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Can New Quality Productivity Promote the Carbon Emission Performance?—Empirical Evidence from China

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Abstract: The new quality productivity (NQP) has the possibility to enhance carbon emission performance that will fortify the groundwork for long-term economic expansion even further. The research examines the panel data of 30 provinces spanning the years 2012 to 2022 for an evaluation framework for NQP and carbon emission performance at the provincial level. Employing fixed effect models, mediation effect analysis, and spatial econometrics, the study explores the effect of NQP on carbon emission performance, its mediating mechanisms, and the spatial spillover effects. The findings indicate that: (1) NQP significantly lowers carbon emissions for every unit of GDP and enhances carbon emission performance, the result holds up when the instrumental variable methods are used. (2) The NQP had a significant contribution on improving carbon emission performance via advancements in green innovation. (3) The NQP does more than directly enhances the regional carbon emission performance, in contrast, it additionally positively influences the carbon emission performance level of adjacent regions by spatial spillover effect. (4) The impact of NQP on carbon emission performance is particularly pronounced in eastern and innovative regions. On this basis, we should vigorously develop the NQP, strengthen cross-regional policy coordination, and promote green and sustainable development.

Keywords: new quality productivity; green innovation; carbon emission performance; spatial spillovers; heterogeneity

1. Introduction

A major contributor to global warming is carbon dioxide, or CO2. It poses a significant threat to global sustainable development [1]. Carbon dioxide is a gas that holds atmospheric heat because it is a greenhouse gas. Because of this, global warming and climate change which can harm infrastructure, interfere with supply chains, and cause volatility in the economy [2]. Resolving climate change is not simply for the environmental, it's a matter of human survival and sustainable development for future generations [3].

Under the new development philosophy, Chinese officials established goals for the nation's endeavors to reach carbon neutrality or peak emissions. Carbon dioxide emissions in China will reach their highest point in 2030, then level off and begin to fall. By 2060, the country will have achieved carbon neutrality and fully implemented a low-carbon, circular economy[4]. Toward this end, China outlined the *14th Five-Year Plan* (2021-2025) for *National Economic and Social Development and the Long-Range Objectives Through the Year 2035* [5]. From 2021–2025, the five-year plan aims to reduce energy intensity by 13.5 percent and carbon dioxide intensity by 18 percent[6]. Aiming to address climate issues and attain sustainable development, carbon intensity must be reduced.

Social productivity has a major role in lowering carbon intensity. Social productivity, particularly NQP, can improve social capacities to address climate issues. From the proposal of the NQP concept in 2023 to China's implementation of its development in 2024, the outline of NQP began to be clear, and the essential element was innovation-driven. Especially driven by technological innovation, this offers a fundamental guideline and action path for accelerating the development of NQP. NQP is an advanced, high-tech, high-efficiency, and high-quality productive force that adheres to new development concepts. It is compatible with the advanced productivity concept of new development and has the ability to deviate from conventional economic growth paths and modes.

Research on whether NQP can enhance carbon emission performance and how it works to support carbon emission reduction performance is scarce. The following are the main points of this research: (1) It explores the NQP's influence on carbon emission performance，providing evidence of a positive relationship that enhances existing empirical research on NQP [7–9]. (2) This study analyzes the function of green innovation as a mediator in the connection between NQP and carbon emission performance, in which elucidating the dynamics of how NQP impacts carbon emission performance. This approach enriches our comprehension of the diverse mechanisms through which NQP influences carbon emission performance [10–12]. (3) When economic and geographical variables are considered together, a geographic Durbin model is born, illustrating that NQP significantly boosts carbon emission performance in adjacent provinces[13]. This study presents innovative insights and methodologies aimed at reducing CO2 emissions. Furthermore, it investigates spatial heterogeneity, revealing that regions in the east and those characterized by innovation are more significantly influenced by the NQP according to carbon emission performance.

