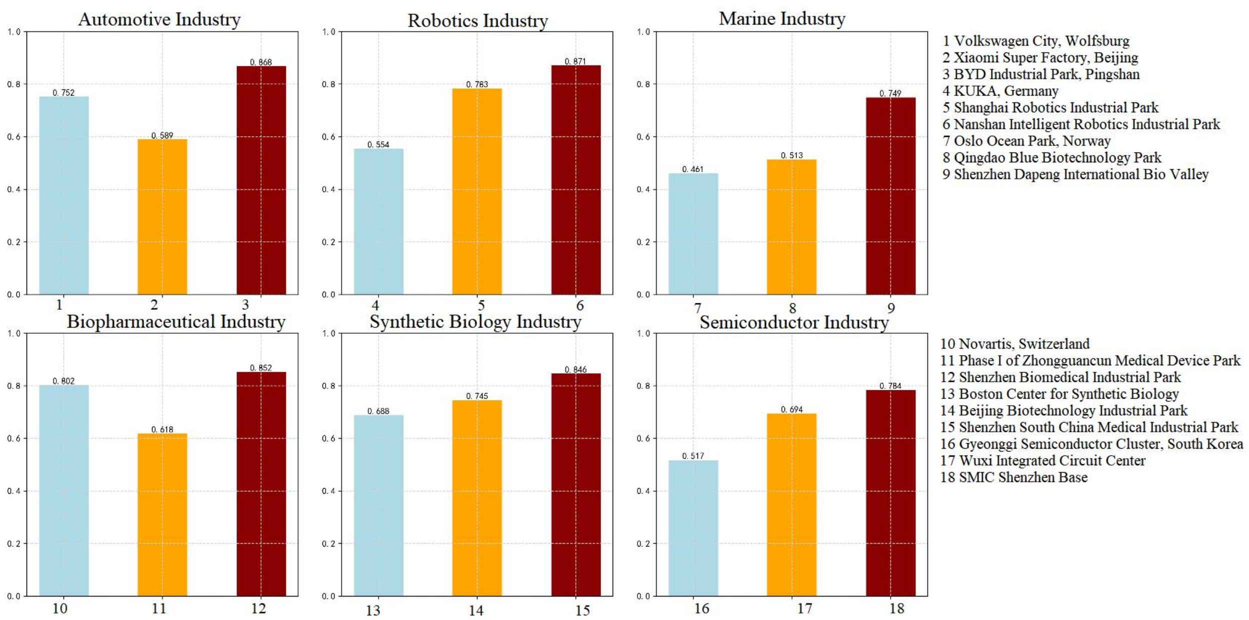

Figure 1. Comparison of spatial mixing degree indices across different types of industrial parks

For example, in the intelligent robotics sector, the entropy index of Shenzhen Nanshan Intelligent Robotics Industrial Park is 0.871, significantly higher than that of Germany’s KUKA Industrial Park (0.554) and the Shanghai Intelligent Robotics Industrial Park (0.783). In the marine industry, the entropy index of Shenzhen Dapeng International Bio Valley is 0.749, which is significantly higher than that of the Oslo Marine Park in Norway (0.461) and the Qingdao Blue Bio-Industrial Park (0.513). Overall, Shenzhen’s industrial parks consistently demonstrate higher spatial mixing degrees compared with similar parks in other domestic regions and overseas (Figure 1). This can partly explain why the output performance of Shenzhen’s industrial parks surpasses that of other Chinese industrial cities, but it does not fully account for the phenomenon of Shenzhen achieving performance levels comparable to those of overseas countries and regions.

3.3. Location–Bid Rent Relationship of New Industrial Spaces

Rent levels constitute an important indicator reflecting the output performance of space. In traditional urban spatial models, rent levels are highly correlated with urban location. Thus, the location–bid rent relationship of industrial spaces represents a key parameter for characterizing spatial performance. Spatially, projects in strategic emerging industries with stronger unit-area output capacity tend to locate closer to city centers and adopt high-density development models (Wei, 2024). This not only enables the effective utilization of limited land resources in central areas but also promotes industrial agglomeration and collaborative development. Moreover, due to their locational advantages, such projects are more competitive in attracting investment and high-level talent.

