ISSN: 2710-0170

Comprehensive Evaluation and Spatial Differentiation of New Productive Forces Across Provinces in China

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Abstract

This article reviews and constructs a theoretical analysis framework for new-quality productive forces, elucidating their inherent connotations from the perspectives of laborers, production factors, and technological innovation. By utilizing panel data from 30 provinces in China spanning from 2012 to 2022, this study employs the entropy method for comprehensive measurement and combines methods such as the Dagum Gini coefficient to empirically analyze the current development status of new-quality productive forces across provinces. The results indicate that the overall new-quality productive forces in China's provinces are showing a positive upward trend, yet regional development disparities are prominent, with the eastern region leading and the western region lagging behind. Additionally, none of the four major regions exhibit a convergence trend, and the development gap between regions continues to widen. Based on this, this article suggests that policymaking should be grounded in the regional differentiation characteristics of new-quality productive forces, strengthen regional innovation collaboration, implement tailored green energy development plans, fully leverage the empowering role of new-quality productive forces, and provide decision-making references for China's green energy transition and high-quality economic development.

Keywords

New Quality Productivity, Entropy method, Dagum Gini coefficient method Green energy development.

1. Introduction

With the profound transformation of the global economic landscape and the accelerated advancement of the technological revolution, the connotation and denotation of productivity are continuously expanding. As a key force enabling high-quality economic development and green energy transition, new-quality productivity has gradually become a research hotspot of common concern in both academic circles and policy-making circles. New-quality productivity facilitates a qualitative leap in productivity through technological innovation, optimized allocation of factors, and upgrading of industrial structure, injecting new impetus into the low-carbon transformation of energy and high-quality growth of the economy. However, the current imbalance in regional economic development in China has led to significant differences in the development level of new-quality productivity across different regions, which not only affects regional coordinated development but also constrains the overall high-quality development of the national economy.

In recent years, China has made certain progress in both theoretical research and practical exploration of new-quality productive forces. Scholars have explored the connotation of new-quality productive forces from multiple dimensions, including labor, production factors, and technological innovation (Wang Jue, Wang Rongji, 2024), arguing that it is the core driving force

ISSN: 2710-0170

for high-quality economic development [1]. However, existing research mostly focuses on theoretical explanations, and there is still a lack of systematic empirical analysis on the quantitative measurement of the development level of new-quality productive forces, as well as regional disparities and convergence characteristics. Against the backdrop of prominent regional development heterogeneity, scientifically measuring the level of new-quality productive forces at the provincial level, identifying the evolution laws of regional disparities, and formulating differentiated policies that are suitable for the transition to green energy have become urgent practical issues to address.

To this end, this paper constructs a theoretical analysis framework for new-quality productive forces, selects panel data from 30 provinces in China from 2012 to 2022, conducts comprehensive measurement using the entropy method, and empirically analyzes the spatiotemporal evolution and sources of differences in new-quality productive forces across provinces by combining methods such as the Dagum Gini coefficient. The study not only depicts the overall evolution trend of new-quality productive forces nationwide but also delves into the development gaps and convergence characteristics among the four major regions. The empirical results show that the overall new-quality productive forces in China's provinces are showing a positive upward trend, but regional development disparities are prominent, with the eastern region leading and the western region lagging in terms of development level. Meanwhile, none of the four major regions exhibits a convergence trend, and the development gap between regions continues to widen. Based on the above findings, this paper suggests that policymakers should leverage the regional differentiation characteristics of new-quality productive forces, strengthen regional innovation collaboration, implement tailored green energy development plans, fully leverage the empowering role of new-quality productive forces, and provide decision-making references for China's green energy transition and high-quality economic development.

2. Theoretical Interpretation of New Productive Forces

Marx and Engels (2003) pointed out that productive forces are the objective material forces that people utilize and transform nature in labor production to meet human needs [2]. Productive forces are mainly composed of laborers, labor objects, and means of production. The combination of laborers' physical and mental abilities with labor objects and means of production is the prerequisite for the actualization of productive forces.