This paper's remaining sections are structured in the following manner: Section 2, we offer an description of earlier research, Section 3 conducts a theoretical analysis and presents our hypotheses. Section 4 details the research strategy, variables, and data. The results and discussion are presented in Section 5. This section covers various topics such as analyses of heterogeneity, methods, spatial effects, and tests for robustness and endogeneity. In the end, Section 6 concludes by summarizing our findings and implications and making policy recommendations.

2. Literature Review

2.1. Research on Carbon Emission Performance

The issue of carbon emission performance has attracted increasing attention over last decade, highlighting the growing sensitivity of scholars to sustainability challenges. To effectiveness and achievements of governance in environmental protection, scholars are concerned about the ways to boost carbon emission performance, which is influenced by a multitude of factors. First, digitalization possesses the capacity for enhancement carbon emission performance. Shao believed that digital finance greatly boosts urban carbon emission performance, primarily through fostering green innovation and facilitating the growth of urban tertiary industry[14,15]. Similarly, Ma's research indicates that digitalization can substantially enhance carbon emission reduction in Chinese cities. By enhancing energy efficiency, transforming industries, and introducing new technologies, digitalization enhances the performance of urban carbon emissions[16].Enterprise digital transformation actively helps to enhance carbon emission performance of enterprises, particularly in manufacturing companies, state-owned enterprises, and non-polluting industries [7].Second, technological innovation can boost carbon emission performance. Enhanced technological capabilities and innovation in clean energy sources are essential for reducing carbon emission intensity. Renewable energy options for example solar, wind, and hydro power are becoming increasingly accessible and affordable, making it easier for industries and individuals to transition away from fossil fuel-dependent energy systems. Additionally, improvements in energy efficiency and conservation measures may similarly lower carbon emissions. While digital transformation helps to mitigate the harmful impact of green innovation on energy-consuming companies' carbon emission reduction performance, green innovation itself can greatly improve this performance[17]. Innovation in environmentally friendly technologies greatly enhances the performance of carbon emissions. Additional paper confirms that the inefficient use of capital and labor reduces carbon emission performance and impedes the positive effect of innovative green technologies on this metric[18]. Third, the central role is played by government policies and regulations in driving the increasement of carbon emission performance. The efficiency and efficacy of regulations have a significant impact on how well a company is able to reduce emissions[19].By implementing strict emission standards and incentivizing the usage of sustainable practices, governments can encourage industries to invest in cleaner technologies and practices. This can be achieved through the implementation of carbon pricing mechanisms, tax incentives, and subsidies for renewable energy projects. Some scholars argue against the strict emission standards. High level of government

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intervention mitigates carbon emission performance. This harmful impacts intensifies when facing greater regional fiscal pressure[20]. The carbon emission performance of the pilot regions has been greatly impacted by China's carbon trading policy. Factors like GDP per capita, urbanization level, and capital-labor ratio have played a crucial player in cutting the intensity of carbon emissions[9]. Finally, other contributing factors include development zones, urbanization, industrial intelligence, spatial distance and corruption. Urban carbon emission performance improved after development zones were set up, and this improvement was apparent even after controlling for time lag effects. By boosting GDP and decreasing carbon emissions, development zones improve carbon emissions performance[21]. As levels of economic development rise, urbanization is discovered to exhibit a more potent inhibitory effect on carbon emission performance[22]. Ironically, local carbon emission performance improves as industrial intelligence improves. The carbon emission performance of nearby regions is significantly impacted negatively by industrial intelligence[23]. Within a 1000-kilometer radius, low-carbon cities significantly reduce local greenhouse gas emissions, improve emission efficiency, and boost the performance of nearby cities in terms of greenhouse gas emissions [13]. Corruption reduces energy efficiency, which exacerbates industrial carbon emissions [24].

