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Dynamic Evolution and Trend Forecasting of New Quality Productive Forces Development Levels in Chinese Urban Agglomerations

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Abstract: New quality productive forces serve as a catalyst for high-quality development and act as a critical driver of Chinese-style modernization. This study evaluated the degree of new quality productive force in China's five major urban agglomerations between 2013 and 2022 using the entropy approach. Additionally, it utilized kernel density estimation, the Dagum Gini coefficient, and Markov chain analysis to explore the spatial and temporal dynamics of these forces and their evolutionary trends. The findings revealed the following: (1) Overall, the new quality productive forces in China's five major urban agglomerations have exhibited a steady upward trend, although the overall level remains relatively low. Among these regions, the Pearl River Delta ranks the highest, followed by the Yangtze River Delta, Beijing–Tianjin–Hebei, Chengdu–Chongqing, and the Urban Cluster in the Middle Reaches of the Yangtze River. Nevertheless, significant potential for improvement persists. (2) The traditional Markov probability transfer matrix suggests that the new quality productive forces in these urban agglomerations are relatively stable, with evidence of "club convergence". Meanwhile, the spatial Markov transfer probability matrix indicates that transfer probabilities are influenced by neighborhood contexts. (3) Over time, the new quality productive forces in Chinese urban agglomerations show a tendency to concentrate at higher levels, reflecting gradual improvement. The developmental state and evolutionary patterns of new quality productive forces in Chinese urban agglomerations are thoroughly evaluated in this paper, along with advice for accelerating their growth to promote Chinese-style modernization.

Keywords: new quality productive forces; urban agglomeration; spatial Markov chain; trend forecasting

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1. Introduction

Throughout the course of human history, significant changes in social life and industrial structure have coincided with major advancements in productivity. Xi Jinping, the General Secretary, has underlined the importance of generating new quality productive forces, investigating various avenues for innovation-driven development, and creating and enhancing new economic drivers and advantages. Therefore, grasping the formation law of new quality productive forces, conforming to the development trend, and accelerating the cultivation of it can not only accelerate economic prosperity and development but also be an important way to help high-quality development. This aligns with global development trends and focuses on advancing future industries and fostering green productivity.

Urban agglomerations serve as key platforms for supporting the high-quality development of China's economy. The five major urban agglomerations—Beijing–Tianjin–Hebei (BTH), the Yangtze River Delta (YRD), the Pearl River Delta (PRD), Chengdu–Chongqing (CC), and the urban cluster in the middle reaches of the Yangtze River (mrYR)—play a pivotal role in shaping the national economy. These regions encompass both the eastern coastal areas and inland territories, functioning as economic powerhouses and driving the growth and integration of the surrounding cities. Today's international competition also manifests more in the competition between urban agglomerations and metropolitan areas. We must take the accumulation of economy, culture, talents, science and technology, and other factors as the support to promote the competitiveness of urban agglomerations and metropolitan areas continuously.

The new quality productive force is a significant development in the context of globalization, and it is both a departure from and closely tied to conventional economic ideas. Traditional economic theories, such as neoclassical economics and the classical school of economics, place a strong emphasis on how labor, capital, and land affect the economy. The new quality productive force carries on this focus on the forces of production. While conventional theories frequently view technological advancement as an external variable, newer theories highlight the importance of components like scientific and technological innovation, digital technology, and intellectual capital. In practice, it is a viable strategy for industrialized nations to advance industrial digital transformation via technical innovation while enabling poorer nations to achieve rapid economic progress. Furthermore, the new quality productive force aligns well with the sustainable development goals that various nations are pursuing. It plays a crucial role in preventing climate change and improving resource utilization efficiency, which is why more academics should dedicate their time to its study.

The advancement of new quality productive force is a vital catalyst for fostering the coordinated development of regional economies. This progress drives the transformation of scientific research achievements into tangible social benefits, supports green and low-carbon initiatives, and contributes to the creation of world class urban agglomerations. Following the Introduction, we will summarize and review the pertinent literature; introduce the data sources and methods; present and interpret the research results; and conclude with discussions, summaries, and targeted suggestions. This study seeks to identify the characteristics of new quality productive forces, offering insights that may aid China and other regions globally in their advancement of these forces. Proposed policy recommendations aim to address current challenges, facilitating improvements and advancing high-quality development.

2. Literature Review

2.1. Theoretical and Empirical Research on New Quality Productive Forces

Firstly, in terms of connotation characteristics, Liu and Zhao (2024) [1] contended that "new", "quality", and "forces" respectively constitute the power source, the pursuit objective, and the core connotation of new quality productive forces. Zhong (2024) [2] investigated the evolution of new quality productive force and deduced that it is an advanced productive force that substitutes capital-driven growth via disruptive technological innovation, with digitalization and the fusion of digitalization and realization being the principal features of its industrial carrier. Secondly, in terms of theoretical logic, Jiang's (2024) [3] comprehensive categorization of the logical structure of new quality productive forces into three categories: production factors, modern industrial system, and institutional environment provides a thorough understanding. Deng (2024) [4] did a detailed study of the theoretical roots, historical development, and practical needs of the important dis-

cussion on new quality productive force, focusing on how it differs from Marxist theory's system of productive forces. Zhang et al. (2024) [5] talked in extensive detail about how new quality productive forces have boosted Chinese-style modernization. They covered from the historical process and theoretical framework to practical problems and ways to deal with them.

Thirdly, in terms of practical paths, Li and Cui (2024) [6], based on the perspective of historical materialism, carefully interpreted the essential connotation of new quality productive forces and proposed effective paths for their cultivation. Zhang et al. (2024) [7] focused on the logical relationship between the deep integration of digital and real economies and new quality productive forces, covering aspects from mechanism analysis to strategic value exploration, as well as breakthroughs in difficulties and path planning. These studies systematically sorted out the core essence, development context, and key issues of new quality productive forces from multiple perspectives, laying a solid foundation for the subsequent in-depth exploration and effectively promoting the continuous deepening and expansion of research in this field.

Numerous studies have explored the measurement and evaluation of new quality productive forces. For instance, Wang (2024) [8] analyzed new quality productive forces by examining the three fundamental elements of productivity: laborers, labor objects, and labor materials. They systematically established an index system to measure these forces across China's provinces and regions, dividing them into distinct categories based on various criteria and investigating regional disparities and spatial–temporal convergence trends over time. Similarly, Wu and Wan (2024) [9] applied an improved Critic-TOPSIS comprehensive evaluation method, the Gini coefficient, and kernel density estimation to assess the new quality productive forces, regional differences, and dynamic patterns across Chinese provinces. Shi and Yu (2024) [10] used spatial econometric models and QAP model analysis to study the convergence and decomposition of the structure of China's new quality productive forces in regions. Additionally, other scholars have examined it in relation to diverse fields, including sustainable economic development [11], agriculture [12], and carbon emission efficiency [13].

2.2. Literature Related to Urban Sustainable Development

There has been abundant study on urban sustainable development. An analysis of 50 country and European urban sustainability indicator frameworks (USIFs) found that most were formed after 2000 and varied in dimensions, subject categories, and indicators. The environmental dimension is predominant, but the institutional dimension is lacking. The regional development level affects 38 common thematic categories and key indicators [14]. In addition, some studies have focused on applying blockchain technology to enhance the safety resilience of chemical industrial parks based on a dynamic reward and punishment mechanism. The results provide empirical evidence for promoting resilient safety investment in chemical industrial parks and enhancing their resilient safety levels [15].

For the purpose of measuring CO_2 emissions and product sequestration in global supply chains, assisting firms in identifying carbon sources and optimizing their supply chains, and advancing developments in carbon accounting and emissions reduction targets, Jesse (2023) [16] constructed an artificial neural network based on actor network theory. This network will serve as a recurrent accounting system. Llena-Macarulla et al. (2023) [17] developed a model from an environmental accounting viewpoint to assess the extent of circular economy engagement in specific Spanish companies, revealing that the degree of environmental management accounting and reporting practices is typically low yet positively correlated with the level of circular economy activity. Malik et al. (2023) [18]

employed various methods to demonstrate that environmental disclosure enhances firm performance, aligning with stakeholder theory. Furthermore, they found that green innovation mediates the relationship between environmental disclosure and performance, supporting sustainable corporate development. These findings jointly provide essential theoretical and practical guidance for promoting urban sustainable development and enhancing the environmental and economic performance of enterprises.

