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Coupling Coordination of New Quality Productive Forces and Low-Carbon Transition: A Study based on Strategic Emerging and Future Industries

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Abstract

Theoretical alignment exists between new quality productivity (NQP) and low-carbon transition (LCT), but their practical coordination is conditional and conflictual. Analysis of China's 2012-2022 provincial data shows the NQP-LCT coupling coordination degree has continuously improved overall, yet exhibits a distinct "east-high, west-low" spatial pattern where regional disparities dominate. It demonstrates positive spatial autocorrelation, with high-high clusters concentrated in the east and low-low clusters in the west and northeast, alongside multipolar/bipolar kernel density trends. Consequently, strict carbon policies should be enforced, NQP's tech leveraged to empower traditional industry decarbonization, and regional complementarity fostered to deepen NQP-LCT synergy.

Keywords

New Quality Productivity; Low-Carbon Transition; Strategic Emerging Industries; Future Industries; Coupling Coordination Degree.

1. Introduction

At the 75th United Nations General Assembly, China committed to achieving carbon peak before 2030 and carbon neutrality before 2060, reflecting China's major power responsibility and firm determination in actively addressing global climate change and promoting green low-carbon transition. Currently, the development and application of a new generation of information technologies, including big data, cloud computing, and artificial intelligence, have profoundly reshaped production factors, spawning new industries, new models, and new momentum, leading new economic development. At the Northeast Comprehensive Revitalization Symposium in September 2023, it was proposed for the first time that planning and deploying strategic emerging industries and future industries, as well as cultivating new quality productivity, are not only major strategies to enhance national development potential but also key approaches to seize development initiative and build new international competitive advantages. In recent years, especially after the Third Plenary Session of the 20th CPC Central Committee, provinces and cities have incorporated the development of new quality productivity tailored to local conditions into the core of regional economic development strategies. What are the short-term and long-term impacts of new quality productivity development on economic low-carbon transition? Can synergy between new quality productivity development and low-carbon transition be achieved? Currently, many scholars have conducted research on the essential characteristics and connotations of new quality productivity, construction of indicator systems and level measurement, spatiotemporal effects, and development paths. Rich research results have been formed around level measurement, spatiotemporal evolution characteristics, core driving factors, and development paths of low-carbon transition. Some scholars have analyzed the positive relationship between new quality

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productivity and low-carbon transition [1]. For example, Ye Tanglin et al. (2024) believe that the development of strategic emerging industries can significantly reduce environmental pollution and is conducive to achieving green development in the Yangtze River Economic Belt, but there are heterogeneous effects among upstream, midstream, downstream regions, and different urban agglomerations[2]; Xu Zheng et al. (2023) argue that developing new quality productivity helps activate technological innovation, optimize industrial structure, and deepen factor supply, releasing green momentum, providing transformation opportunities, and expanding low-carbon pathways for achieving carbon peak and carbon neutrality[3]. Some scholars have analyzed the impact of economic development level, industrial structure, and technological level on the coordination between new quality productivity development and low-carbon transition. Yang Weixin et al. (2024) analyzed the important strategic significance of properly handling the synergy between digital economy development and the achievement of the "dual carbon" goals[4]; Liao Lehui et al. (2024) found that the impact of new quality productivity on low-carbon economic development exhibits a significant dual threshold effect based on green technological innovation[5].

While existing research often examines only the unidirectional impact of new quality productivity (NQP) on low-carbon transition (LCT), analysis of their synergistic relationship is lacking. This paper addresses this gap by: exploring NQP-LCT intrinsic consistency/conflicts; constructing evaluation indices to measure their coupling coordination; analyzing its trend and regional differences; decomposing disparities using the Dagum Gini coefficient; examining spatial correlation (Moran's I) and distribution dynamics (kernel density); and proposing policy recommendations.Theoretical Analysis of the Relationship between New Quality Productivity Development and Low-Carbon Transition.

2. Theoretical Analysis of the Relationship between New Quality Productivity Development and Low-carbon Transition

2.1. Intrinsic Consistency between Developing New Quality Productivity and Economic Low-Carbon Transition

New Quality Productivitystems from revolutionary tech breakthroughs, optimized factor allocation, and industrial upgrades. It signifies leaps in labor/factors/tools, marked by total factor productivity-characterized by innovation, quality focus, and advanced nature. Its carriers: 8 emerging sectors (e.g., info-tech, EVs, green tech) and 9 future fields (e.g., quantum, AI, humanoid robots), driven by disruptive innovation that reshapes industries. This process intrinsically aligns with low-carbon transition.

First, the development of New Quality Productivity can respond to the needs of economic low-carbon transformation through the continuous advancement of low-carbon energy technology supply. New Quality Productivity emphasizes innovation-driven development; in the energy sector, it can promote progress in low-carbon energy technologies such as solar energy, wind energy, hydropower, and hydrogen energy. These new energy technologies are the core support of a low-carbon economy. New Quality Productivity accelerates the application of low-carbon energy technologies across different industries through technological spillover effects. On the other hand, the development demands of the low-carbon economy also drive New Quality Productivity to focus on green energy technology innovation. For example, to achieve low-carbonization in the construction industry, it is necessary to develop solar thermal and photovoltaic technologies suitable for building integration, which stimulates innovation in distributed energy technologies within New Quality Productivity.

Second, the development of New Quality Productivity can assist carbon emission monitoring, management, and low-carbon production through digitalization and intelligence. Digital technologies such as big data, artificial intelligence, and the Internet of Things (IoT) can provide

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precise monitoring and management tools for the low-carbon economy. By installing numerous IoT sensors during industrial production processes, carbon emission data can be collected in real time. For example, in steel enterprises, IoT sensors monitor energy consumption and carbon emissions during the blast furnace ironmaking process. Then, big data analysis technology is used to identify potential areas for energy saving and carbon reduction. Artificial intelligence algorithms can also optimize and adjust production processes based on real-time data, thereby reducing carbon emissions and achieving synergy between New Quality Productivity and the low-carbon economy in production.