2.2. Research on NQP

Scholars are now conducting research on NQP. NQP dramatically enhances environmental, social, and governance performance[25]. Innovation is what propels NQP, and its key motor is the development of innovative green technologies. NQP is primarily driven by breakthrough green technological innovation, which also serves as a crucial tool for its development and promotion[26].In Chinese agricultural development, NQP plays an important role. NQP can facilitate good level of development by encouraging breakthroughs, collaboration, transparency, and joint innovation among its subsystems[27].Policy support, market demand and technological innovation greatly affect the green productivity of high-tech retail enterprises, assisting in the sustainable growth of their green and NQP[28]. The NQP play an important part in green development by enhancing technology and refining industrial structure[29].

3. Research Hypotheses

3.1. The Mechanism by Which the NQP on Carbon Emission Performance

3.1.1. The Function of NQP to Science and Technology

The function of NQP to science and technology is reflected through the three productivity elements of laborer, subject of labor and tools of labor.

Through technological innovation and management innovation，NQP has greatly improved labor productivity, reduced labor intensity, improved labor environment and effectively shortened labor time. For example, the application of new production tools such as robots and artificial intelligence enables workers to do more efficient and precise work, thus reducing physical burden and carbon emissions. The rising awareness of labor force to protect the environment plays a constructive role in boosting carbon emission reduction. In the working environment and production process, workers practice the concept of environmental protection can promote carbon emission decline. In manufacturing, the labor force reduces energy consumption and waste emissions by improving production processes and optimizing production processes. In the service sector, workers reduce carbon emissions by promoting paperless office and reducing the use of paper such as printing and photocopying. The labor force also actively participates in environmental protection activities of enterprises, such as afforestation and waste classification, to contribute to improving the environment. As a result, new productivity changes the laborer and reduces carbon emissions.

The role of new productivity on subject of labor is mainly reflected in expanding the types and forms of labor objects, improving the quality and utilization efficiency of labor objects, and promoting the upgrading and improvement of related industries. Firstly, the expansion of traditional subject of labor. Driven by the new productivity, the types and forms of traditional labor objects have been expanded. With the help of emerging technologies, new substances are extracted from nature and replace traditional, energy-consuming and polluting substances. Secondly, the emergence of new labor objects. In the process of using emerging technologies, a large number of new labor objects have

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been produced. These new labor objects often have higher added value and wider application fields. Thirdly, quality improvement. New productivity also improves the utilization efficiency of labor objects by optimizing production processes and resource allocation. Under the circular economy model, people can reduce the exploitation and consumption of new resources by recycling and reusing waste materials.

The influence of new productivity on tools of labor is comprehensive. Thanks to the rapid advancements in emerging digital technologies for example AI, big data and so on, labor tools are evolving towards an intelligent direction. Advanced labor tools, such as intelligent robots and automated production lines, not only facilitate remote control but also enable independent, precise, flexible, and safe operations. Traditional labor tools may suffer from personal errors and time lags during the use of traditional tools of labor, whereas new labor tools significantly reduce error rates and enhance production efficiency and flexibility through intelligent analysis, optimization, and autonomous decision-making capabilities. These tools often incorporate green low-carbon technology, significantly reducing fossil fuel usage and consumption, thus effectively achieving energy conservation and emission reduction. This is not simply aids in protecting the ecological environment but also aligns with the need for a shift in economic growth patterns amidst the global energy crisis. In summary, the influence of new productivity on labor tools is profound. It not only drives the intelligent transformation of labor tools and enhances production efficiency but also promotes the adoption of green low-carbon technology in labor tools. These changes not only bolster the economic efficiency and competitiveness of enterprises but also help to the sustainable development of the entire nation.

3.1.2. NPQ Can Reduce the Energy Consumption Intensity

The development of NPQ can boost the enhancement of overall factor productivity and reduce the energy consumption intensity by promoting the following ways:

First, the NQP drives the transformation of production mode and the improvement of efficiencies. New quality productive are centered on technological innovation and promote the transformation of production mode by introducing new technologies, processes, materials, and equipment. The widespread application of information technology, artificial intelligence, and big data has changed the production mode of manufacturing and service industries, driving them towards intelligent, automated, and efficient development, and promoting efficiency improvement. New quality productive promotes efficiency improvement, which reduces the resource and energy consumption per unit product of the same quality, enhances energy utilization efficiency, and lowers carbon emissions. This ultimately leads to a scenario where both the economy and carbon emissions are boosted.