The minimum wage serves as a significant indicator of a country's and city's sustainable growth; Matthew and Shang (2024) [19] employed random forests and neural networks to forecast the minimum wage across 162 nations. In the energy sector, Suárez-Fernández et al. (2024) [20] employed the DEA methodology to verify that HRM policies that prioritize diversity, inclusion, and employee development can improve corporate eco-efficiency. This underscores the importance of HRM in the promotion of sustainable corporate development. Li et al. (2023) [21] contributed to research on the relationship between digital finance and innovation from the perspective of cities by combining traditional and digital financial support, accounting for regional differences, expanding and deepening theories in related fields, and assisting cities in developing digital finance development strategies tailored to their specific circumstances.

2.3. Urban Agglomeration and Relevant Research Methodologies

The growth of urban agglomerations has received a lot of attention lately, and numerous studies have utilized urban agglomerations as geographic units. These studies have significant implications for economic development and regional integration. For example, Shmidt et al. (2016) [22] confirmed that agglomerations could alleviate the region's production diversification issues, achieve efficient land utilization, and optimize transportation and housing municipal infrastructure. Kii (2021) [23] measured the future population of 21st century urban agglomerations in 115 countries/regions using urban agglomerations as a geographic unit. Roland et al. (2013) [24] studied environmental issues arising from interactions between atmospheric, terrestrial, and marine ecosystems in coastal urban agglomerations. Utilizing the Kolkata urban agglomeration in India as a geographic scope, Sahana et al. (2018) [25] employed the urban sprawl matrix to examine urban spatial patterns and growth trends.

Zambom and Dias (2013) [26] provided a comprehensive summary of the theoretical foundations of kernel density estimation, illustrating its application through an econometric dataset example. Brandes et al. (2024) [27] utilized kernel density estimation to classify the driving factors of urban land use and road network scale models, contributing to improved road condition recognition for autonomous driving systems. The Gini coefficient, a tool mostly used to decompose the sources of differences, was used by Gong and Ma (2023) [28] to examine regional variations in SO_2 emissions of enterprises in China, while Li et al. (2024) [29] applied it to uncover regional inequalities in digital economy development. A extended recovery modeling framework based on state-dependent Markov processes was presented by Dhulipala et al. (2021) [30], allowing for the prediction of post-disaster hazard event sequences. Similarly, Albasri et al. (2022) [31] used Markov modeling to predict trends in functional patterns of urban land use in Al-Najaf, Iraq, to provide an outlook for urban land planning over the next decade. Combining kernel density estimation, the Gini coefficient, and Markov chain analysis offers a powerful approach for investigating spatiotemporal variations, dynamic evolution, and trend prediction of complex phenomena [32].

The existing research has focused on emphasizing the theoretical importance of new quality productive forces. Despite their importance, there is a lack of quantitative studies on the new quality productive forces of the five major urban agglomerations. According to

the aforementioned literature, the marginal contribution of this paper is twofold: first, it systematically reviews literature pertaining to the new quality productive forces of urban agglomerations, encompassing studies on new quality productive forces and sustainable urban development, thereby providing readers with a more comprehensive understanding of the concept; second, it establishes an index system for assessing the development level of new quality productive forces from the perspectives of new quality laborers, the objects of new quality, and the new quality materials. This approach enhances the current theoretical discourse on new quality productive forces and offers a more systematic methodology for evaluating its development. It offers robust decision assistance for China to expedite the establishment of new quality productivity and foster high-quality development.

3. Methods and Data Sources

3.1. Construction of the Indicator System

Our research is focused on three dimensions: new quality laborers, new quality labor objects, and new quality labor materials. We have developed an evaluation index system, as shown in Table 1, based on the index construction methods outlined in the literature of Wang (2024) [8] and Zhu et al. (2024) [33]. It is important to note that new quality laborers are defined by more than specific skills or production experience. They require a comprehensive set of qualities, including strong overall quality, innovative thinking, and mathematical and intellectual abilities. Modern economies need highly skilled labor to sustain growth and maintain their competitive advantage [34]. According to Huang et al. (2023) [35], talent competitiveness is now a crucial metric for assessing regional and national growth. The level of high productive laborers can be measured by looking at both the inputs and outputs of human capital. This includes the government's annual spending on education, science and technology, the number of patents granted each year, the GDP per capita, and the enrollment numbers in colleges and universities. When it comes to the object of labor, it is no longer just about raw materials or simple processing of semi-finished products. It now includes new energy, new materials, and a wide range of other material and non-material objects. New energy and materials help reduce the burden on the environment, while data informatization improves work efficiency, keeping with the new era of informatization and environmental sustainability. To measure the new quality labor objects, factors such as the number of large-scale industrial enterprises, artificial intelligence enterprises, urban parks and green space areas, and urban sewage treatment rate are considered. As for labor materials, while traditional labor relies on machinery, equipment, and computers, digital technologies like IoT, AI, big data, and cloud computing are more important to new quality labor [36]. The advancement of technology has the potential to transform the way we work, leading to significant improvements in production and quality of life. This potential is inspiring and should drive us to explore digital innovation and digitalization further. In this context, metrics such as the per capita volume of telecommunication services, the percentage of internet users per 100 people, the digital financial inclusion index [37], the deployment of industrial robots [38], and the quantity of green patents granted serves as indicators for the degree of inventive labor practices, signaling the promising future that technology offers.

Table 1. Evaluation index system of the new quality productive force development level of urban agglomeration.

System Layer	Guideline Layer	Indicator Layer	Explanatory Notes	Indicator Nature	Weight
Laborer	Investment in human capital	Investment in scientific research	The government's annual financial expenditure on science	+	0.1295
		Investment in education	The government's annual financial expenditure on education	+	0.0633
	Human capital output	Number of patents granted	Number of patents granted per year	+	0.099
		Level of economic development	GDP per capita	+	0.0257
		Level of higher education	Number of students enrolled in higher education	+	0.0802
Objects of labor	Emerging industries	Quality of enterprise development	Number of industrial enterprises above designated size	+	0.0512
			Number of AI companies	+	0.1722
	Green and environmentally friendly	Environmental protection efforts	The area of green space in the city's parks	+	0.0976
			Municipal sewage treatment rate	+	0.0008
Labor materials	Digital infrastructure	Level of the Internet	Telecommunications traffic per capita	+	0.1023
			Internet broadband subscribers per 100 people	+	0.0286
	Digital capabilities	Level of digital	Digital Financial Inclusion Index	+	0.0139
			Industrial robot applications	+	0.0207
			Number of green patents granted	+	0.1146

"+" represents that this indicator plays a positive role in promoting new quality productive force.

3.2. Research Methods

3.2.1. Entropy

Currently, there are multiple methods for measuring indicator weight, which aim to reduce subjective bias. The entropy weighting method assigns weights based on the characteristics of the data itself, which reduces the influence of subjective judgment and makes the results more objective. The specific steps for applying the entropy method are as follows:

$$X^* = \frac{X - \min(X)}{\max(X) - \min(X)} \tag{1}$$

$$P_{ij} = \frac{X_{ij}^*}{\sum_{i=1}^{n} X_{ij}^*} \tag{2}$$

$$e_j = -k \sum_{n=1}^{n} \left(P_{ij} \times lnP_{ij} \right) \tag{3}$$

$$w_j = \frac{1 - e_j}{\sum_{j=1}^{n} 1 - e_j} \tag{4}$$

$$Score = \sum_{j=1}^{n} \left(w_j \times X_{ij}^* \right) \tag{5}$$

X^* is the indicator after standardization.

3.2.2. Dagum Gini Coefficient

In order to investigate the spatial disparities and origins of the new quality productive force development level in China's five largest urban agglomerations, this study uses the Gini coefficient method to break down the differences into three categories: hypervariable density, intra-group differences, and inter-group differences. This approach effectively

addresses issues related to the sources of spatial differentiation and the overlap among subsamples. The specific steps are as follows:

$$G = \sum_{j=1}^{k}\sum_{h=1}^{k}\sum_{i=1}^{n_j}\sum_{r=1}^{n_k}\frac{|\ y_{ji} - y_{hr}\ |}{2n^2\overline{y}} \tag{6}$$

$$\overline{Y_h} \le \cdots \overline{Y_j} \le \cdots \le \overline{Y_k} \tag{7}$$

$$G_{jj} = \frac{\frac{1}{2\overline{Y_j}}\sum_{i=1}^{n_j}\sum_{r=1}^{n_j}|y_{ji} - y_{jr}|}{n_j^2} \tag{8}$$

$$G_w = \sum_{j=1}^{k} G_{jj}p_j s_j \tag{9}$$

$$G_{jh} = \sum_{i=1}^{n_j}\sum_{r=1}^{n_h}\frac{|y_{ji} - y_{hr}\ |}{n_j n_h(\overline{Y_j} + Y\overline{Y_h}\ )} \tag{10}$$

$$G_{nb} = \sum_{j=2}^{k}\sum_{h=1}^{j-1} G_{jh}\left(p_j s_h + p_h s_j\right)D_{jh} \tag{11}$$

$$G_t = \sum_{j=2}^{k}\sum_{h=1}^{j-1} G_{jh}\left(p_j s_h + p_h s_j\right)1 - \left(D_{jh}\right) \tag{12}$$

$$D_{jh} = \frac{d_{jh} - p_{jh}}{d_{jh} + p_{jh}} \tag{13}$$

$$d_{jh} = \int_0^{\infty} dF_j(y)\int_0^{y}(y - x)dF_h(x) \tag{14}$$

$$p_{jh} = \int_0^{\infty} dF_h(y)\int_0^{y}(y - x)dF_j(y) \tag{15}$$

In this context, the number of regions is k, samples is n, samples within each area are n_j and n_h, and the new quality productive force in each region is y. The above formula satisfies the following conditions: $G = G_w + G_{nb} + G_t$.