Taking Shenzhen as an example, a comparison across different land-use types within the same location shows that some plots designated for emerging industries in core areas have already achieved higher unit output efficiency than commercial and office land in the same area. Conversely, when comparing the same land-use type across different locations, some non-core new industrial land parcels demonstrate unit revenue levels that surpass those of similar plots located in the core area. Under high-density development conditions (FAR $\geqslant$ 3.0) with relatively small land areas, the spatial boundaries between industrial and commercial functions tend to blur, and the two become highly coupled within the same spatial domain. While such highly mixed spatial forms improve land-use efficiency to a certain extent, they also pose challenges for planning and management—particularly in contexts where multiple stakeholders are involved and land-use rights are highly fragmented. Balancing spatial rationality with distributive equity of returns thus becomes a pressing issue to be addressed in policy design.

Analyzing the functional characteristics of strategic emerging industries and their fit with spatial carriers helps to develop a more systematic understanding of the locational logic underlying advanced manufacturing and related industries in central urban districts or core areas. According to the traditional urban spatial structure theory established on the Alonso bid rent model, manufacturing has typically been considered more suitable for peripheral urban locations in order to minimize costs and achieve functional separation (Figure 2 and Figure 3). However, strategic emerging industries exhibit attributes distinct from traditional manufacturing in terms of industrial structure, technological trajectory, and spatial requirements, thereby challenging the explanatory power of such theoretical assumptions. Their greater reliance on knowledge spillovers, R&D collaboration, and innovation ecosystems drives them to cluster in dense, high value-added central urban areas, reconstructing the organizational logic of industrial space. As a result, the spatial distribution logics built upon traditional location theories and bid rent models are increasingly inadequate for fully capturing the contemporary development patterns of new industrial spaces.

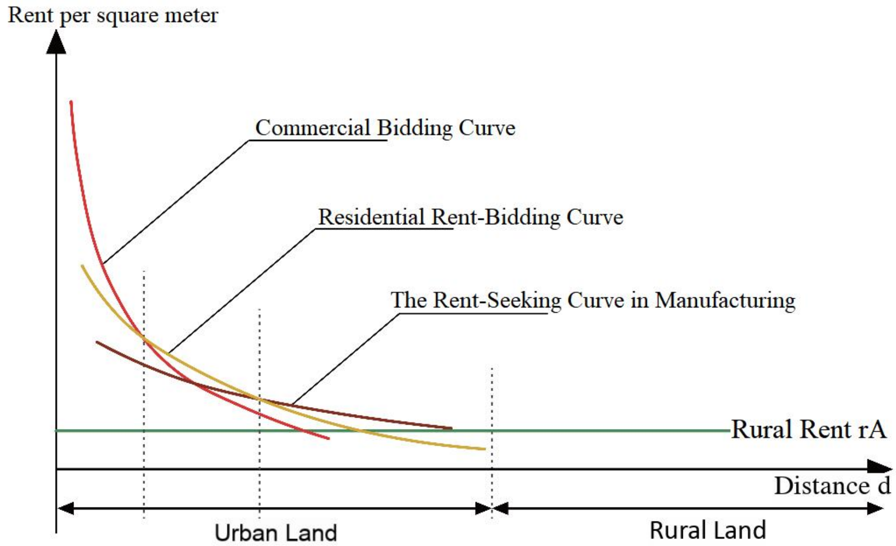

Figure 2. Manufacturing located in the third concentric zone in Alonso's "location–bid rent" model

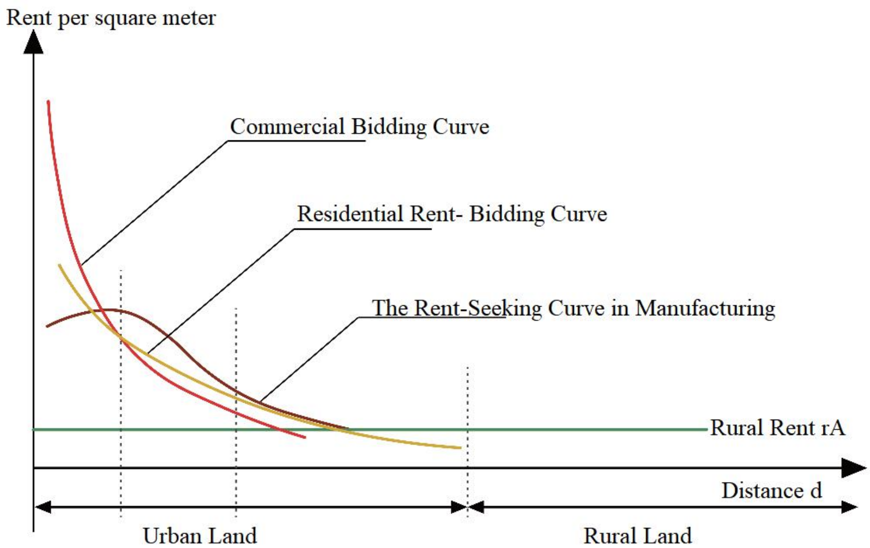

Figure 3. Certain new industries and advanced manufacturing sectors enter the core zone, challenging the traditional Alonso model

4. Discussion

Based on the above analysis of all samples in terms of industrial space intensification and functional mixing, the following conclusions can be drawn:

(1) For Shenzhen and other domestic industrial cities, higher levels of industrial space intensification and functional mixing can partly explain the differences in output efficiency between the two. However, since the differences in intensification and functional mixing are smaller than the actual differences in per-unit output, this suggests that production factors such as talent and technology, together with spatial ontological elements, jointly influence the output efficiency of industrial spaces.