Second, the NQP facilitates the optimal allocation and synergetic exertion of production factors. Through optimizing the combination of elements such as labor, capital, land, knowledge, technology, management, and data, the effectiveness of distributing resources is enhanced. The advancement of new quality productive guarantees the smooth flow and efficient allocation of production factors. Through the establishment of a unified national market and by minimizing factors that impede the development, the processes of production, distribution, circulation, and consumption are streamlined, and the efficiency of resource allocation is elevated.

Through the above discussion, it can be found that NQP affects carbon emissions from three aspects: laborer, subject of labor and tools of labor, and also transform production mode and facilitate the optimal allocation of production factors, thereby reducing carbon emission intensity, finally enhancing its carbon emission performance.

In summary, we presents the following hypotheses:

Hypothesis 1. *The NQP in China significantly affects carbon emission performance.*

3.2. Mechanisms by Which Green Innovation Influence Carbon Emission Performance

Green innovation refers to an innovative activity in the process of product development, production, service and management, which adopts concepts and technical tools to cut environmental pollution, reduce resource consumption and enhance energy efficiency. This

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innovation not only focuses on economic benefits, but also emphasizes ecological and social benefits, reflecting the needs of sustainable development and circular economy. The evolution of NQP is congruent with the trend toward environmentally friendly technological advancements. NQP emphasizes green technological innovation, especially key and disruptive technological breakthroughs. These technological breakthroughs have not only promoted the upgrading and transformation of traditional industries, but also spawned green industries and emerging industries, providing strong technical support for green innovation. In terms of digital technology, digital transformation is able to greatly enhance green innovation in manufacturing enterprises, having an especially noticeable impact on substantive green innovation[30]. The reason why green technology innovation can become the core of NQP is that it can effectively solve resource and environmental issues and support the improvement and advancement of the economic structure. By increasing resource utilization efficiency and decreasing pollutant emissions, green technologies not only assist in reducing current environmental pressures, but also create a strong basis for sustainable development in the future.

We can derive the following hypotheses from the previous discussion:

Hypothesis 2. *Green innovation in Chinese provinces may positively moderate the relationship between NQP and carbon emission performance.*

3.3. Spatial Effects of NQP on Carbon Emission Performance

NQP is often accompanied by technological innovation and industrial upgrading, which not only occur within a specific region or industry, but may also affect surrounding areas or related industries through technology diffusion and industrial transfer. In the field of green innovation, the promotion and application of new technologies, new materials and new processes can reduce carbon emission intensity and improve energy efficiency, which is not only limited to the place where innovation occurs, but may also spread to surrounding areas through supply chains, industrial chains and other channels. By contrast, the establishment of a carbon emission trading market has sparked controversy among scholars. According to Quan and Duan’s study[31], The emission trading system did not result in considerable spatial spillovers, which reduces worries regarding possible carbon leakage. However, carbon emission trading market also can prompt companies to pay more attention to carbon emission performance and adjust production strategies by buying or selling carbon emission credits, which may cross regional boundaries. Therefore, the carbon emission performance of a province is impacted not just by the NQP of the province, in addition to being impacted by the surrounding areas' carbon emission performance's spillover effect. Both positive and negative demonstration effects and competitive effects are possible outcomes of this spillover effect.

We can derive the following hypotheses from the previous discussion:

Hypothesis 3. *NQP may have a spatial spillover effect on carbon emission performance.*

4. Variables, Model and Data

4.1. Variables

4.1.1. Explained Variable

At the microeconomic level, most often, businesses' carbon emission intensity is dividing the carbon emissions at the enterprise level by the operating income of enterprises. At the macroeconomic level, carbon emission intensity is expressed by dividing the carbon emissions of every province by GDP. Among them, the carbon emission accounting method adopts the emission factor method [32,33], which is specifically the sum of energy consumption at the provincial level, which is weighted with the corresponding standard coal conversion coefficient and carbon emission coefficient.