2.1. New productive forces and laborers

The requirements of new productive forces for the labor dimension are reflected in three levels: ideological concepts, professional skills, and production efficiency. At the ideological concept level, the focus is on fully stimulating the innovative initiative of social subjects, cultivating a sense of responsibility for innovation, and building a favorable environment for innovative development. At the professional skill level, efforts are made to cultivate the technical literacy of workers that adapts to the needs of industrial transformation, accumulating human capital that supports high-quality development. At the production efficiency level, continuous improvement in labor productivity is pursued to resolve practical contradictions in the process of economic development and facilitate industrial iteration and upgrading.

2.2. New productive forces labor object

From the perspective of labor objects, the practical orientation of new-quality productive forces primarily encompasses two major fields: the cultivation of new-quality industries and ecological environment governance. At the industrial level, a new round of international industrial transfer poses external shocks and internal challenges to China's industrial structure, urgently requiring the construction of a modern industrial system with international

ISSN: 2710-0170

competitiveness through industrial collaboration and deep integration. At the ecological level, the resource and environmental constraints caused by the traditional extensive growth model are increasingly prominent. New-quality productive forces inherently embody the value orientation of ecological civilization, requiring the minimization of ecological loss in the process of industrial transfer, and promoting the coordinated evolution of industrial upgrading and ecological circulation with digital transformation as the technical support.

2.3. New productive forces and means of production

From the perspective of labor objects, new-quality productive forces are embodied in both new-quality industries and ecological environment. Facing the challenges posed by international industrial transfer, China should promote coordinated integration of industries and build a modern industrial system. At the same time, it should abandon the development model that sacrifices the environment, guide industrial transfer with ecological awareness, and leverage digitalization to achieve industrial upgrading and ecological circulation.

3. Calculation of the Level of New Productive Forces

3.1. Construction of evaluation framework

Based on the definition of the connotation of new-new productive forces, and referring to the approach of Wang Jue and Wang Rongji (2024), a comprehensive evaluation framework for new-new productive forces is constructed from three dimensions: laborers, labor objects, and means of production.

3.1.1. Worker dimension

Seven indicators are selected to measure laborers. The average years of education per capita are used to reflect the average education level per capita. Referring to the research method of Fu Linghui (2010), the education level of the labor force is divided into five levels, and the vector angle method is used to measure the structure of laborers' human capital [3]. The proportion of college students to the total population is used to reflect the structure of students in higher education institutions. GDP per capita is used to measure the relationship between economic output and population. The average wage of on-the-job workers is used to represent per capita wage. The proportion of employees in the tertiary industry to the total employment is used to reflect the proportion of employees in the tertiary industry. The China Regional Innovation and Entrepreneurship Index (IRIEC) compiled by the Enterprise Big Data Research Center of Peking University is adopted to measure entrepreneurial activity. This index can multi-dimensionally, objectively, and in real-time show the vitality of innovation and entrepreneurship in various regions of China.

3.1.2. Labor object dimension

It covers 6 indicators. Referring to the approach of Lv Yanwei and Sun Hui (2014), the proportion of emerging strategic industries is measured by the ratio of the added value of emerging strategic industries to GDP; the number of robots is determined by the ratio of the number of robots to the total population; forest coverage is the proportion of forest area to total land area; environmental protection efforts are reflected by the proportion of environmental protection expenditure to government public financial expenditure; pollutant emissions are measured by the ratio of sulfur dioxide emissions, wastewater emissions, and general industrial solid waste generation to GDP; industrial waste treatment is also included in the consideration of labor objects [4].

3.1.3. Production material dimension:

It includes 8 tertiary indicators. Traditional infrastructure is measured by highway mileage and railway mileage; digital infrastructure is reflected by fiber length and per capita number of

ISSN: 2710-0170

Internet broadband access ports; overall energy consumption is measured by the ratio of energy consumption to GDP; renewable energy consumption is the ratio of renewable energy power consumption to total electricity consumption; per capita patent quantity is the ratio of patent grants to total population; R&D investment is measured by the ratio of R&D expenditure to GDP; referring to the research of Zhao Tao et al. (2020), the digital economy is measured from two dimensions: Internet development and digital financial inclusion; enterprise digitization is measured by using keywords appearing in the annual reports of listed companies, locating enterprises at the provincial level, and calculating the sum and average of word frequency [5].