3.2.3. Kernel Density Estimation

In order to conduct a comprehensive analysis of the dynamic evolution trend of the development of new quality productive forces in China, this paper also implements the kernel density estimation method. Kernel density estimation is a non-parametric technique that effectively characterizes the distribution pattern of data across time [39]. The following are the precise steps:

$$f(x) = \frac{1}{Nh}\sum_{i=1}^{N} K\left(\frac{X_i - x}{h}\right) \tag{16}$$

$$K(x) = \frac{1}{\sqrt{2\pi}}e^{-\frac{x^2}{2}} \tag{17}$$

X_i refers to independent and evenly distributed observed values, $K(x)$ is the kernel function, h is the bandwidth, N is the total number of observed samples, and x is the mean of the observed values. Since it establishes how bias and variation are equalized in the density estimate, the bandwidth h selection is particularly significant. A smaller bandwidth leads to a sharper and more detailed kernel density curve, capturing finer variations in the

data, which improves the estimation accuracy. However, this can also increase noise and lead to overfitting. Conversely, a larger bandwidth smooths the curve, reducing sensitivity to minor fluctuations but potentially obscuring important features of the data distribution.

3.2.4. Markov Chain

The traditional Markov chain is a robust analytical tool for categorizing data into distinct types and analyzing their dynamic behaviors over time. For discrete time data, it calculates the probability and trend of each event, offering valuable insights into the transfer characteristics of different levels of new quality productive forces. Markov chains are denoted as $\{X(t), t \in T\}$, where T represents the set of time series, as shown in Formula (18), where $X(t)$ represents the state at time t, and P denotes the conditional probability. This property simplifies the analysis of complex temporal processes, enabling the identification of patterns and the prediction of long-term trends in the evolution of new quality productive forces. By focusing on the immediate past state, the Markov chain provides a straightforward yet effective framework for modeling and interpreting temporal transitions [30].

$$P\{X(t) = j|X(t-1) = i, X(t-2) = i_{t-2}, \cdots, X(0) = i_0\} = \{X(t) = j|X(t-1) = i\} \tag{18}$$

The transition probability from state i to state j is identified as P_{ij}. The state transition probability matrix is the matrix composed of all P_{ij}. A powerful instrument for examining the dynamics of state transitions is the state transition probability matrix. By dividing each type into approximately similar quantities based on predefined criteria, the matrix provides a framework for forecasting future states. This predictive capability makes it particularly useful for examining trends and patterns in systems like the evolution of new quality productive forces, where understanding transitions between states is essential. The transition probability can be expressed according to Equation (19):

$$P_{ij} = \frac{n_{ij}}{n_j} \tag{19}$$

The traditional $k \times k$ state transition probability matrix is transformed into k-independent $k \times k$ conditional transition matrices, each of which corresponds to a different spatial lag condition. This enhancement significantly improves the model's capacity to account for spatial heterogeneity, allowing it to capture the influence of neighboring regions' characteristics on the transition probabilities. By incorporating spatial dependencies, the spatial Markov chain provides a more nuanced understanding of the spatial dynamics at play, offering insights into how regional interactions influence the evolution of states over time.

The spatial Markov probability matrix is calculated by using the spatial geographical distance weight matrix:

$$W = \begin{cases} \frac{1}{d^2}, i \neq j \\ 0, i = j \end{cases} \tag{20}$$

The above research methods all have their key points. The Dagum Gini coefficient is particularly effective in decomposing differences, dividing them into intra-regional, inter-regional, and super-variable density components to highlight the sources of spatial disparity. Kernel density estimation excels in describing the global distribution of data, providing insights into overall patterns and forms. The Markov chain, on the one hand, focuses on analyzing transitions between different urban levels, compensating for kernel density estimation's inability to capture detailed dynamic changes within regions. Additionally, the spatial Markov chain addresses the traditional chain's limitation in reflecting spatial spillover effects by incorporating spatial factors into the analysis. This method retains

the advantage of traditional Markov chains in assessing state transitions over time while emphasizing the role of spatial interactions in the evolution of new quality productive forces. These research methods complement each other and comprehensively investigate the spatiotemporal evolution of the new quality productive forces in China's five urban agglomerations.

3.3. Data

Five significant Chinese urban agglomerations are the subject of this study, which utilizes the years 2013–2022 as the sample interval. Numerous publications, such as the China City Statistical Yearbook, China statistics Yearbook, China Science and Technology Statistical Yearbook, province statistical yearbook, and statistics bulletin of each city, provided the data needed for this investigation. The interpolation method was used to guarantee consistency and completeness in cases of missing data, allowing for a thorough and precise analysis of the study's goals.

4. Results

4.1. New Quality Productive Forces Development Level Measurement and Difference Decomposition

4.1.1. Level Measurement

The degree of new quality productive forces in China's five major metropolitan agglomerations was assessed using the entropy approach between 2013 and 2022. The calculation results are visually represented in Figure 1.

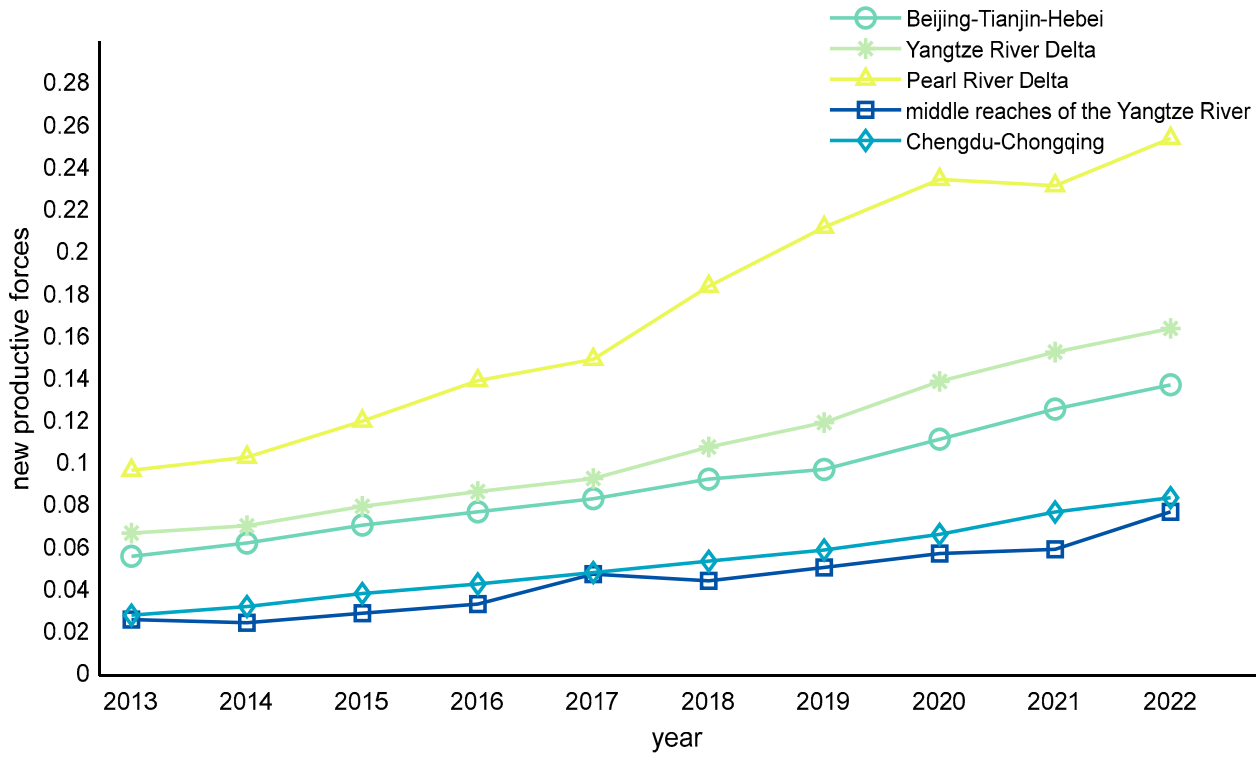


Figure 1. The trend of new quality productive forces in the five major urban agglomerations.