Third, New Quality Productivity promotes the research and development of high-performance, low-carbon, and environmentally friendly new materials, providing low-carbon guarantees for product upgrades. For example, the development of biodegradable plastic materials, which can decompose faster in natural environments, reduces the long-term pollution caused by traditional plastics. Additionally, in the automotive manufacturing sector, the development and application of new lightweight and high-strength materials can reduce vehicle weight, lower energy consumption, and meet the requirements for product low-carbonization. These new materials driven by New Quality Productivity provide the material foundation for product upgrades under a low-carbon economy.

In summary, strategic emerging industries and future industries are characterized by innovation leadership, technology and knowledge intensity, and low resource consumption. Therefore, compared to traditional industries reliant on fossil energy, these industries themselves have lower carbon emission levels. On the other hand, the advancements in energy-saving and emission-reduction technologies, clean energy substitution, and production process optimization brought by these industries ensure their low-carbon development path. It is reasonable to believe that the development of strategic emerging industries and future industries has an endogenous consistency with economic low-carbon transformation.

2.2. Conditionality of Carbon Emission Reduction Effects in Strategic Emerging Industries and Future Industries

Although strategic emerging industries and future industries have low-carbon characteristics compared to traditional industries, they are not zero-carbon industries, and their carbon emission reduction effects are conditional.

In the development of the new energy photovoltaic industry, although photovoltaic power plants and wind turbines produce almost no carbon emissions during operation, and the construction of wind farms can even promote local ecological improvement, there are carbon emissions in the production stages such as silicon material purification and solar cell manufacturing for photovoltaic panels. Similarly, the wind power industry generates carbon emissions during the production and processing of raw materials like steel and composite materials for wind turbine manufacturing, as well as during turbine assembly.

Hydrogen fuel cell vehicles emit only water during operation and do not produce carbon dioxide or other greenhouse gases. However, if hydrogen is produced by fossil fuel reforming (such as natural gas reforming), significant carbon emissions occur. Carbon emissions are nearly zero only when hydrogen is produced by water electrolysis using renewable energy. Additionally, if high-pressure gaseous or liquid hydrogen storage methods are used, there will be some carbon emissions during infrastructure construction and operation.

In the New Energy Vehicle industry, New Energy Vehicles produce almost no exhaust emissions during use, significantly reducing carbon emissions in the transportation sector. However, processes such as battery production do result in some increase in carbon emissions; taking lithium batteries as an example, lithium mining, preparation of battery cathode materials, anode materials, and battery assembly all involve certain carbon emissions. Additionally, the

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construction of charging infrastructure for New Energy Vehicles and battery recycling and disposal also involve carbon emission issues.

For the new materials industry, if some green and environmentally friendly new materials based on bio-based materials are developed and applied, the carbon emissions during the production process are lower compared to traditional petroleum-based materials, and their environmental pollution after disposal is also relatively small, making it close to a "zero-carbon industry." However, the production process of high-performance composite materials in the new materials industry may involve complex processes such as high temperature and high pressure, which consume considerable energy and thus generate certain carbon emissions. For example, the production of carbon fiber requires a large amount of energy input from precursor preparation to carbonization and other processes.

The casting, processing, and assembly stages of high-end CNC machine tools in the high-end equipment industry require high energy consumption. For example, melting metals during the casting process requires a large amount of thermal energy, and operations such as cutting and grinding during processing also consume electrical energy. The manufacturing of aerospace equipment involves complex material processing and assembly, resulting in relatively high energy consumption and carbon emissions.

Some future industries have carbon emission issues that require evaluation. Currently, the quantum information industry is mainly concentrated in laboratories and small-scale application demonstration stages. Quantum bits require ultra-low temperature environments, and the cooling systems of devices such as quantum computers consume a certain amount of energy. The energy consumption and carbon emissions of large-scale construction of quantum computing centers and other facilities need further assessment.

2.3. Practical Difficulties in the Coordination between New Quality Productivity Development and Low-Carbon Transition

2.3.1. The Explosive Growth of Artificial Intelligence Will to Some Extent Impact Energy Demand

The Third Plenary Session of the 20th Central Committee of the Communist Party emphasized "improving policies and governance systems to promote the development of strategic industries such as new generation information technology, artificial intelligence, aerospace, new energy, new materials, high-end equipment, biomedicine, and quantum technology, guiding the healthy and orderly development of emerging industries" [6]. Currently, AI constitutes a key technology of the digital economy and the core driving force for developing emerging and future industries. As of the third quarter of 2023, the number of AI enterprises in China and the United States accounted for nearly half of the global total, with China accounting for 15%[7]. The scale of China's core AI industry has reached 500 billion yuan, and its computing power ranks second in the world[8].

Although artificial intelligence technology shows significant potential in improving energy utilization efficiency, the consumption of massive computing power and electrical resources during its training process should not be underestimated. For example, large models such as ChatGPT and Bloom consume about ten times the energy of a traditional Google search for a single computational request. The International Energy Agency (IEA) predicted in its "Electricity 2024" report that by 2026, the electricity demand of AI data centers is expected to reach 90 terawatt-hours[9]. Huatai Securities' strategic research report holds an optimistic outlook, forecasting that by 2030, the annual electricity consumption of data centers in China and the United States will reach 1.7 trillion kWh and 1.2 trillion kWh respectively, both more than six times the 2022 levels. Considering the widespread adoption prospects of AI technology, the significant upward trend in electricity consumption has become increasingly apparent. In the coming years, how to ensure the supply to meet this sharply rising electricity demand

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remains uncertain, undoubtedly posing severe tests and challenges to the transformation of China's energy structure.

2.3.2. The Construction of Big Data Centers Puts Certain Pressure on Energy Consumption

New quality productivity relies on the data-driven digital economy. With the acceleration of digital transformation in industries and enterprises, the demand for data collection, storage, algorithms, and computing power has significantly increased. Consequently, the construction of data centers has experienced explosive growth, posing short-term challenges to energy consumption and carbon emissions.