Accounting for CO_2 emission is essential for evaluating carbon emission performance. Nevertheless, CO_2 itself is not classified an air pollutant, and there is no global detection system globally. Consequently, the IPCC have developed a methodology for estimating national CO_2 emissions produced due to burning fossil fuels containing carbon and the carbon content inherent in that energy, which is widely implemented internationally. From this, it can be concluded that the carbon emissions from fossil fuels are equal to the energy consumption multiplied by the carbon emission factor. Due to its association with the attributes, quality, and efficiency of energy fuels, tt is possible to further decompose the carbon emission factor by multiplying the fuel's calorific value by the carbon content per unit calorific value, and then by the combustion efficiency.

Referring to the study by Aamir and Rehman[34],the formula to calculate carbon emissions from fossil energy consumption is as follows:

$$C_j = \sum_{i=1}^{8} E_i \times SCC_i \times CEC_i \times \frac{44}{12} \tag{1}$$

where C refers to the sum of carbon emissions in j province, i refers to the sorts of fossil energy, including coke, coal, crude, kerosene, diesel, gasoline, fuel oil and natural gas. E refers to the consumption of type i fossil energy. SSC refers to the standard coal conversion coefficient of type i and CEC is carbon emission coefficient of type i. 44 /12 is the molecular ratio of carbon dioxide to carbon.

The equation utilized to compute carbon intensity is as following.

$$CEG_j = \frac{C_j}{GDP_j} \tag{2}$$

where CEG denotes the carbon emission performance in j province, calculated by dividing j province's total annual carbon dioxide emissions by the region's gross domestic product. The above CEG is a commonly used measurement method to carbon emission performance, and some scholars use the total-factor CO_2 emission performance index to measure CO_2 emission performance[35]. Following Tang, Wang and Wan[36], CEG, simple and intuitive, serves as explained Variable. Based on the calculation results of the above formula(2), we draw the spatial distribution map of CEG in 2022. As shown from Figure 1, the provinces with high CEG index, more than 0.51, were largely involved in northern areas, while the provinces exhibiting lower CEG index, less than 0.33,were primarily distributed in the south. This means that the northern provinces consume more carbon per unit of GDP than the southern provinces. This may also be related to the fact that the energy industry was predominantly in the northern provinces, while the light industry was more in the southern provinces.

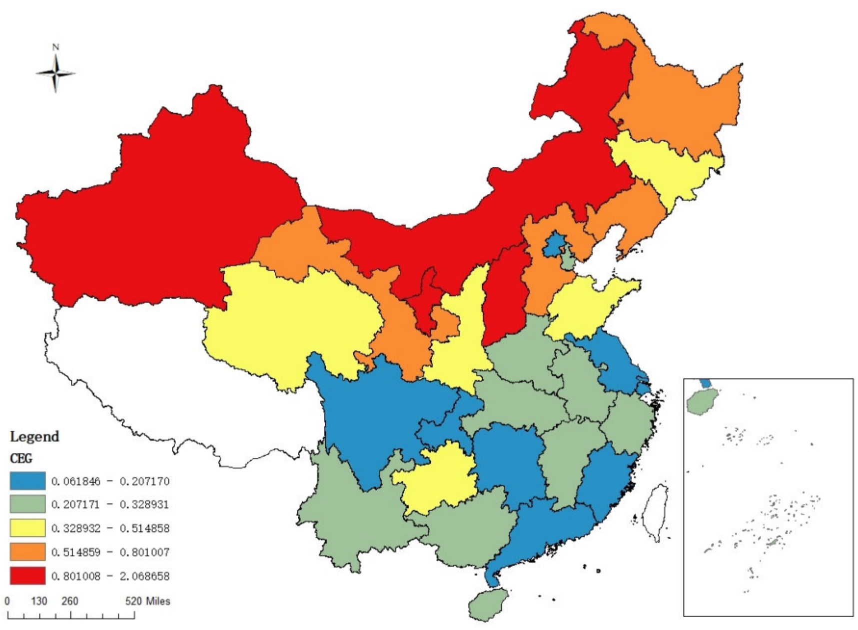

Figure 1. Spatial distribution of *CEG* in China in 2022. Note: This map was produced in accordance with the standard map provided by the National Administration of Surveying, Mapping and

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Geoinformation, with the map review number GS(2019)1822. The base map has undergone no modification.