From Figure 1, several key observations can be made. The overall level of new quality productive forces remains relatively low, consistently below 0.3 throughout the study period. This indicates a substantial potential for improvement in these regions. Despite yearly fluctuations, there is a steady overall increase. During the research period, the policy papers on encouraging industrial restructuring and changing the strategy of economic

development were consistently strengthened, and they have all had a greater impact. However, certain years exhibited declines, which may result from abrupt alterations in the external environment.

The specific data can be found in Table 2, which provides a detailed breakdown of the new quality productive forces levels for each year and urban agglomeration. The BTH city cluster experienced steady growth throughout the study period, with a notable acceleration in growth from 2019 to 2022 compared to 2012–2019. As nationally important urban agglomerations, the BTH, the YRD, and the PRD have robust infrastructures and substantial cash reserves, which allowed them to sustain steady growth throughout the pandemic. Over the course of the inquiry, the YRD urban agglomeration likewise had steady expansion, with its growth rate in 2017 surpassing that of the previous examination period. Out of all the clusters, the PRD urban agglomeration grew the fastest, showing a clear rising trend in comparison to the other areas. However, a slight decline in 2021 was observed before resuming growth. The urban agglomerations in the mrYR maintained steady growth from 2013 to 2016, grew rapidly in 2017, and then slowed down in the subsequent years. The CC urban agglomeration increased steadily, and the speed was stable during the investigation period.

Table 2 also shows that the PRD urban agglomeration has been leading the other four urban agglomerations, followed by the YRD and BTH. The YRD began to outpace BTH in growth rate after 2017, causing the gap between them to widen. The mrYR and CC regions consistently lagged behind the other three agglomerations, with a small gap between them. The smallest gap occurred in 2017 (0.001); after which, CC slightly pulled ahead. However, by 2022, the gap between the two began to narrow again. In 2017, innovative technologies—such as the Internet of Things, big data, and artificial intelligence—became broadly accepted across a range of industries after progressively maturing from their early use. As the world's hubs for global trade and financial cooperation, the PRD and the YRD were able to make better use of the new technologies during this process and turn them into profitable outcomes.

Table 2. The level of new quality productive forces of the five major urban agglomerations.

	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Beijing–Tianjin–Hebei	0.055	0.061	0.070	0.076	0.082	0.092	0.096	0.111	0.125	0.137
Yangtze River Delta	0.066	0.070	0.079	0.086	0.092	0.107	0.119	0.138	0.152	0.163
Pearl River Delta	0.096	0.102	0.119	0.138	0.149	0.183	0.211	0.234	0.231	0.253
middle reaches of the Yangtze River	0.025	0.024	0.028	0.033	0.047	0.044	0.050	0.057	0.058	0.076
Chengdu–Chongqing	0.027	0.031	0.038	0.042	0.047	0.053	0.058	0.066	0.076	0.083

4.1.2. Level Difference Decomposition

The results of the Dagum Gini coefficient method analysis are presented in Table 3.

The data from 2013, 2018, and 2022 were used to make the graph in Figure 2. This shows how the new quality productive forces changed over time in the five largest urban areas. The graph clearly shows the trend of the new quality productive forces at the start, middle, and end of the study period. Vertically, each city cluster demonstrated significant progress during the study period, particularly the PRD, followed by BTH and YRD. Horizontally, the mrYR and CC have maintained a disadvantaged status, necessitating targeted policy funding adjustments, a deeper exploration of their unique attributes, and enhanced collaborative interactions with other city clusters to dismantle geographical barriers.

Table 3. The Gini coefficient and decomposition results of the new quality productive forces in the five major urban agglomerations.

		2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Intra-group	Beijing–Tianjin–Hebei	0.372	0.356	0.362	0.363	0.352	0.361	0.366	0.373	0.411	0.409
	Yangtze River Delta	0.402	0.378	0.371	0.362	0.359	0.353	0.349	0.359	0.381	0.385
	Pearl River Delta	0.523	0.526	0.509	0.489	0.475	0.484	0.479	0.472	0.465	0.472
	middle reaches of the Yangtze River	0.601	0.569	0.534	0.509	0.372	0.468	0.454	0.451	0.461	0.458
	Chengdu–Chongqing	0.395	0.361	0.338	0.311	0.480	0.282	0.275	0.269	0.291	0.299
Inter-group	BTH—YRD	0.416	0.398	0.401	0.407	0.401	0.413	0.424	0.423	0.433	0.435
	BTH—PRD	0.518	0.518	0.514	0.508	0.500	0.521	0.541	0.526	0.509	0.514
	BTH—mrYR	0.686	0.662	0.649	0.645	0.547	0.639	0.644	0.643	0.623	0.624
	BTH—CC	0.634	0.609	0.604	0.603	0.623	0.598	0.600	0.596	0.588	0.589
	YRD—PRD	0.492	0.490	0.479	0.461	0.452	0.457	0.459	0.453	0.454	0.458
	YRD—mrYR	0.639	0.611	0.586	0.564	0.443	0.537	0.527	0.536	0.537	0.534
	YRD—CC	0.556	0.521	0.505	0.481	0.539	0.454	0.441	0.448	0.474	0.472
	PRD—mrYR	0.640	0.621	0.594	0.569	0.457	0.535	0.518	0.518	0.518	0.522
	PRD—CC	0.542	0.524	0.504	0.479	0.541	0.447	0.429	0.427	0.442	0.447
	mrYR—CC	0.543	0.510	0.478	0.451	0.457	0.416	0.403	0.402	0.408	0.409
Contribution rate %	Intra-group	17.71	17.48	17.37	17.14	18.45	16.92	16.80	17.03	17.84	17.92
	Inter-group	49.35	48.29	48.67	50.05	43.43	51.36	52.36	52.51	48.96	48.39
	Super-variable density	32.94	34.23	33.96	32.81	38.12	31.72	30.84	30.46	33.20	33.69