3.2. Measurement method

3.2.1. Entropy method

The entropy method is an objective weighting approach based on information entropy theory, widely applied in the calculation of weights for comprehensive evaluation index systems. Its fundamental principle is to measure the information content implied by the degree of data dispersion by calculating the information entropy of each indicator, and then determine the contribution of that indicator to the differentiation of evaluation objects. A smaller information entropy indicates a higher degree of dispersion in the indicator data, a greater amount of effective information carried, and a correspondingly higher weight in the evaluation system; conversely, the weight is lower. Before assigning weights to indicators, it is necessary to preprocess the original indicator data. Referring to the research by Wang Fuxi et al. (2020), this paper adopts the range normalization method to process the indicator data [6].

For positive indicators:

$$x_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)} \tag{1}$$

For reverse indicators:

$$x_{ij} = \frac{\max(x_j) - x_{ij}}{\max(x_j) - \min(x_j)} \tag{2}$$

$$\omega_{ij} = \frac{X_{ij}}{\sum_{i=1}^{m} X_{ij}} \tag{3}$$

Calculate the information entropy of the indicator e_j ,where m is the number of years of evaluation:

$$e_j = -\frac{1}{\ln m} \sum_{i=1}^{m} \omega_{ij} \ln \omega_{ij} \tag{4}$$

Calculate the redundancy of information entropyρ_j:

$$\rho_j = 1 - e_j \tag{5}$$

and the required indicator weights λ_j:

$$\lambda_j = \frac{\rho_j}{\sum_{j=1}^{n} \rho_j} \tag{6}$$

Calculate the level of new quality productive forces based on the proportion of indicators $\omega_{ij}$and the corresponding weightsλ_j:

$$U_i = \sum_{j=1}^{m} \lambda_j \tag{7}$$

3.2.2. Dagum Gini coefficient and its decomposition method

The Dagum Gini coefficient and decomposition method is a method capable of measuring regional disparities. The Gini coefficient can be decomposed into three parts: within-region disparities, between-region disparities, and super-variability density (Zhu Di, Ye Linxiang, 2022)In this paper, the above - mentioned method is used to calculate and decompose the Gini coefficients of various regions in China respectively [7]. The overall Gini coefficient is defined

ISSN: 2710-0170

as shown in Equation (8), where k represents the number of regional divisions, n represents the number ofprovinces, $Y_{ji}(Y_{hr})$ epresents the level of new quality productive forces of province i(r) in regionj(h) , $n_j(n_h)$ represents the number of provinces in region j(h), and $\overline{Y}$ represents the average level of new quality productive forces of all provinces.

$$G = \frac{\sum_{j=1}^{k}\sum_{h=1}^{k}\sum_{i=1}^{n_j}\sum_{r=1}^{n_h}|Y_{ji}-Y_{hr}|}{2n^2\overline{Y}} \tag{8}$$

$$G_{jj} = \frac{\frac{1}{2\overline{Y}}\sum_{i=1}^{n_j}\sum_{r=1}^{n_j}|Y_{ji}-Y_{jr}|}{n_j^2} \tag{9}$$

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

Equation (9) and Equation (10) represent the Gini G_{jj} coefficient of region j and the Gini G_{jh} coefficient between region j and region h respectively. Among them, $\overline{Y}_j(\overline{Y_h})$ it represents the average value of the new quality productive forces in region j(h).