4.1.2. Explanatory Variable

NQP is used as the explanatory variable. The existing techniques for assessing *NQP* are typically categorized into two categories including subjective weighting method and objective weighting method. Because the former gives different weights to each indicator according to the subjective judgment of experts, it is difficult to avoid the impact of personal subjective preferences in practice. The second method can avoid the shortcomings of the former, and has the characteristics of objectivity, scientificity and wide applicability, which provides a scientific basis for multi indicator comprehensive evaluation. The study uses the entropy method in the objective weighting method to calculate *NQP* as following: First, put together the measurement matrix, $X = \{x_{ij}\}_{m*n}$, here x_{ij} is the data for indicator j in sample i, n represents the sample size and m denotes the total quantity of indicators to be evaluated. Second, to reduce the impact of differences in indicator definitions and characteristics, the preliminary data was standardized using the extreme difference approach. To avoid logarithmic meaninglessness when calculating entropy values, a real number of a smaller scale can be added to each 0 value, such as 0.01. Positive indicators are determined by the formula: $x' = \frac{x_{ij}-x_{min}}{x_{max}-x_{min}}$. Negative indicators are formulated in a similar manner: $x' = \frac{x_{min}-x_{ij}}{x_{max}-x_{min}}$. where x_{max} and x_{min} refer to the maximum and minimum values of the elements in the columns where the indicator vector x_{ij} is located. Third, weight is calculated as follows: $y_j = \frac{x'_{ij}}{\sum_{j=1}^{n} x'_{ij}}$. Then information entropy is calculated, represented by the $e_j = -k\sum_{j=1}^{n} y_j ln y_j$, where $k = \frac{1}{\ln m}$. Difference coefficient of the *j*th indicator is $d_j = 1 - e_j$. The *j*th indicator's weight is expressed as $w_i = \frac{d_j}{\sum_{j=1}^{n} d_j}$. Fourth, The calculated results of multi-index comprehensive score denoted as $S = \frac{w_j}{\sum_{j=1}^{m} w_j}$.

To assess *NQP*, to find the weights, the entropy method is used [37], while The entropy weight-TOPSIS method was used to determine the index system[38]. Consequently, The entropy method are utilized to measure the *NQP*[39]. Referring to Han,et al. and Shao, et al.[38,40] ,most of the literature uses entropy method as the measurement method. The evaluation index system of *NQP* is constructed from the three criterions of laborer, subject of labor and tools of labor, as presented by Table 1.

Table 1. Criteria, factor measurement method for *NQP* index system.

Goal	Criteria	Level 1	Level 2	Level 3	Measurement Method	Direction of Effect
NQP	Laborer	Labor productivity	Economic output	GDP per capita	GDP/total population	+
			Economic income	Wage per capita	Average wage of employees	+
			Employment structure	Employment proportion of tertiary industry	Employment in tertiary industry/total employment	+
		Labor quality	Education	Proportion of higher Education	Average years of education per capita	+
			Education expenditure	Intensity of education spending	Education expenditure/total fiscal expenditure	+
			Education for future	Student structure	Number of enrolled students/total population	+