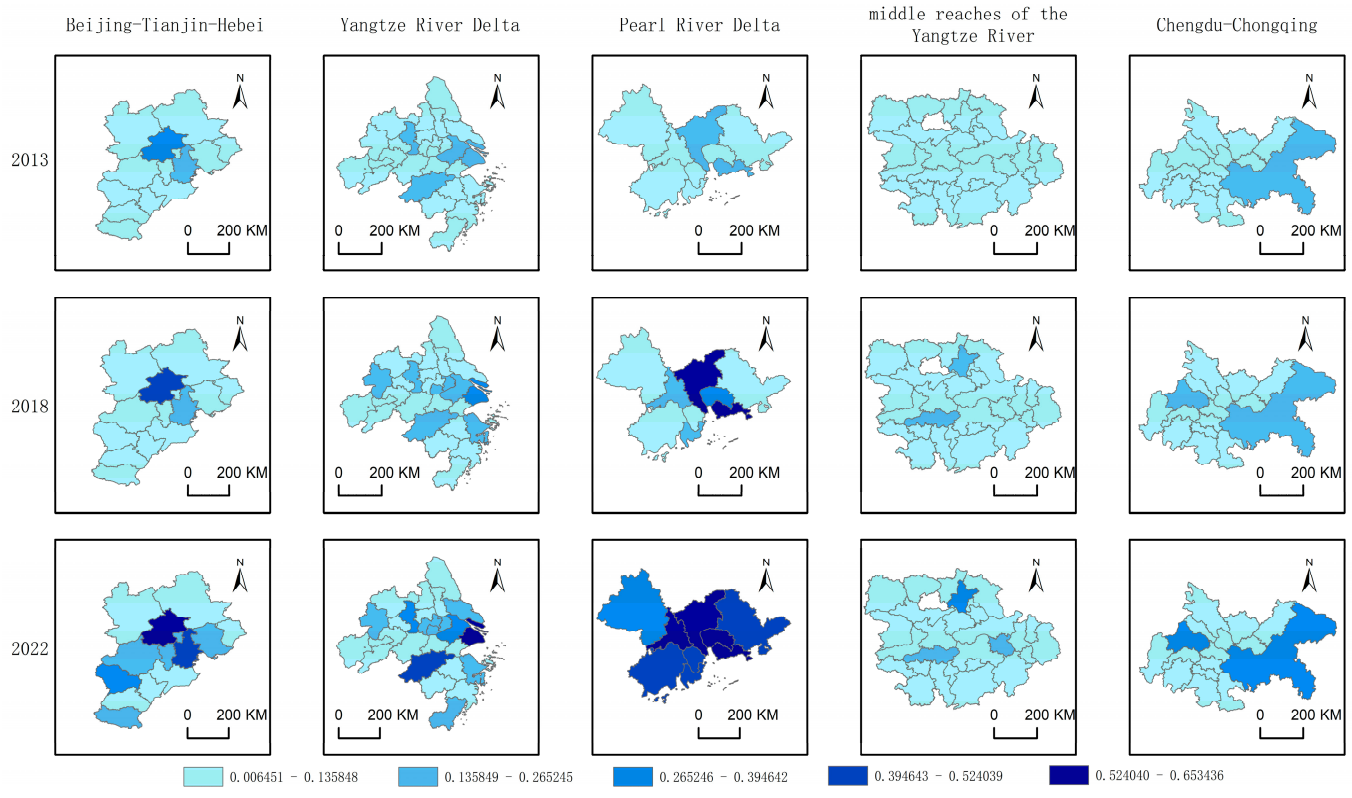


Figure 2. Spatial distribution of the new quality productive forces levels in the five major urban agglomerations.

From Figure 3, the BTH city cluster shows a relatively stable state, with the Gini coefficient ranging from 0.352 to 0.411; among which, the regional development difference was the smallest in 2017, the development gap was larger in 2021, and the Gini coefficient was larger in the two years after the observation period. The Gini coefficient of the YRD urban agglomeration was between 0.349 and 0.402, with the smallest regional development

difference in 2019 and the largest in 2013. Over time, the Gini coefficient displayed a U-shaped trend, initially declining and then rising. The PRD urban agglomeration's Gini coefficients fell between 0.465 and 0.526, with the biggest development gap occurring in 2014 and the smallest in 2021. Its development gap is progressively closing, as seen by the Gini coefficient's fluctuations and decline over time.

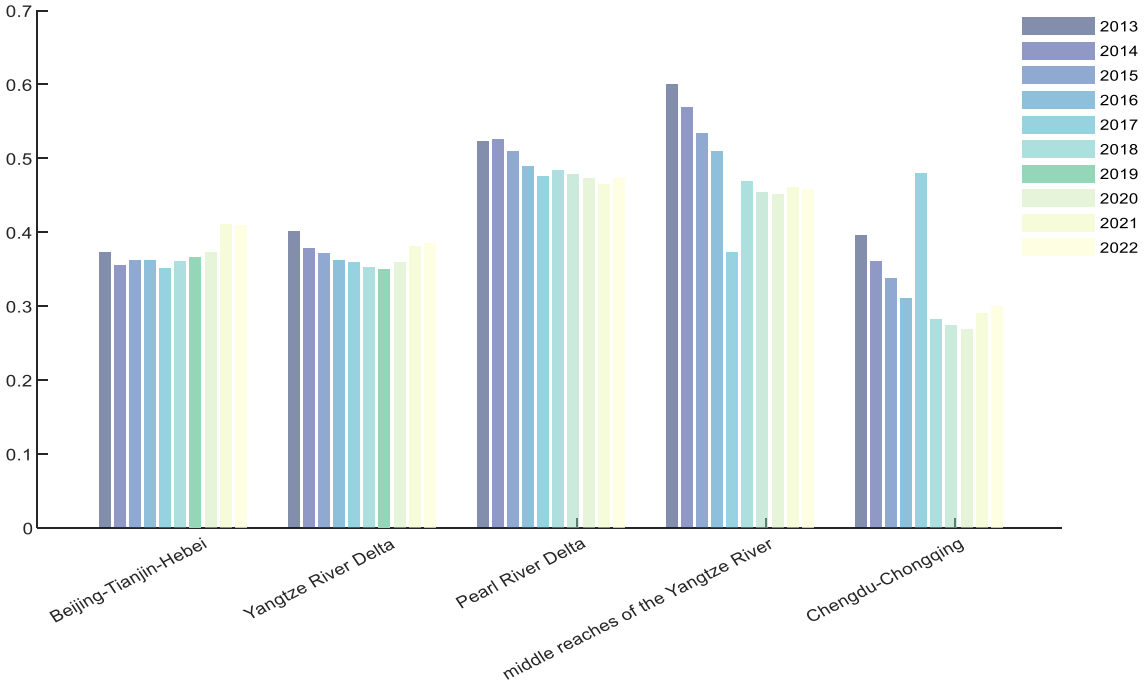


Figure 3. The trend of regional differences in the five major urban agglomerations.

Among the five urban agglomerations, the mrYR have the largest variation span of Gini coefficients, ranging from 0.372 to 0.601, with the smallest difference in 2017 and the largest gap in 2013. The Gini coefficient gradually decreased with the length of time, and the development difference within the urban agglomerations in the mrYR is narrowing year by year. The Gini coefficient of the CC urban agglomeration ranged from 0.269 to 0.48, with the largest gap in 2017 and the smallest gap in 2020. Except for 2017, the Gini coefficient of the CC urban agglomeration gradually decreased with the length of time, and the differences within urban agglomerations are also gradually narrowing.

The fact that there were not many disparities among some of the city clusters (BTH, YRD, and PRD) during the observation period indicates that they have evolved quite evenly and can support one another. The idea that "the first to get rich leads the latter to get richer" is perfectly reflected in the two city clusters (mrYR and CC) where intra-group differences have decreased. This suggests that some underdeveloped cities have advanced more quickly and have gradually caught up to the more developed ones.

Notably, in Figure 4, the contribution rate of the inter-group differences is the largest, with an average of 0.235 and an average of 49.3%. However, the role of super-variable density, ranking second, should not be underestimated. It has a significant average contribution rate of 0.158 and 33.2%. With an average contribution of 0.083 and 17.5%, intra-group differences make up the least significant, but still significant, contribution. Essentially, inter-group inequalities and the important role of super-variable density are the main factors influencing the disparities of the five major urban agglomerations.

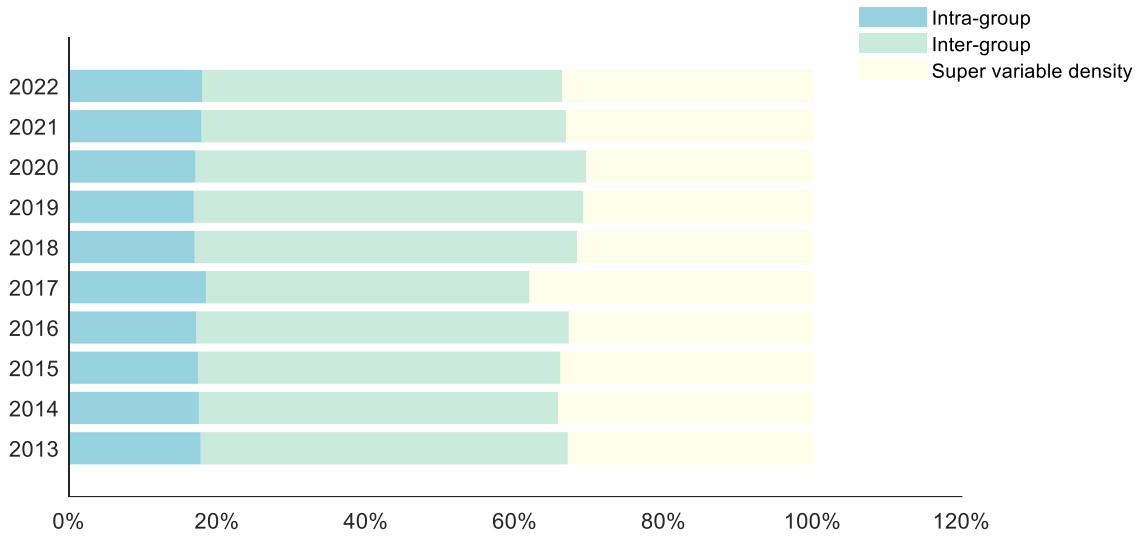


Figure 4. Sources of regional differences and their contribution rates in the five major urban agglomerations.