The definitions of the following variables are:

$$P_j = \frac{n_j}{n} \tag{11}$$

$$S_j = \frac{n_j\overline{Y_J}}{n\overline{Y}} \tag{12}$$

$$M_{jh} = \int_0^{\infty} dF_j(Y)\int_0^{Y}(Y-x)dF_h(x) \tag{13}$$

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

$$D_{jh} = \frac{M_{jh}-N_{jh}}{M_{jh}+N_{jh}} \tag{15}$$

D_{jh} represents the relative impact of new quality productive forces between region j and region h, and M_{jh} represents the difference in the level of new quality productive forces between regions, that is, in regions j and h , the mathematical expectation of the sum of all sample values where$Y_{ji} - Y_{hr} > 0$ .N_{jh} represents the trans - var first - order density distribution function. The within - region disparity G_w, the between - region disparityG_{nb}, and the trans - var component G_t are as follows:

$$G_{ww} = \sum_{j=1}^{k} G_{jj}P_jS_j \tag{16}$$

$$G_{nb} = \sum_{j=2}^{k}\sum_{h=1}^{j-1} G_{jh}D_{jh}\left(P_jS_h + P_hS_j\right) \tag{17}$$

$$G_t = \sum_{j=2}^{k}\sum_{h=1}^{j-1} G_{jh}\left(P_jS_h + P_hS_j\right)\left(1 - D_{jh}\right) \tag{18}$$

3.3. Data and Explanation

The new quality productive forces indicator system consists of 27 sub - indicators. The sample scope is the panel data of 30 provinces in China (excluding Hong Kong, Macau, Taiwan, and Tibet) from 2012 to 2022. The data sources include the China Industrial Statistics Yearbook, China Energy Statistics Yearbook, China Environmental Statistics Yearbook, and the statistical yearbooks of various provinces, etc. Due to the presence of a small amount of missing data in the original data, in order to reduce sample loss, the missing data are processed using the analogical method or the interpolation method.

ISSN: 2710-0170

3.4. Estimation Results

Based on the data collection and processing work completed in the previous sections, and in conjunction with the newly constructed comprehensive evaluation framework for new-quality productivity, this study calculates the level of new-quality productivity across 30 provinces in China from 2012 to 2022. The specific results are presented in Table 1. Analyzing from the perspective of growth rate, all provinces have achieved positive improvements in their new-quality productivity levels, with Guangdong Province experiencing the highest growth rate at 168% and Guangxi Province experiencing the lowest at 35%. At the mean level, there is a significant development gap between regions, with the eastern region having the highest average level of new-quality productivity and the western region having the lowest.

Table 1. The Levels of New quality productive forces of 30 Provinces across the Country from 2012 to 2022