For a long time, the construction model of data centers has been high in carbon emissions. During the civil engineering phase, data center construction commonly uses high-carbon emission materials such as concrete, rubber, and rock wool sandwich panels. Although these materials do not directly produce carbon emissions during data center operation, they hinder the reduction of overall lifecycle carbon emissions. Data center construction often involves extensive outdoor work relying on primary energy sources such as diesel and gasoline, resulting in exhaust gases being directly emitted into the atmosphere. Additionally, the construction period often exceeds 20 months, accompanied by prolonged consumption of large amounts of primary energy, causing significant carbon emissions and other environmental pollution.

In the overall cost structure of data center operations, electricity consumption costs account for 56.7%. According to data aggregation and analysis forecasts from the Industry Information Network, by 2020, the annual electricity consumption of data centers in China had exceeded 200 billion kilowatt-hours, representing 2.7% of the national total electricity consumption, equivalent to the annual power generation of two Three Gorges Hydropower Plants. It is expected that by 2025, the annual electricity consumption of data centers will surge to 395.2 billion kilowatt-hours, increasing its share to 4.1% [10]. PUE (Power Usage Effectiveness, the ratio of total energy consumption of a data center to the energy consumption of information technology equipment) is widely regarded as an important standard for measuring data center energy efficiency. According to the "2021 China Data Center Market Report," the average PUE of data centers nationwide is 1.49, yet a considerable proportion of data centers have PUE values exceeding 1.8, even reaching 2.0. In summary, there is an inherent conflict between goals and methods in the construction and operation of data centers.

2.3.3. Digitalization Faces Carbon Emission Pressure in the Short Term

The core of new quality productivity is digital productivity. Digitalization brings many conveniences, but every online search, streaming content consumption, email sent, and billions of daily activities worldwide continuously increase global electricity demand, accompanied by rising carbon dioxide emissions. By the end of 2023, the number of global internet users exceeded 5.3 billion, with China’s internet users reaching 1.092 billion, and the internet penetration rate rising to 77.5%. With the popularization of cloud computing, streaming services, and cashless payments, the demand for online and digital services continues to grow steadily.

A report from the Borderstep Institute pointed out that in 2020, greenhouse gas emissions from production processes, digital terminals, and infrastructure operation and disposal accounted for 1.8% to 3.2% of global total emissions; The Shift Project reviewed about 170 studies on the environmental impact of digital technology and noted that from 2013 to 2018, the share of digital technology in global carbon dioxide emissions increased from 2.5% to 3.7% [11]. Mobile internet access is a significant source of energy consumption because electromagnetic waves attenuate through buildings, vegetation, and weather conditions, requiring higher transmission power. The carbon emissions embedded in a single mobile phone exceed 70 kilograms.

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Watching 30 minutes of video on Netflix produces 28 to 57 grams of carbon dioxide emissions. Playing one hour of 4K video, whether on a tablet or television, consumes approximately 220 to 370 watt-hours of electricity, with corresponding carbon dioxide emissions between 100 and 175 grams, roughly equivalent to driving a small car for one kilometer [11]. It should be noted that the carbon emission impact of digitalization is often not easily perceived but should not be ignored.

2.3.4. New Energy Substitution is Constrained by Technical Barriers

According to data released by the National Energy Administration of China, the total installed capacity of clean energy power generation in China reached 930 million kilowatts by the end of 2020, including 370 million kilowatts of hydropower, 250 million kilowatts of photovoltaic power, and 280 million kilowatts of wind power. Clean energy accounted for 42.4%, an increase of 14.6% compared to 2012. The rise in the proportion of clean energy is mainly attributed to significant advances in new energy and material technologies, effectively reducing costs.

However, the usage proportion of new energy in the overall energy structure remains insufficient, and the effective utilization rate of new energy power generation is still low. According to statistics from the National Energy Administration, regions such as Xinjiang, Gansu, and Inner Mongolia face difficulties in absorbing new energy power due to lagging development in new energy storage technologies and the lack of breakthroughs in low-load operation technology for thermal power units, resulting in wind and solar power curtailment rates still exceeding 15%. In addition, there are significant gaps in the construction of standards for Carbon Capture, Utilization, and Storage (CCUS) technology, the unification of greenhouse gas emission measurement standards, evaluation of carbon dioxide adsorption efficiency, and research on the concurrent development of new and traditional energy sources. Currently, CCUS technology remains mainly at the laboratory research stage, with high economic costs, and has not yet been widely applied in the industrial sector. In industry, if enterprises adopt CCUS technology in the carbon dioxide emission process, it is expected to increase overall operating costs by 10% to 20%.

In summary, the relationship between the development of strategic emerging industries and future industries, which underpin new quality productivity, and the economic low-carbon transition is theoretically inherently consistent. However, in reality, achieving coordination between the two is conditional and may even involve certain conflicts and contradictions.

3. Research Design on the Coordinated Relationship between New Quality Productivity Development and Low-Carbon Transition

3.1. Data Sources

The data used in this study are mainly derived from the annual editions of the China Industrial Statistical Yearbook, China Energy Statistical Yearbook, China Environmental Statistical Yearbook, China Science and Technology Statistical Yearbook, as well as provincial statistical yearbooks, corporate annual reports, and the China Emission Accounts and Datasets (CEADs). The research sample covers data from 30 provinces in China's mainland between 2012 and 2022 (excluding Hong Kong, Macau, Taiwan, and Tibet due to data unavailability). Considering the presence of minor missing values in the original data, this paper employs the median imputation method to handle missing data in order to minimize sample loss.

3.2. Comprehensive Evaluation Indicators for the Development of New Quality Productivity

This study mainly refers to the method of Han Wenlong et al. [12], establishing primary evaluation indicators from two perspectives: substantial elements and penetrative elements. These are further subdivided into 12 secondary indicators and 18 tertiary indicators. The

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weights are calculated using the entropy weight method mentioned earlier in this paper, as shown in Table 1.