From Figure 5, the Gini coefficient between BTH and the YRD (0.398–0.435) was the smallest, indicating minimal differences, while disparities with the PRD (0.500–0.541), the mrYR (0.547–0.686), and CC (0.588–0.634) were more pronounced, though some gaps narrowed over time. The YRD and PRD showed stable differences (0.452–0.492), while gaps with the mrYR (0.443–0.639) and CC (0.441–0.556) gradually decreased, despite a temporary spike in 2017. Similarly, disparities between the PRD and the mrYR (0.457–0.640) and CC (0.427–0.542) exhibited a downward trend, particularly in the latter case, highlighting improved regional coordination. Overall, the YRD and PRD demonstrated higher levels of development with smaller disparities, while the mrYR and CC steadily reduced their gaps with other regions, reflecting progress in regional balance.

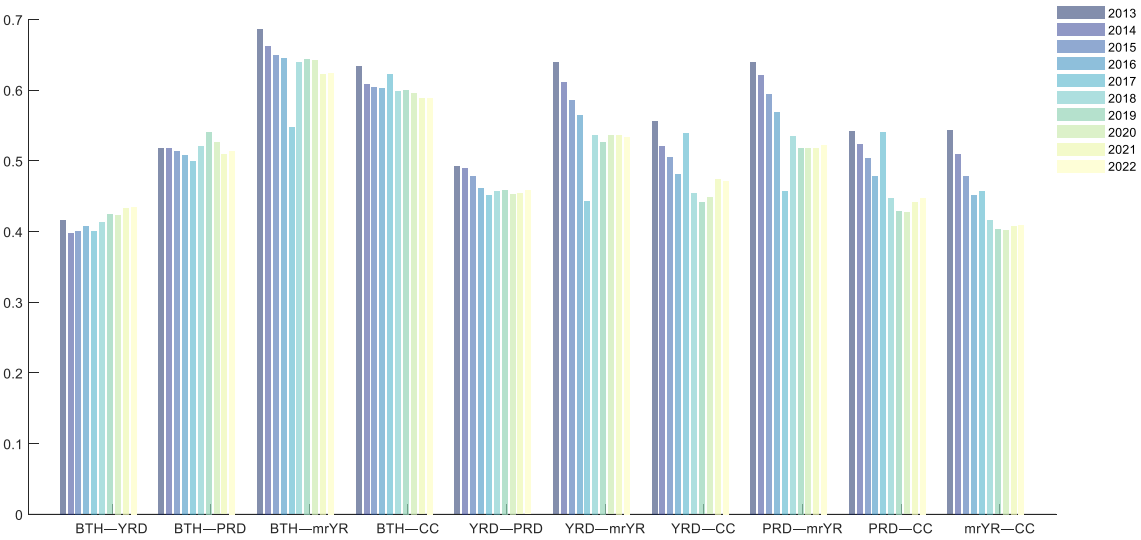


Figure 5. Trends of regional differences among the five major urban agglomerations.

The gap between the majority of city clusters is generally closing, as shown in Figure 4. This suggests that some city clusters that started out with less development have benefited from the growth of industries tailored to local conditions and ongoing policy adjustments, which has allowed them to develop more quickly later on. It is thought that eventually the commonwealth will be realized.

4.2. Spatiotemporal Dynamic Evolution

4.2.1. Kernel Density Estimation Curve Analysis

In Figure 6, the curves for BTH, YRD, and PRD show a distinct rightward shift, while the mrYR and CC exhibit a slight rightward trend, indicating overall growth in the productive forces. The declining height and narrowing width of the main peaks suggest enhanced regional development balance and a gradual narrowing of inter-regional differences, potentially leading to a more coordinated development pattern. These results are corroborated by the results of the Gini coefficient mentioned above. However, trailing phenomena highlight persistent disparities in productive forces among the regions. Additionally, the presence of lateral peaks in some curves reflects internal polarization within certain urban agglomerations. The polarization phenomenon may be attributed to the fact that certain cities within the urban agglomeration have adapted to the changing times and have developed technologies such as the Internet and artificial intelligence, while others have failed to achieve this level of development due to a lack of talent and capital, weak infrastructure, and gradually moving to the opposite ends of the spectrum.

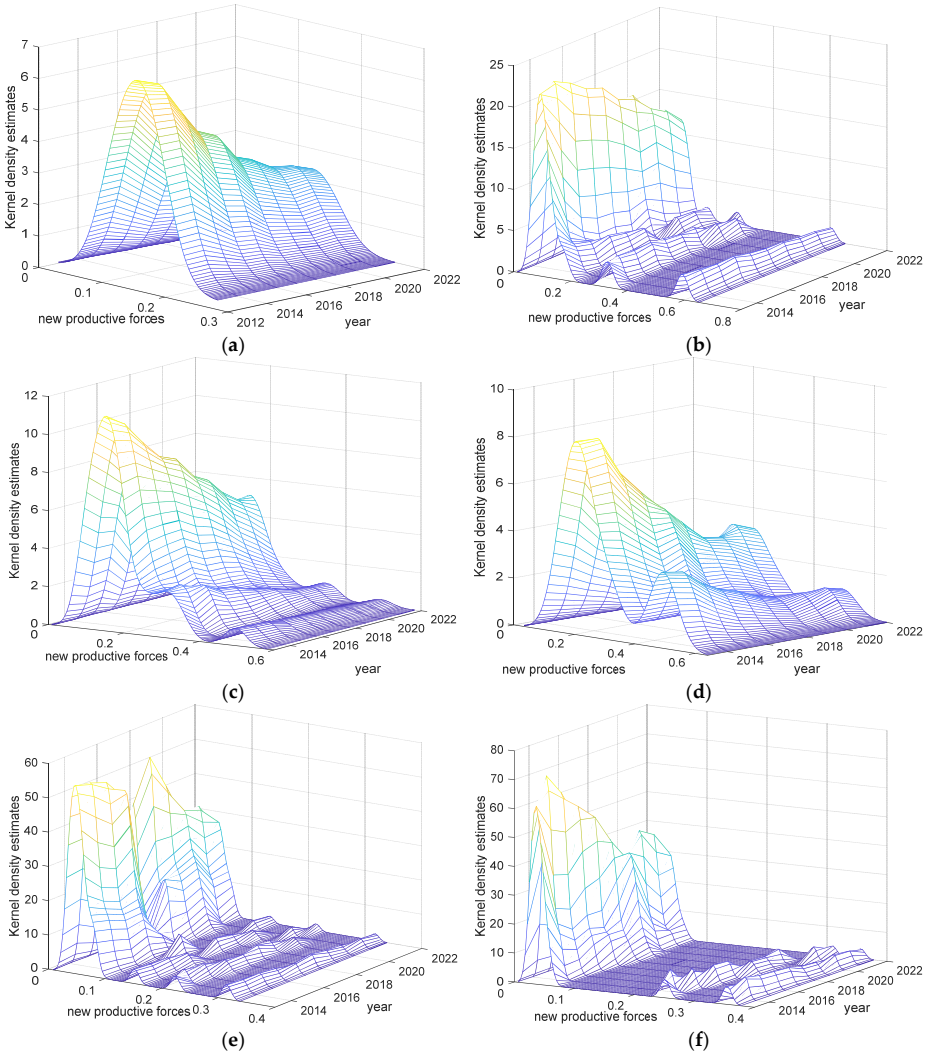


Figure 6. Kernel density estimation of the overall and individual five major urban agglomerations. (**a**) Five urban agglomerations overall. (**b**) Beijing–Tianjin–Hebei. (**c**) Yangtze River Delta. (**d**) Pearl River Delta. (**e**) Middle reaches of the Yangtze River. (**f**) Chengdu–Chongqing.

4.2.2. Traditional Markov Transition Probability Matrix Analysis

All cities were assigned to one of four states (k = 1, 2, 3, 4): low, middle-low, middle-high, or high. Transitions from a lower to a higher state were defined as "upward transitions", while the opposite were labeled as "downward transitions". State changes involving movement across multiple levels were classified as "jump transitions" [40]. Table 4 presents the traditional Markov transition probability matrix results, calculated with a one-year lag, reflecting the overall and individual dynamics of the urban agglomerations from 2013 to 2022.

Table 4. Markov transfer probability matrix for the five major urban agglomerations.