(2) For Shenzhen and overseas countries/regions, the two exhibit similar levels of spatial output efficiency, but significant differences in spatial intensification and diverse patterns in functional mixing. This indicates that production factors such as talent and technology in developed countries and regions provide stronger support for the output efficiency of industrial spaces.

(3) This study also observes that the bid rent capacity of some strategic emerging industries has significantly surpassed that of commercial and service land in the same locations, demonstrating strong payment capacity and high-output characteristics in core urban areas. This phenomenon breaks through the constraint of the Alonso curve on the spatial zoning of industrial land. Representative industries such as electronic information, integrated circuits, the digital economy, and new energy rely heavily on the agglomeration effects of knowledge-intensive factors, reinforcing their spatial tendency to cluster around R&D hubs and high-end service clusters (Huang, 2023). This indicates that high value-added industries not only differ from traditional industrial models in their technological pathways but also exhibit stronger centrality preferences in spatial organization, a conclusion that has been supported by other studies (Xu, 2021).

These findings suggest that under the drive of new quality productive forces, the organizational paradigm of industrial space is undergoing profound restructuring. Its spatial logic is no longer solely constrained by land rent costs but is increasingly driven by a combination of factors such as knowledge flows, technological innovation, and capital concentration. This paradigm shift has transformed urban core areas from traditionally defined “high-rent, non-industrial zones” into the preferred carriers of new productive forces, characterized by higher levels of intensification and functional mixing consistent with the features of central urban spaces. This implies that industrial space supply policies targeting new quality productive forces should emphasize the cultivation and regulation of spatial intensification and functional mixing. At the same time, such policies should avoid one-sided reliance on “high-intensity” development or “office-building-oriented” models. A healthy process of industrial cultivation must also fully respond to the developmental needs of talent, enterprises, and technology.

5. Conclusion

This study systematically reviews and empirically analyzes the spatial characteristics of strategic emerging industries and advanced manufacturing in Shenzhen and other representative domestic and international cities, from multiple dimensions including spatial density, functional mixing, and locational distribution. The results show that Shenzhen significantly outperforms in terms of both spatial intensification and functional integration of strategic emerging industries. Its high-density and highly mixed land-use patterns not only meet the pressing demands of limited urban land resources and industrial upgrading but also provide a solid spatial foundation for inter-firm collaborative innovation and resource sharing.

At the same time, some new industrial land parcels in Shenzhen ’ s core areas already demonstrate a bid rent capacity surpassing that of traditional commercial and office land, reflecting the strong adaptability and spatial restructuring capacity of emerging industries in high-value locations. The findings suggest that, in addition to production factors such as talent and technology, spatial ontological elements can also partly explain the high output efficiency of new industrial spaces.

By extension, current industrial space policies should establish more adaptive linkages between the development of new quality productive forces and the supply and distribution of industrial spaces. On the one hand, policy guidance should be strengthened to promote the agglomerated development of innovative enterprises in strategic emerging industries, optimize spatial resource allocation, and enhance overall industrial efficiency. On the other hand, the traditional planning logic of industrial land use should be transcended to build a more integrated, high-efficiency, and adaptive system of industrial spaces.

As new quality productive forces continue to evolve, the organizational logic of industrial spaces will also keep iterating. Therefore, it is essential to conduct in-depth research on the interactive mechanisms among industry, space, and policy, so as to provide a systematic cognitive framework for the evolution of industrial spaces and deliver scientific support for the cultivation and accommodation of future industries.

Author Contributions:

Yiyao Yang, Qi Wang, and Leixian Guo contributed to the conceptualization, methodology, and data analysis of the study. Qijun Li provided guidance on theoretical framing and critical revisions of the manuscript. Leixian Guo supervised the overall project and coordinated the research process. All authors have read and agreed to the published version of the manuscript.

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Not applicable.

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Not applicable.

Conflict of Interest:

The authors declare no conflict of interest.

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