		2012	2014	2016	2018	2020	2022	Growth Rate
Eastern Region	Beijing City	0.1633	0.1933	0.2277	0.2628	0.2945	0.417	155%
	Tianjin City	0.0983	0.1146	0.1321	0.1497	0.1763	0.206	110%
	Hebei Province	0.1	0.1119	0.1243	0.1447	0.1586	0.1762	76%
	Shandong Province	0.1266	0.1435	0.1607	0.1901	0.2259	0.292	131%
	Jiangsu Province	0.1794	0.1904	0.2129	0.2621	0.3172	0.4089	128%
	Shanghai City	0.1296	0.1426	0.1598	0.1981	0.2403	0.3477	168%
	Zhejiang Province	0.1732	0.1809	0.2224	0.2348	0.2799	0.3782	118%
	Fujian Province	0.1048	0.2999	0.1361	0.1559	0.1808	0.22	110%
	Guangdong Province	0.179	0.1982	0.2212	0.3006	0.3551	0.5093	185%
	Hainan Province	0.0416	0.0491	0.0598	0.0706	0.0829	0.1065	156%
	Regional Average	0.1296	0.1624	0.1657	0.1969	0.2311	0.3062	136%
Central Region	Shanxi Province	0.0845	0.0921	0.0926	0.1112	0.1183	0.1329	57%
	Anhui Province	0.0871	0.0961	0.1122	0.1364	0.1552	0.2149	147%
	Jiangxi Province	0.0785	0.0861	0.1038	0.1135	0.1378	0.1637	108%
	Henan Province	0.091	0.0955	0.1118	0.1338	0.1425	0.1653	82%
	Hubei Province	0.1226	0.1341	0.1501	0.169	0.1916	0.2424	98%
	Hunan Province	0.1065	0.109	0.115	0.1252	0.1449	0.187	76%
	Regional Average	0.095	0.1022	0.1143	0.1315	0.1484	0.1844	94%
Western Region	Inner Mongolia	0.0855	0.1005	0.1096	0.1176	0.1257	0.142	66%
	Guangxi Province	0.0835	0.0919	0.0906	0.0968	0.1038	0.1128	35%
	Chongqing City	0.0905	0.0964	0.1118	0.1275	0.14	0.1619	79%
	Sichuan Province	0.14	0.1581	0.1681	0.1932	0.2072	0.2362	69%
	Guizhou Province	0.0722	0.08	0.0864	0.0961	0.1081	0.1123	56%
	Yunnan Province	0.1145	0.1246	0.1391	0.1482	0.1483	0.1591	39%
	Shaanxi Province	0.0877	0.0995	0.1122	0.1328	0.1494	0.1861	112%
	Gansu Province	0.058	0.0699	0.0799	0.0919	0.1047	0.1143	97%
	Qinghai Province	0.0768	0.0809	0.094	0.1142	0.1224	0.1291	68%
	Ningxia	0.0451	0.055	0.0633	0.0903	0.0971	0.1148	154%
	Xinjiang	0.0695	0.0805	0.0868	0.0959	0.1007	0.1157	67%
	Regional Average	0.0839	0.0943	0.1038	0.1186	0.1279	0.144	72%
Northeastern Region	Liaoning Province	0.0959	0.1082	0.1122	0.1279	0.1392	0.1616	68%
	Jilin Province	0.0679	0.0813	0.0934	0.1016	0.1169	0.127	87%
	Heilongjiang Province	0.0723	0.0851	0.0887	0.0984	0.1086	0.1192	65%
	Regional Average	0.0787	0.0915	0.0981	0.1093	0.1216	0.1359	73%

ISSN: 2710-0170

4. Analysis of the Level of New Productive Forces

4.1. Temporal Trends and Regional Differences in the Level of New Productive Forces

4.1.1. Analysis of the Overall Level of New Productive Forces

From 2012 to 2022, the overall new quality productivity level of China's 30 provinces has shown a significant increase, with a growth rate reaching 155%. This growth trend reflects the substantial achievements China has made in economic transformation and upgrading, green and low-carbon development, and scientific and technological innovation. It indicates that all provinces have made continuous efforts to improve economic operation efficiency, optimize industrial structure, and promote high-quality development.

Specifically, the growth rate of new productive forces in all provinces is positive, confirming the positive effects of economic transformation nationwide. In terms of absolute growth figures, provinces in the eastern region generally have higher rates, but those in the central and western regions, as well as the northeastern region, have faster growth rates, reflecting the accelerated pace of local efforts in adjusting economic structures and promoting the development of emerging industries.

In terms of inter-regional differences, although there is an overall growth, the growth rates vary significantly across different regions. The eastern region generally experiences stable and relatively slow growth, while the central and western regions, as well as the northeastern region, have seen more pronounced increases. This is closely related to the intensified efforts in industrial upgrading, infrastructure construction, and green transformation in these regions.

4.1.2. Analysis of the level of new productive forces in the four major regions

This study divides the provinces in China into four major regions based on their geographical locations: the eastern, central, western, and northeastern regions. It focuses on analyzing the dynamic trends of new-quality productivity development in each region from 2012 to 2022. Combining the data collation results with the preceding charts, it can be observed that the levels of new-quality productivity in all four regions have shown a year-on-year increase during the study period. The specific characteristics are as follows: The level of new-quality productivity in the eastern region has always been higher than the national average, increasing from 0.1296 in 2012 to 0.3062 in 2022, with a significant growth rate; the central, western, and northeastern regions have been consistently lower than the national average, and there are obvious regional differentiation characteristics. Specifically, the level of new-quality productivity in the northeastern region increased from 0.0787 in 2012 to 0.1359 in 2022. From 2012 to 2014, it was close to the national average, but the gap gradually widened after 2014, and it was surpassed by the central and western regions from 2018 onwards. The initial development levels of the central and western regions were similar (from 2012 to 2014), but their trajectories diverged from 2015 onwards, with the central region accelerating its growth rate and gradually surpassing the western region.