	$t/t+1$	1	2	3	4	n
Total	1	0.773	0.219	0.009	0	233
	2	0	0.791	0.209	0	211
	3	0	0.010	0.872	0.117	196
	4	0	0	0.010	0.990	197
Beijing–Tianjin–Hebei	1	0.758	0.242	0	0	33
	2	0	0.710	0.290	0	31
	3	0	0	0.852	0.148	27
	4	0	0	0	1	26
Yangtze River Delta	1	0.833	0.167	0	0	66
	2	0	0.774	0.226	0	62
	3	0	0	0.881	0.119	59
	4	0	0	0	1	56
Pearl River Delta	1	0.818	0.182	0	0	22
	2	0	0.714	0.286	0	21
	3	0	0.053	0.789	0.158	19
	4	0	0	0	1	19
middle reaches of the Yangtze River	1	0.686	0.286	0	0.029	70
	2	0	0.614	0.371	0.014	70
	3	0	0.035	0.737	0.228	57
	4	0	0.036	0.036	0.927	55
Chengdu–Chongqing	1	0.675	0.325	0	0	40
	2	0	0.650	0.350	0	40
	3	0	0	0.743	0.257	35
	4	0	0	0	1	29

For the BTH city cluster, 75.8% of the cities still maintained a low level of new quality productive forces after one year, and 24.2% of the cities moved upward to a middle-low level after one year, while 71% of the cities still maintained a middle-low level one year later, and 29% of the cities moved upward to a higher level. One year later, 85.2% of the cities maintained a middle-high level, and 14.8% of the cities moved upward to a high level. Cities with high levels still maintained high levels a year later.

The Markov transfer probability matrix about the five urban agglomerations is shown in Table 4.

According to the results in Table 4, (1) there is a general upward tendency among the five largest urban agglomerations, and all urban agglomerations have the probability of upward transfer at t + 1 moment. In particular, the PRD and the mrYR are slightly different, and their middle-high and high levels show signs of decline. (2) "Jump transitions" across multiple levels are rare, with most transfers occurring between adjacent levels. For example, in the mrYR, occasional "jump transitions" occur but are far less frequent than adjacent-level transitions. (3) The diagonal elements of the transition probability matrix are significantly larger than the non-diagonal elements. This indicates a pronounced tendency for cities to retain their current development levels, demonstrating stability in their progression.

4.2.3. Spatial Markov Transition Probability Matrix Analysis

The traditional Markov chain treats each city as an independent entity, disregarding the potential influence of neighboring regions [41]. To address this limitation, the spatial Markov chain method incorporates a spatial geographical weight matrix, enabling an analysis of how the neighborhood background affects the level transfer probabilities of a city's new quality productive forces. It supplies a more comprehensive understanding of the spatial interdependencies and interactions that influence regional development dynamics.

The spatial Markov transfer probability matrix type for China's five largest metropolitan agglomerations from 2013 to 2022 is displayed in Table 5. When the level of the neighborhood is higher than its level, it has a significant promotion effect on positive transfer. For example, suppose a city with a high level is its neighborhood. In that case, the probability of the city with a low level is increased, $P_{23|4}(0.412) > P_{23}(0.209)$, which indicates that the neighborhood with a high level has a driving effect on the growth of new quality productive forces in this region. Having a relatively low-level city as a neighborhood will "drag" down the high-level city, for example, $P_{43|3}(0.030) > P_{43}(0.010)$.

Table 5. The probability matrix of the overall spatial Markov chain transfer of the five major urban agglomerations.

The Type of Neighborhood	*t*/*t* + 1	1	2	3	4	*n*
1	1	0.968	0.032	0	0	31
	2	0	0	0	0	0
	3	0	0	0.750	0.250	4
	4	0	0	0	1	9
2	1	0.831	0.153	0.016	0	124
	2	0	0.960	0.040	0	25
	3	0	0	0.750	0.250	8
	4	0	0	0	1	16
3	1	0.588	0.412	0	0	68
	2	0	0.809	0.191	0	152
	3	0	0.019	0.932	0.05	104
	4	0	0	0.030	0.970	66
4	1	0.700	0.300	0	0	10
	2	0	0.588	0.412	0	34
	3	0	0	0.812	0.188	80
	4	0	0	0	1	106

Table 6 presents the Markov transfer probability matrix for urban spaces within the BTH region, revealing the influence of neighborhood contexts on the transition dynamics of new quality productive forces. When two low-level cities are adjacent, the probability of upward transfer decreases compared to the traditional Markov scenario (e.g., for low-level neighborhood types, $P_{12|1}(0) < P_{12}(0.242)$). Conversely, a low-level city surrounded by higher-level neighborhoods exhibits an increased probability of upward transfer (e.g., for high-level neighborhood types, $P_{23|4}(0.380) > P_{23}(0.290)$). These results highlight the critical role of neighborhood contexts in facilitating or hindering upward transitions in new quality productive forces levels.

Table 6. Markov transfer probability matrix in the Beijing–Tianjin–Hebei region.

The Type of Neighborhood	*t*/*t* + 1	1	2	3	4	*n*
1	1	1	0	0	0	1
	2	0	0	0	0	0
	3	0	0	0	0	0
	4	0	0	0	0	0
2	1	0.800	0.200	0	0	5
	2	0	1	0	0	2
	3	0	0	0.670	0.330	3
	4	0	0	0	1	1
3	1	0.670	0.330	0	0	12
	2	0	0.875	0.125	0	8
	3	0	0	1	0	3
	4	0	0	0	1	13
4	1	0.800	0.200	0	0	15
	2	0	0.620	0.380	0	21
	3	0	0	0.860	0.140	21
	4	0	0	0	1	12

For a city in the YRD (Due to the layout limitations, only the spatial Markov transfer probability matrix of the Beijing–Tianjin–Hebei urban agglomeration is displayed.), if its neighborhood level is lower than its own, the probability of its upward transfer will be "dragged down"; if the neighborhood level is higher than its own, the probability of improvement will increase. For the inner cities of the PRD, when the neighborhood is at a higher level, it will help the lower-level areas to move upward and will restrain the probability of the higher-level areas moving upward. For the inner cities in the mrYR, some lower-level cities have the higher level of the neighborhood, which can make them "jump transitions". Neighborhoods that are above their level can push lower-level areas upward. For the CC city cluster, when the neighboring cities are at a high level, it will move upward.

When the neighborhood's background conditions are taken into account, the migration trend of the new quality productive forces of each city within the urban agglomeration exhibits notable changes. This strongly supports the idea that the change in the new quality productive forces has a spatial permeability or spillover effect. The spatial lag effect must be tested for statistical significance using a hypothesis test. Assuming that the neighborhood's state type has no bearing on the level transfer of a city's new quality productive forces, the test formula is as follows:

$$Q_b = -2\log\left\{\prod_{l=1}^{k}\prod_{i=1}^{k}\prod_{j=1}^{k}\left[\frac{m_{ij}}{m_{ij}(S)}\right]^{n_{ij}(S)}\right\} \tag{21}$$

The degree of freedom for those unadjusted is 36. At a confidence level of $\alpha = 0.005$, where $p = 0$, the hypothesis that the type of transfer of the level of new quality productive forces in the city is spatially independent is rejected.

4.3. Level Forecast

The long-term development tendency of the new quality productive forces level among the five major urban agglomerations is forecasted and shown in Table 7. Using the traditional Markov method, we iterated k times ($k \to \infty$) to solve the limit probability matrix. The results show that, over time, the level in most cities reaches a high level, with some cities at a middle-high level. This suggests a general pattern of continual progress as the new quality productive forces gradually move from lower to higher levels. When considering the influence of the neighborhood background, the evolution trend becomes

more dynamic. Over the long term, regions with low new quality productive forces (types 1 and 2) will gradually develop upward toward a high level, reflecting the "club convergence" effect. The "Matthew effect" phenomenon will gradually diminish, and the regions will converge to a higher level. For regions with initially higher productive forces (type 3), they may both increase and decrease, depending on the neighboring regions. However, despite this variability, most regions still reach a high level in the end. The new quality productive forces level will ultimately reach a high level, influenced by neighboring regions with higher productive forces.

Table 7. Prediction of the trends within the five major urban agglomerations.

	Status Type		**1**	**2**	**3**	**4**
Traditional Markov transfer	Initial state		0.570	0.130	0.150	0.150
	Homeostasis		0	0.00	0.080	0.920
Space Markov transfer	Homeostasis	1	0	0	0	1
		2	0	0	0	1
		3	0	0.040	0.370	0.590
		4	0	0	0	1

Overall, the new quality productive force in Chinese cities shows a positive prospect, and it will gradually improve over time. Cities located adjacent to areas with higher levels of new quality productive forces tend to experience an upward shift in their own levels. Cities near regions with lower levels of productive forces also show an improvement, although at a slower pace. This interaction highlights the general trend of progress, with regions gradually catching up and improving over time, reflecting the interconnectedness and dynamic influence of neighboring areas.

Low costs and their own resource endowments have allowed less developed cities to gradually develop industrial sophistication, a knowledge-skilled workforce, and environmental friendliness while focusing on economic development. By leveraging cutting-edge information technology and an efficient logistics system, the new quality productive forces will transcend geographical boundaries and achieve the most efficient distribution of production resources on a global scale. Capital, technology, talent, and other resources can be allocated more precisely and swiftly to regions and enterprises with the highest potential based on market demand, enhancing resource utilization efficiency, lowering production costs, fostering closer coordination of global industrial and supply chains, promoting deeper economic integration among nations, and establishing a mutually beneficial and advantageous development scenario.