Table 1. Comprehensive Evaluation Indicator System for the Development of New Quality Productivity

Dimension	Primary Indicators	Secondary Indicators	Tertiary Indicators	Measurement Method	Indicator Attributes	Weight
Substantial Elements	New Laborers	Number of New Laborers	R&D Personnel in Emerging Industry Technologies	Number of R&D Personnel in Emerging Technology Enterprises	+	0.062
Substantial Elements	New Labor Materials	New Production Tools	Industrial Robot Penetration Rate	Number of Robots / Total Population	+	0.055
Substantial Elements	New Labor Materials	New Infrastructure	Number of 5G Mobile Users	Number of 5G Mobile Users	+	0.018
Substantial Elements	New Labor Objects	New Energy	New Energy Utilization Efficiency	GDP/New Energy Power Generation	+	0.072
Substantial Elements	New Labor Objects	New Materials	Output Value of the New Materials Industry	Operating Revenue of New Materials-Related Listed Companies	+	0.069
Substantial Elements	New Labor Objects	New Materials	Number of New Materials Listed Enterprises	Number of New Materials-Related Listed Companies	+	0.043
Penetration Factors	New Technology	Technology Research and Development	Investment in High-Tech R&D Funding	R&D Expenditure of High-tech Enterprises	+	0.065
Penetration Factors	New Technology	Technology Research and Development	Number of High-tech R&D Institutions	Number of R&D Institutions in High-tech Enterprises	+	0.078
Penetration Factors	New Technology	Innovation Output	Number of Invention Patent Applications by High-tech Enterprises	Number of Invention Patent Applications by High-tech Enterprises	+	0.082
Penetration Factors	New Technology	Innovation Output	Number of Artificial Intelligence Patent Applications	Number of Artificial Intelligence Patent Applications	+	0.066
Penetration Factors	New Technology	Innovation Output	Sales Revenue of New Products in Emerging Industries	Sales Revenue of New Products in Emerging Technology Enterprises	+	0.071
Penetration Factors	New Technology	Innovation Output	Innovation and Entrepreneurship Activity Level	Entrepreneurship Activity Level	+	0.016
Penetration Factors	Production Organization	Intelligentization	Number of E-commerce Enterprises	Number of Enterprises with E-commerce Transaction Activities	+	0.037
Penetration Factors	Production Organization	Intelligentization	Number of Artificial Intelligence Enterprises	Quantity of Artificial Intelligence Enterprises	+	0.064
Penetration Factors	Production Organization	Digitalization	Enterprise Digitalization	Enterprise Digitalization Level	+	0.087
Penetration Factors	Production Organization	Greening	Completed Investment in Industrial Pollution Control	Data are sourced from the Statistical Yearbooks of various provinces	+	0.027
Penetration Factors	Data Elements	Big Data Generation	Mobile Internet Broadband Access Ports	Number of Mobile Internet Broadband Access Ports	+	0.020
Penetration Factors	Data Elements	Big Data Processing	Revenue from Data Processing and Operation Services	Revenue from Data Processing and Operation Services	+	0.067

3.3. Comprehensive Evaluation Indicators of Low-Carbon Transition

When constructing the evaluation index system for Low-carbon Transition, this paper refers to the related research by Liu Tan et al. [13]. To avoid duplication between the indicators of New Quality Productivity and Low-carbon Transition, some optimizations were made to the Low-

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carbon Transition indicators. Under the premise that all data are available, this paper constructs a comprehensive evaluation index system covering five primary indicators: Low-carbon Production, Low-carbon Environment, Low-carbon Technology, Low-carbon Life, and Low-carbon Energy, with 12 secondary indicators. The weights are calculated using the entropy weight method, as shown in Table 2.

Table 2. Comprehensive Evaluation Index System for Low-carbon Transition

Primary Indicators	Secondary Indicators	Measurement Method	Indicator Attributes	Weight
Low-carbon Production	Carbon Emissions per Unit GDP	Carbon Emissions / GDP	-	0.012
	Carbon Emissions from Industrial Production per Unit Added Value	Carbon Emissions from Industrial Production Process / Industrial Added Value	-	0.014
	Carbon Emissions from Agricultural Activities per Unit Agricultural Output Value	Carbon emissions from agricultural activities/Primary industry output value	-	0.007
Low-carbon environment	Carbon sink density	Carbon sink volume/area	+	0.087
	Forest coverage rate	Forest coverage rate	+	0.073
Low-carbon technology	Number of green invention patent authorizations	Quantity of green invention patent authorizations	+	0.254
	Number of Green Utility Model Patent Grants	Quantity of Green Utility Model Patent Grants	+	0.229
Low-Carbon Life	Carbon Emissions from Residential Consumption	Carbon Emissions from Residential Consumption/Residential Consumption Expenditure	-	0.051
	Carbon Emissions from Household Waste Treatment	Carbon Emissions from Household Waste Treatment	-	0.007
	Carbon Emissions Generated from Transportation and Construction Processes	Carbon Emissions Generated from Transportation and Construction Processes	-	0.027
Low-Carbon Energy	Proportion of Zero-Carbon Energy	Zero Carbon Energy Consumption / Energy Consumption Category	+	0.085
	Proportion of New Energy Power Generation	New Energy Power Generation / Total Power Generation	+	0.153

4. Empirical Analysis of the Coupling Coordination Degree between New Quality Productivity Development and Low-Carbon Transition

4.1. Characteristic Analysis of the Coupling Coordination between New Quality Productivity Development and Low-Carbon Transition

4.1.1. Overall Characteristics

Table 3 reports the overall calculated data characteristics of the coupling coordination degree. From the perspective of coordination types, the coupling coordination degree between the two has achieved a leap from low coupling to moderate coupling, rising from 0.272 in 2012 to 0.405 in 2022. Regarding lag types, although New Quality Productivity was relatively lagging

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throughout the sample period, this indicates that the development speed of New Quality Productivity-carried by strategic emerging industries and future industries-is still insufficient relative to the demands of the low-carbon transition, and its potential to empower the low-carbon transition has not been fully released. This is closely related to the "conditionality" of carbon emissions inherent in new quality industries and the energy challenges encountered during their development process, as pointed out in the theoretical analysis.