Table 2 presents the Gini coefficient of new-quality productive forces in the four major regions from 2012 to 2022, further reflecting the internal development disparities within each region. The eastern region has a relatively high level of new-quality productive forces overall, but the Gini coefficient fluctuates, rising from 0.181 in 2012 to 0.224 in 2022, with notable fluctuations in 2015 (down to 0.171) and 2021 (upward). The Gini coefficient in the central region increased from 0.085 in 2012 to 0.109 in 2022, with a small increase and overall balanced development, only gradually recovering after dropping to a low of 0.074 in 2017. The Gini coefficient in the western region decreased from 0.158 in 2012 to 0.134 in 2022, showing an overall downward trend but with significant fluctuations, slightly recovering after reaching a low of 0.133 in 2016. The Gini coefficient in the northeast region has been at a low level for a long time, decreasing

ISSN: 2710-0170

from 0.079 in 2012 to 0.069 in 2022, and slightly recovering after reaching a minimum of 0.053 in 2015.

In summary, the development of new productive forces in the four major regions exhibits differentiated characteristics: the eastern region has a high level but significant fluctuations, the central region has a low level but stable development, the western region has a low level and significant fluctuations, and the northeastern region remains in a low-level range. This result indicates that there is a significant gap in the development of new productive forces among different regions in China, and there is obvious heterogeneity in the development trends of each region.

Table 2. Dagum Gini Coefficients of New Productive Forces Development Levels in the Four Major Regions of China from 2012 to 2022

year	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Eastern Region	0.181	0.176	0.211	0.171	0.173	0.181	0.188	0.188	0.193	0.218	0.224
Central Region	0.085	0.080	0.079	0.077	0.078	0.074	0.077	0.075	0.079	0.093	0.109
Western Region	0.158	0.150	0.149	0.149	0.144	0.133	0.130	0.139	0.125	0.127	0.134
NortheasternRegion	0.079	0.059	0.065	0.073	0.053	0.049	0.060	0.055	0.056	0.060	0.069

According to the table data, the main sources of differences in new quality productivity across the four major regions are inter-regional disparities (Gb), intra-regional disparities (Gw), and super-variability density (Gt). Among them, inter-regional disparities (Gb) contribute the most, with an average value of 0.1320, accounting for 62.47%; intra-regional disparities (Gw) come next, with an average value of 0.0474, accounting for 23.97%; super-variability density (Gt) contributes the least, with an average value of 0.0332, accounting for 21.36%. From the perspective of temporal changes, intra-regional disparities remain stable, fluctuating in a "U" shape; inter-regional disparities increase year by year, indicating that regional disparities are widening; super-variability density gradually decreases, indicating that the impact of fluctuation factors on differences in new quality productivity is gradually weakening.

Table 3. Dagum Decomposition of New Productive Forces Development Levels in the Four Major Regions of China from 2012 to 2022

year	Regional Gap			Contribution Rate（%）			Dagum Gini Coefficient
	Gw	Gb	Gt	Gw	Gb	Gt	
2012	0.0474	0.1081	0.0422	23.97%	54.67%	21.36%	0.1977
2013	0.0453	0.1037	0.0416	23.78%	54.39%	21.83%	0.1906
2014	0.0515	0.1318	0.0389	23.16%	59.34%	17.50%	0.2222
2015	0.0448	0.1082	0.0395	23.28%	56.21%	20.51%	0.1924
2016	0.0446	0.1155	0.0353	22.83%	59.10%	18.07%	0.1954
2017	0.0443	0.1197	0.0337	22.39%	60.55%	17.07%	0.1977
2018	0.0455	0.1270	0.0315	22.31%	62.27%	15.42%	0.2040
2019	0.0464	0.1340	0.0297	22.08%	63.80%	14.12%	0.2101
2020	0.0461	0.1451	0.0267	21.16%	66.57%	12.27%	0.2179
2021	0.0517	0.1749	0.0223	20.77%	70.27%	8.96%	0.2489
2022	0.0541	0.1843	0.0233	20.68%	70.40%	8.92%	0.2617
Mean	0.0474	0.1320	0.0332	23.97%	62.47%	21.36%	0.2126