5. Discussion

The results of this paper align with Wang's (2024) [8] findings that the eastern regions of China exhibit higher levels of new quality productive forces. The total disparity primarily arises from inter-regional variations, while regionally, the emergence of enhanced productivity has positive spatial clustering traits. This finding aligns with the results of Fu [42] and further indicates the necessity to improve equitable growth among groups. This supports the idea that the level of new quality productive forces is closely tied to economic development. In this paper, coastal urban agglomerations benefit from stronger economic growth, technological innovation, and extensive policy support, along with a concentration of innovative enterprises and skilled human resources. In contrast, the inland agglomerations are lagging behind the eastern regions in economic development, resulting in weaker levels. Therefore, targeted regional support measures are necessary to ensure that the eastern regions can continue to lead and help stimulate development in other areas [12].

Unlike the traditional Markov model, the spatial Markov transfer probability matrix reveals notable changes in the transfer probabilities based on the neighborhood context, reflecting the influence of the surrounding regions. Cities located near regions with high levels of new quality productive forces experience an increased probability of upward transfer, which fosters growth. This spatial dimension helps explain the "club convergence" phenomenon: when cities are adjacent to regions with low productive forces, the likelihood of an upward transfer rises, while the downward transfer decreases. This dynamic promotes the growth of high-level cities in those areas, further confirming the "club convergence" driven by spatial spillover effects. Similarly Shi's (2024) [10] use of the spatial convergence model led to similar conclusions that there is absolute club convergence in the region and that most of the regional NQP levels exhibit accelerated rates of convergence in response to perturbations in the influencing factors.

Strategies greatly support the coordinated growth of the economy in the context of China's regional economic development, which, in turn, shapes a particular geographic pattern. Therefore, strategic planning at the national level plays the role of the core driving force and profoundly affects the overall trend and pattern of the regional economy. According to scholar Xia's (2023) [43] classification of the modernization of China's economic system, it has been in the stage of urban network economy since 2013, with the characteristics of multi-level and multi-faceted coordinated development based on urban networks. The BTH, YRD, and PRD city clusters are the eastern coastal area, and its policy tilt can be traced back to the "two big picture" strategic concept in the 1980s and then the rapid economic development of the eastern coastal area, playing a good leader role [44]. Therefore, the level of new quality productive forces of urban agglomerations located in coastal areas is higher than that in inland areas.

On the one hand, the development foundation of the three leading urban agglomerations is better because of earlier policies. On the other hand, economically developed areas are more likely to cause the accumulation of talents and resources, forming a siphon effect and reaching more cooperation in finance, science and technology, energy, and other aspects. However, in the era of the knowledge economy in which all elements are highly mobile, geographical barriers are gradually broken, and various subjects are more and more inclined to cross geographical boundaries and seek interactive learning across regions to promote innovation [45]. The new quality productive forces in different regions will gradually increase, and with the reduction in transportation costs between regions and the improvement of Internet efficiency, the difference between regions will gradually decrease.

There are also a few shortcomings and limitations. The selected data span from 2013 to 2022 due to availability, potentially resulting in omissions in the historical development of neoplastic productivity; additionally, the data are confined to the five major urban agglomerations in China, which may not provide insights for certain regions. Furthermore, the selected method may have certain limitations, as the kernel density estimation results are highly sensitive to the bandwidth parameter, and varying bandwidths can result in significant discrepancies in the density curves, thereby influencing the interpretation of the dynamic distribution of new quality productive forces. Markov chain modeling requires partitioning the state space; however, the manner of division may be subjective, and varying division strategies can influence the outcomes. In my forthcoming research, we will maintain focus on the advancement of new quality productive forces, broaden the study's scope, further combine it with green innovation and industrial structures, and study its specific impact mechanism and endeavor to employ alternative measurement methodologies for analysis.

6. Conclusions and Policy Implications

6.1. Conclusions

(1) From a spatial and temporal perspective, the overall new quality productive forces in Chinese cities demonstrate a steady upward trend, though differences exist among urban agglomerations. The line charts, bar charts, and core density charts show that, while the new quality productive forces are increasing, the overall level remains relatively low, with significant room for improvement. The growth rate has accelerated in recent years. Spatially, there are noticeable differences in the new quality productive forces across urban agglomerations, primarily driven by inter-group disparities and super-variable density. The ranking of urban agglomerations is as follows: Pearl River Delta > Yangtze River Delta > Beijing–Tianjin–Hebei > Chengdu–Chongqing > middle reaches of the Yangtze River. This distribution pattern is similar to that of new quality productive forces in promoting high-quality agricultural development [12]. However, these differences are expected to decrease over time.

(2) The new quality productive forces in Chinese cities are stable when observed from the standpoint of temporal and geographical evolution, and the levels of neighboring regions obviously have an impact. The traditional Markov transition probability matrix reveals that the new quality productive forces are generally stable and show a steady growing trend. At this point, a "jump transition" is difficult to perform, because most level transfers take place inside adjacent levels. The spatial Markov transition probability matrix further reveals that a geographical spillover effect significantly alters the horizontal transfer probability of new quality productive forces, which aligns with Xu's (2024) [46] research findings. A basis for comprehending the "club convergence" phenomenon, whereby places with comparable levels of productive forces tend to converge over time as a result of the impact of nearby areas, is provided by this spatial dynamic.

(3) From the standpoint of long-term development and evolution patterns, Chinese cities' new quality productive forces exhibit a consistent trend toward high concentrations. They gradually increase over time and finally show a trend of high-value concentrations. The effects of varied neighbor backgrounds vary. Cities with low, middle-low, and middle-high levels of new quality productive forces tend to converge toward a high stable state over time. In contrast, for cities with an initial middle-high level of productive forces, the evolution of their new quality productive forces becomes more diverse, reflecting greater variability. However, despite this diversity, most of these cities still tend to reach a high level in the long run. This pattern highlights the significant role of neighboring regions in shaping the trajectory of a city's productive forces, with the overall trend being toward improvement and convergence to higher levels.

6.2. Policy Implications

(1) Promote the development of low-level cities and reduce the differences in new quality productive forces in urban agglomerations. The research shows that there are trailing and polarization phenomena in the five major urban agglomerations, which reflects the unbalanced development of urban agglomerations, and the coordination mechanism still needs to be improved, which has not been able to play a synergistic effect on and promotion role of urban cities. To rectify the uneven spatial distribution of regional economic development and expedite the establishment of new integrated urban agglomerations, it is imperative to optimize functional division and industrial configuration by promoting complementary relationships between peripheral and core cities, thereby mitigating competition, and to enhance infrastructure, particularly in transportation, logistics, and digital connectivity, to facilitate resource flow.

(2) Improve the regional development mechanism and reduce the differences in the new quality productive forces among urban agglomerations. Therefore, we should effectively utilize the guiding role of national development planning to establish and optimize the new mechanism of regional coordinated development. To enhance its development, a multi-level governance system should be established, wherein national policies offer guidance and regional governments formulate practical strategies accompanied by performance assessments. Enhance labor quality by broadening access to education and technical training, easing transfers from low-end to high-end industries, and promoting green industrial transformation by favoring contemporary, sustainable industries aligned with local resources and strengths.

(3) Fully leverage spatial spillover effects and promote coordinated development. According to the research, there is a clear geographical spillover effect in new quality productive forces, and the nearby areas have a big impact on the local areas. It is crucial to remove administrative and spatial barriers by creating cross-regional networks for infrastructure, public services, and environmental governance. Optimize the regulations to enhance resource flow efficiency. The cooperative framework focused on urban agglomeration serves as the main platform for promoting collaboration and interaction among regions, thereby optimizing spatial synergies to improve connectivity and overall developmental effectiveness.

(4) Innovative production relations must be taken into account in order to produce new quality productive forces. While production relations react to the progress of productive forces, productive forces also have an impact on production relations. Throughout history, shifts in the social division of labor, organizational hierarchy, and resource allocation have all coincided with shifts in the productive forces. New technologies, industries, models, and driving factors must be implemented in order to progress productive forces and promote the development of new quality productive forces. Establishing a new type of production relations that successfully interacts with these new factors is imperative [47]. Because production relations and productive forces move in ways that are at odds with each other, a new type of production relations needs to be set up as soon as possible to keep up with the progress of productive forces [48]. Fostering global economic growth and improving mutually beneficial cooperation among different regions require this method.

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