Table 3. Coupling Coordination Degree Calculation Results at the National Level

Year	New Quality Productivity	Low-Carbon Economy	Coupling Coordination Degree	Coordination Type	Lag Type
	(Comprehensive Score)	(Comprehensive Score)	(D)		
2012	0.041	0.192	0.272	Low Degree	Relatively Lagging New Quality Productivity
2013	0.048	0.199	0.289	Low Degree	Relatively Lagging New Quality Productivity
2014	0.055	0.204	0.301	Moderate	Relatively Lagging New Quality Productivity
2015	0.060	0.217	0.312	Moderate	Relatively Lagging New Quality Productivity
2016	0.067	0.228	0.324	Moderate	Relatively Lagging New Quality Productivity
2017	0.074	0.232	0.332	Moderate	Relatively Lagging New Quality Productivity
2018	0.082	0.240	0.343	Moderate	Relatively Lagging New Quality Productivity
2019	0.091	0.251	0.356	Moderate	Relatively Lagging New Quality Productivity
2020	0.102	0.258	0.367	Moderate	Relatively Lagging New Quality Productivity
2021	0.127	0.287	0.398	Moderate	Relatively Lagging New Quality Productivity
2022	0.133	0.297	0.405	Moderate	Relatively Lagging New Quality Productivity

4.1.2. Regional Characteristics

To analyze and compare the regional characteristics of coupling coordination, this study divides the sample into four main regions: Eastern, Central, Western, and Northeastern, with the calculation results shown in Table 4. From 2012 to 2022, the coupling coordination degree of the Eastern region consistently ranked first. This advantage is likely mainly due to the long-term accumulated economic development advantages, a well-established innovation ecosystem, and a high degree of industrial agglomeration, which give it significant strengths in developing knowledge- and technology-intensive emerging and future industries such as the new generation of information technology, high-end equipment, and biomedicine. These industries themselves have relatively low carbon emission intensity, and their digital and intelligent technologies can effectively empower traditional industries to reduce emissions, thereby supporting a higher coupling coordination degree.

The coupling coordination degree in the Central region is moderate, while the Western and Northeast regions have the lowest coordination degrees and face greater challenges. This is mainly due to: first, in terms of industrial structure and path dependence, the Western region is a traditional energy base rich in coal, oil, and gas resources in China, and the Northeast region is a traditional heavy industry base, with economic growth strongly dependent on high-carbon industries. Although the Western region has an endowment advantage in new energy resources, its low-carbon potential in emerging industries such as new energy has not been fully converted

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into a high overall regional coordination degree due to technological bottlenecks, insufficient infrastructure, and lack of industrial support. Second, the development of new quality industrial carriers is insufficient. Compared to the Eastern region, the Central-Western and Northeast regions lag behind in attracting and cultivating technology-intensive, innovation-driven emerging and future industries, limiting the technical support role of new quality productivity in the low-carbon transition.

Table 4. Calculation Results of Coupling Coordination Degree at the Regional Level

Region	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	Mean D	Development Stage	Average Growth Rate (%)
Eastern Region	0.354	0.373	0.386	0.403	0.419	0.432	0.448	0.468	0.486	0.539	0.551	0.442	Moderate	4.558
Central Region	0.264	0.282	0.289	0.301	0.317	0.330	0.340	0.353	0.365	0.392	0.411	0.331	Moderate	4.543
Western Region	0.211	0.226	0.238	0.244	0.252	0.256	0.264	0.272	0.279	0.295	0.290	0.257	Low Degree	3.261
Northeast Region	0.244	0.259	0.268	0.275	0.281	0.283	0.284	0.291	0.299	0.319	0.326	0.284	Low Degree	2.988

4.2. Decomposition of the Differences in the Coupling Coordination Degree between the Development of New Quality Productivity and Low-Carbon Transition

4.2.1. Overall and Intra-Regional Differences

The dynamic change of the overall Gini coefficient of the Coupling Coordination Degree shows a trend of first decreasing and then increasing. The Gini coefficient decreased from 2012 to 2014, reaching its minimum value of 0.161 in 2014. However, starting from 2015, it increased year by year, reaching the maximum value of 0.209 within the sample period in 2022, with an overall growth rate of 2.5% in the Gini coefficient.

From the perspective of intra-regional differences, the Eastern region has the highest Gini index, with its trajectory showing a pattern of rising, then falling, and rising again. During the observation period, the Central region’s Gini coefficient was not only lower than that of the Eastern region but also lower than those of the Western and Northeastern regions. However, the growth rate of differences within the Central region was higher than in the other three major regions, indicating a significant increase in internal disparities. The Western region’s Gini coefficient ranks second only to the Eastern region. The Northeastern region’s Gini coefficient shows a downward trend, with the smallest intra-regional growth rate of 0.9%, indicating a relatively slow increase in disparities within the Northeastern region.

4.2.2. Inter-Regional Differences

Inter-regional differences are significant and overall higher than intra-regional differences. Results during the observation period show that the difference between the Eastern and Western regions is the largest among all regional pairs, with the highest Gini coefficient and the most pronounced disparity. This deeply reflects the gap between the developed Eastern coastal areas and the underdeveloped Western areas in terms of their capacity and effectiveness in achieving low-carbon transformation based on New Quality Industries. According to Table 6, the growth rates of differences between the Central and Northeastern regions and between the Eastern and Northeastern regions are 6.7% and 4.4%, respectively, indicating that disparities between the Central-Northeastern and Eastern-Northeastern regions are increasing rapidly year by year, and inter-regional differences are continuously expanding.

4.2.3. Sources and Contributions of Differences

As shown in Table 5, since 2012, inter-regional differences have consistently dominated, with their contribution to the overall disparity remaining between 63% and 74%. Intra-regional differences contribute the least to the overall disparity, ranging only from 28% to 40%. The contribution of hyper-variability density to the overall disparity is lower than that of inter-regional differences but higher than intra-regional differences, ranging from 40% to 51%. Notably, the trends of the three major contributing factors are relatively stable, indicating that inter-regional gaps will continue to dominate the overall disparity.