To assess whether there is a convergence characteristic in the overall development level of new-quality productive forces across the country, this paper adopts the approach of Sun Liwei

ISSN: 2710-0170

and Guo Junhua (2024)and employs the β convergence model for analysis [8]. The β convergence model is primarily designed to examine whether provinces with lower levels of new-quality productive forces can narrow the gap with provinces with higher levels of development at a certain convergence rate.

The results of the β convergence test are presented in Table 4 below. The test indicates that the estimated β coefficient is significantly positive, suggesting that the overall development level of new-quality productive forces across the country does not exhibit β convergence characteristics. This means that provinces with lower levels of new-quality productive forces cannot rapidly converge towards those with higher levels, leading to a continuous widening of regional disparities. However, the absolute value of the coefficient estimate is close to 0.1, indicating that this widening trend is slow. The primary reason for this result is the significant differences in economic development levels, policy environments, resource allocation, and market conditions across different regions, and these differences are expected to persist for an extended period of time.

Table 4. β-Convergence Test Results of the National New Productive Forces Development Level

Region	National
β	0.1005***
	(0.0171)
N	300
R^2	0.1041

Note: The values in square brackets are the standard errors of the regression coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels respect

5. Conclusions and Suggestions

This article constructs a comprehensive evaluation index system for new-quality productive forces from three dimensions: laborers, labor objects, and means of production. Using various statistical analysis methods, it empirically measures and analyzes the development level of new-quality productive forces in 30 provinces in China from 2012 to 2022. The research shows that the overall level of new-quality productive forces in all provinces across the country continues to grow, but there are significant differences in growth rates; the level is high and fluctuating in the eastern region, relatively low and stable in the central region, fluctuating greatly and overall low in the western region, and continuously low in the northeastern region, with significant regional differences; in convergence analysis, the development level of new-quality productive forces does not exhibit β convergence. This result indicates that due to significant differences in economic development levels, policy environments, resource allocation, and market conditions among different regions, and the long-term existence of these differences, the gap in the level of new-quality productive forces between regions will continue to expand, albeit at a relatively slow rate.

Based on the above research conclusions, in order to promote the high-quality development of China's new productive forces, it is recommended to implement differentiated cultivation strategies based on the actual regional development situations: the eastern region should lead the high-end upgrading of industries through innovation-driven development, the central region should actively undertake industrial transfer and expand advanced manufacturing clusters, the western region should cultivate green and low-carbon industries relying on its unique resource endowments, and the northeastern region should accelerate the digital transformation of traditional advantageous industries. At the same time, it is necessary to improve the regional collaborative innovation mechanism, promote the cross-regional optimal

ISSN: 2710-0170

allocation of innovation factors such as technology, capital, and talent, and strive to narrow the development gap between regions. Continuously increase R&D investment and human capital accumulation, deepen collaborative innovation in industry-university-research-application, and accelerate the transformation and application of scientific and technological achievements. Empower green and low-carbon development through digital transformation, improve the collaborative support system of finance, taxation, and banking, promote the development and utilization of renewable energy according to local conditions, achieve the coordinated promotion of industrial upgrading and ecological environment protection, and provide lasting impetus for the green transformation of energy and high-quality economic development.

Acknowledgments

This study was supported by the Undergraduate Innovation and Entrepreneurship Training Program of Anhui University of Finance and Economics (Grant No. 202510378241).

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