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Table 5. Gini Coefficients and Contribution Rates of the Coupling Coordination Degree

particular year	Overall differences	regional					interregional					Contribution (%)		
		the east	central section	western part	north-eastern	east-central	east-west	East-Northeast	China-West	central-northeastern	west-northeast	regional	intra-regional	super-changeable
2012	0.164	0.132	0.043	0.095	0.058	0.175	0.263	0.122	0.206	0.065	0.101	28.902	63.354	40.744
2013	0.162	0.134	0.048	0.100	0.058	0.168	0.258	0.125	0.201	0.066	0.101	29.902	64.354	41.744
2014	0.161	0.132	0.059	0.099	0.058	0.172	0.251	0.119	0.202	0.072	0.099	30.902	65.354	42.744
2015	0.170	0.143	0.059	0.115	0.055	0.176	0.261	0.131	0.211	0.076	0.108	31.902	66.354	43.744
2016	0.174	0.155	0.063	0.108	0.045	0.180	0.266	0.138	0.219	0.085	0.102	32.902	67.354	44.744
2017	0.178	0.157	0.059	0.120	0.045	0.175	0.270	0.147	0.226	0.089	0.106	33.902	68.354	45.744
2018	0.182	0.162	0.056	0.122	0.057	0.178	0.274	0.148	0.243	0.104	0.106	34.902	69.354	46.744
2019	0.185	0.159	0.057	0.131	0.054	0.178	0.279	0.152	0.247	0.107	0.111	35.902	70.354	47.744
2020	0.192	0.167	0.060	0.147	0.054	0.181	0.286	0.162	0.246	0.111	0.122	36.902	71.354	48.744
2021	0.203	0.169	0.068	0.146	0.053	0.196	0.305	0.168	0.263	0.119	0.121	37.902	72.354	49.744
2022	0.209	0.175	0.062	0.133	0.060	0.194	0.322	0.186	0.268	0.124	0.121	38.902	73.354	50.744
growth rate (%)	2.495	2.869	4.163	3.698	0.873	1.109	2.049	4.402	2.716	6.731	1.913	3.016	1.476	2.219

4.3. Spatial Correlation Analysis of the Coupling Coordination Degree between New Quality Productivity Development and Low-Carbon Transition

4.3.1. Global Spatial Autocorrelation

To verify whether there is spatial correlation in the coupling coordination degree between the two, this paper calculates the global Moran's I index, as shown in Table 6. The Moran's I indices are all greater than 0, and the P-values are all less than 0.05, with significant test results. The results indicate that the coupling coordination degree has a significant positive spatial autocorrelation. From the trend analysis, the Moran's I index overall shows a decline followed by a rise, indicating that the agglomeration trend of this coupling coordination degree has further strengthened during this period.

Table 6. Moran's I Index of the Coupling Coordination Degree

Year	Moran's I Index	Z Statistic	Accompanying Probability	Test Results
2012	0.298	2.727	0.003	Significant
2013	0.271	2.506	0.006	Significant
2014	0.258	2.398	0.008	Significant
2015	0.257	2.396	0.008	Significant
2016	0.236	2.224	0.013	Significant
2017	0.228	2.181	0.015	Significant
2018	0.232	2.228	0.013	Significant
2019	0.242	2.297	0.011	Significant
2020	0.290	2.711	0.003	Significant
2021	0.299	2.786	0.003	Significant
2022	0.299	2.754	0.003	Significant

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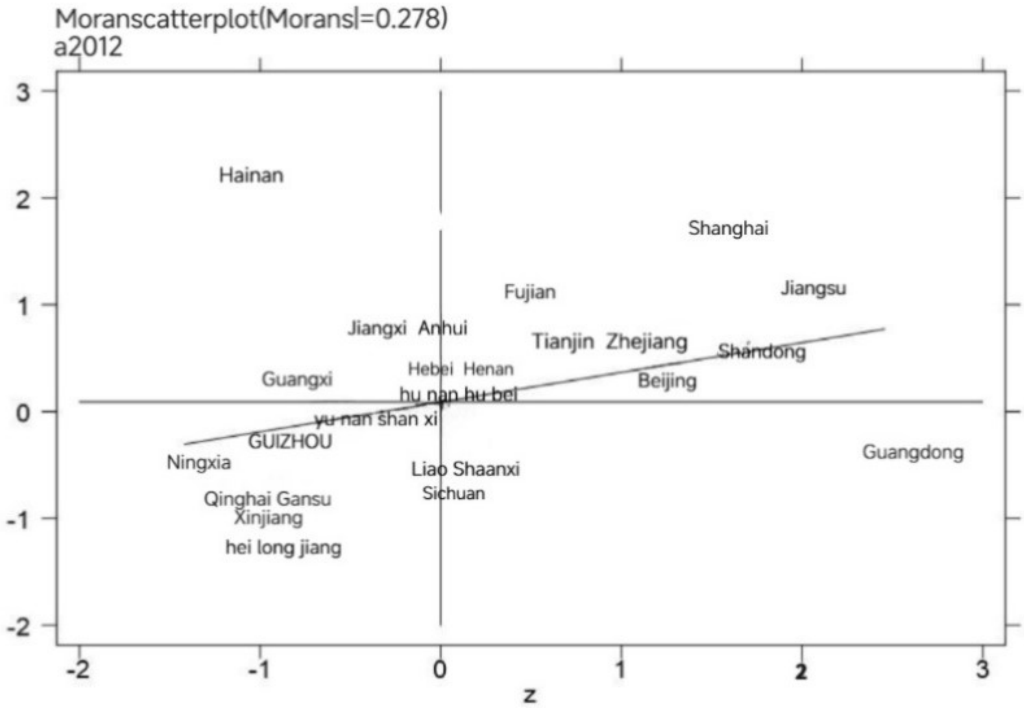
4.3.2. Local Spatial Autocorrelation

"High-High" Clustering Areas: These are mainly stably distributed in the eastern coastal regions, such as Guangdong, Jiangsu, Zhejiang, Shanghai, Beijing, and their surrounding provinces and cities. This fully reflects that the eastern region, relying on developed industrial clusters-especially new generation information technology, high-end equipment, new energy, and other sectors-possesses strong innovation capabilities and relatively well-established low-carbon infrastructure, forming significant spatial synergy and spillover effects in promoting the deep integration of New Quality Productivity and low-carbon transition. However, as shown in Figure 1b, some provinces show signs of falling out of the "High-High" cluster, indicating the need to pay attention to the dynamic changes and competition in regional coordination levels.

"Low-Low" Clustering Areas: These are mainly distributed in the western regions, such as Gansu, Qinghai, Ningxia, Xinjiang, and other areas. These regions generally face relatively lagging economic development, difficulties in transforming traditional industries, insufficient cultivation of New Quality Industries-especially technology-intensive future industries-and technical bottlenecks such as new energy consumption, resulting in an overall low level of synergy between New Quality Productivity development and low-carbon transition, forming spatial clusters of low-level traps. Inner Mongolia, as a major energy province, has long hovered at a low coordination level and is a typical representative of the western "Low-Low" cluster.

This clear spatial differentiation pattern of eastern "High-High" clustering and western-northeastern "Low-Low" clustering is highly consistent with the previously analyzed regional characteristics, further confirming that the development level of industries supporting New Quality Productivity and their adaptability to regional resources, environment, and industrial structure are key forces shaping the spatial pattern of coupling coordination degree. Strengthening inter-regional synergy and linkage is urgently needed to break the low-level clustering trap and promote coordinated development.



a. Moran’s I Scatterplot in 2012

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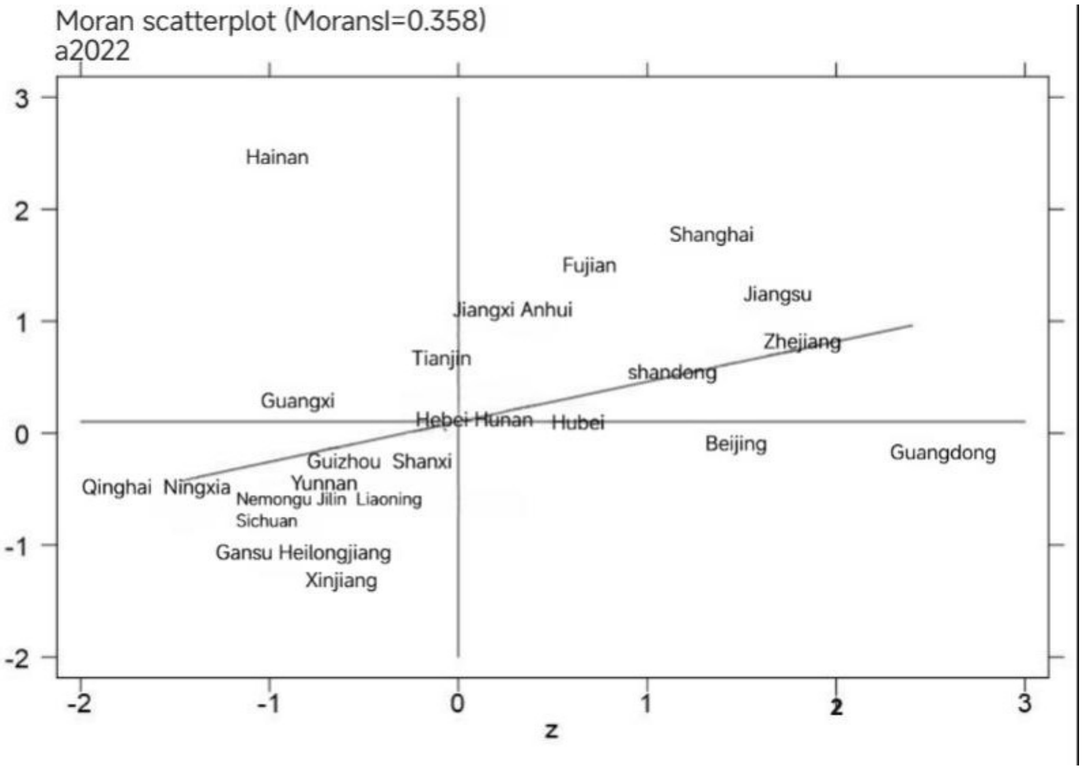
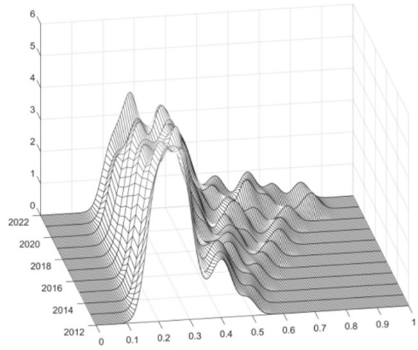


b. Moran's I Scatterplot in 2022

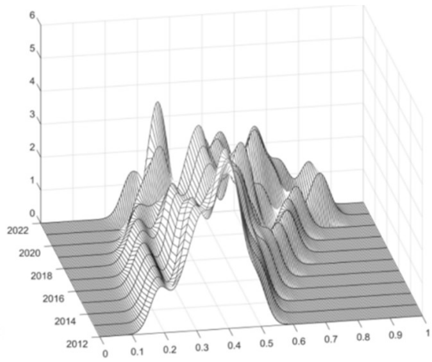
Figure 1. Moran's I Scatterplots of Coupling Coordination Degree in 2012 and 2022

4.4. Distribution Dynamics of the Coupling Coordination Degree between New Quality Productivity Development and Low-Carbon Transition

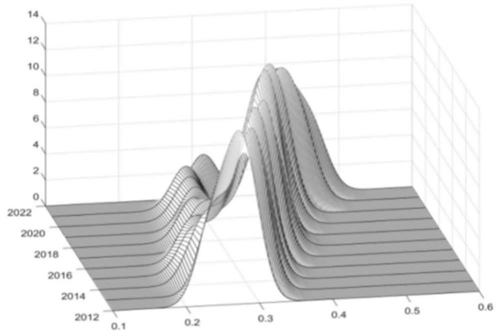
Nationally, the coupling coordination degree between new quality productivity development and low-carbon transition demonstrates overall improvement but widening provincial disparities and emerging polarization. The rightward shift of the distribution curve's main peak confirms enhanced coordination levels, while its broadening width reflects expanding absolute gaps between provinces-consistent with the rising Dagum Gini coefficient. Multi-peak distribution patterns indicate intensifying divergence: a minority of high-coordination provinces elevate the national average, yet most cluster at low-to-moderate levels. Regionally, the Eastern region exhibits the most rapid progress (marked rightward curve shift), but its declining peak height, broadening curve, and multi-peak structure reveal sharp internal disparities in advancing emerging/low-carbon industries. The Central region shows overall advancement with growing internal gaps, transitioning from single to dual peaks signaling bipolarization between industrially advantaged and lagging provinces. The Western region achieves modest gains with persistent internal gaps; its multi-peak distribution and right-skewed tail highlight localized successes (e.g., Sichuan's leadership in information technology and clean energy), though insufficient to overcome regional lag. The Northeast region displays the slowest progress (minimal rightward shift), where rising peak height and narrowing width suggest provinces converging toward the regional mean, yet broadening curve and dual peaks confirm persistent absolute disparities between relatively advanced and lagging areas.



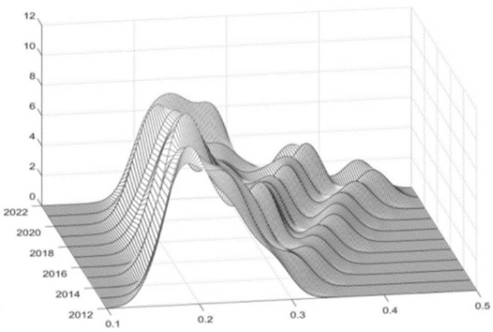
a. Overall Coupling Coordination Degree Kernel Density Estimation



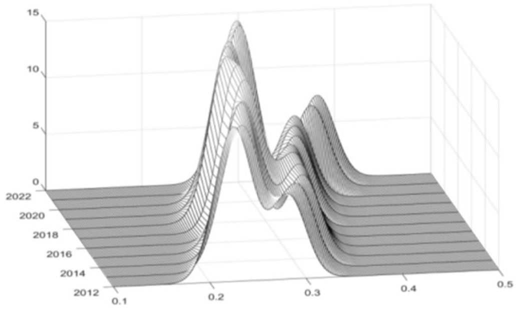
b. Eastern Region Coupling Coordination Degree Kernel Density Estimation



c. Central Region Coupling Coordination Degree Kernel Density Estimation



d. Western Region Coupling Coordination Degree Kernel Density Estimation



e. Northeast Region Coupling Coordination Degree Kernel Density Estimation

Figure 2. Kernel Density Estimation of the Coupling Coordination Development between New Quality Productivity Development and Low-Carbon Transformation in the Overall and Four Major Regions

5. Conclusion and Recommendations

Based on China's 2012-2022 provincial data, this study finds: The NQP-low-carbon transition coupling coordination degree shows annual improvement yet remains moderate overall, with eastern regions leading while western/northeastern areas lag. The overall Gini coefficient followed a U-shaped trend, indicating widening disparities driven primarily by inter-regional differences. Spatially, significant positive autocorrelation exists, featuring eastern high-high clusters and western/northeastern low-low clusters. Nationally and regionally, coordination degreescontinue rising but exhibit polarizing trends with expanding gaps.

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Based on the research conclusions of this paper, the following policy recommendations are proposed: First, ensure the low-carbon and green development of strategic emerging industries and future industries through comprehensive measures such as strict carbon reduction policies, compliance governance, fiscal and tax incentives, and guidance from the carbon trading market. The government can formulate specific carbon emission quotas and emission standards for strategic emerging industries and future industries, setting upper limits on carbon emission intensity during manufacturing processes to encourage enterprises to optimize production processes and reduce carbon emissions. For facilities in the new generation information technology industry, such as data centers, carbon emission indicators per unit of energy consumption should be established to promote the adoption of more efficient cooling systems and energy-saving equipment. In the new materials industry, financial subsidies should be provided to enterprises engaged in the research and use of green and environmentally friendly new materials to reduce their R&D and production costs. For high-end equipment manufacturing enterprises adopting low-carbon technologies, tax reductions such as exemptions from corporate income tax or value-added tax should be granted to encourage the purchase of advanced energy-saving equipment and technologies. Strategic emerging industries and future industries should be incorporated into the carbon trading market.

Second, leverage new quality productivity development as technological support for low-carbon transition, empowering traditional industries through digital solutions. (1) Advance emission reduction and "negative carbon" technologies-defined as CO_2absorption via ecological enhancement or technological capture. Prioritize Carbon Capture, Utilization and Storage (CCUS) for hard-to-abate sectors (e.g., cement, power generation), utilizing captured CO_2in food processing, chemicals, or enhanced oil recovery. Simultaneously boost R&D in battery tech, hydrogen, and smart grids. (2) Implement digital transformation using big data, AI, and IoT: Deploy Energy Management Systems (EMS) for real-time monitoring/optimization of energy use; install sensors to enable predictive maintenance and process optimization through data analytics; employ intelligent logistics systems to reduce transport emissions. (3) Accelerate new energy storage R&D to resolve renewable curtailment; adopt distributed energy/smart grids to enhance renewable utilization efficiency and security; integrate AI and big data to build new energy-centered power systems, advancing clean energy substitution.

Third, develop new quality productivity according to local conditions to achieve regional economic/resource complementarity and deepen synergy with low-carbon transition. Industrially advanced eastern regions possess inherent advantages for tech-intensive sectors (e.g., information technology, humanoid robots, future networks), while energy/resource-rich central/western regions excel in foundational industries (e.g., new energy, biomanufacturing, energy storage). Critically, the "East Data, West Computing" strategy resolves the conflict between data centers' need for economic proximity and energy constraints. Achieving deep regional synergy requires: enterprise-level measures (carbon tech, smart energy systems, zero-carbon industrial parks); spatial governance policies; and a new energy-dominated power system enabling "West-to-East Electricity Transmission" and "East Data, West Computing." Without this multi-scale integration, synergy remains superficial. Thus, beyond local adaptation, spatial governance anchored in renewable energy infrastructure is essential for elevating coordination.

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