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		Labor spirit	Creative spirit	Human investment for innovation	R&D personnel full-time equivalent	+
			Enterprising spirit	Entrepreneurial activity	Startups per 100 people	+
	Subject of labor	Level of industrial development	Level of informatization	Level of enterprise informatization	Number of e-commerce enterprises/total number of enterprises	+
			Proportion of strategic industries	Proportion of emerging strategic industries	Added value of emerging strategic industries/GDP	+
			Industry of the future	Robot installation density	Number of industrial robots installed in the region * (regional industrial employment/total national employment)	+
NQP	Subject of labor	Ecological environment	Green ecology	Green Resources	Forest cover ratio	+
				Environmental protection efforts intensity	Environmental protection expenditure/government public finance expenditure	+
			Green production	Quality of pollution control	Chemical oxygen demand emissions/GDP	-
					Sulfur dioxide emissions/GDP	-
				Achievements of green inventions	Number of green patent applications/number of patent applications	+
	Tools of labor	Material labor Tools	Infrastructure	Traditional infrastructure	Highway mileage	+
					Rail mileage	+
				Digital infrastructure	Fiber length	+
					Number of Internet broadband access ports per capita	+
			Level of energy utilization	Energy intensity	Energy consumption/GDP	-
				Level of green energy consumption	Low-carbon index of energy consumption structure	+
			Capacity of energy utilization	Capacity of pollution control	Capacity of waste gas treatment facilities	+
		Intangible labor Tools	Level of technological innovation	Per capita quantity of patents	Number of patents granted/total population	+

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	Economic investment in new products	New product development funds/GDP	+
Digitalization level	Digital economy	Digital economy index	+
	Enterprise digitalization	Enterprise digitalization level	+

Following the application of the entropy approach to ascertain the weight of indicators at various levels, the study calculated the *NPQ* index of each province from 2013 to 2022. As shown in Figure 2, we selected the representative year 2022 and drew the spatial distribution map of *NQP* in 2022. We found that *NQP* demonstrated a gradual downward trend from coastal to inland. Among the provinces, Guangdong, Jiangsu and Zhejiang ranked high, more than 0.44, in *NQP*, while among inland provinces, Gansu and Qinghai, less than 0.16, ranked low. The results were consistent with study Zhang et al.[41] that "East coast to west inland diffusion" is the spatial evolutionary trend exhibited by high-value areas. This may be related to the fact that the eastern coastal areas are active in technological innovation and the inland areas are dependent on resource industries.

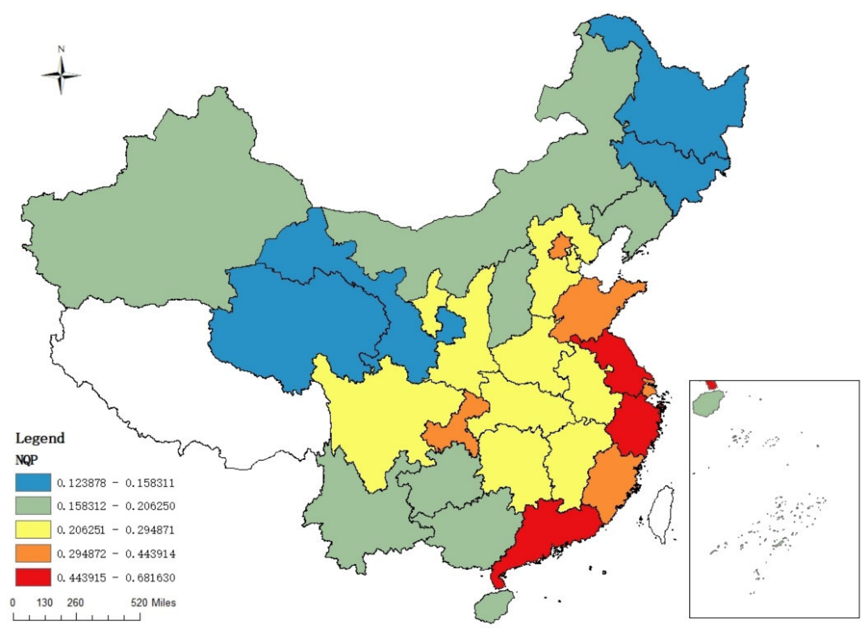

Figure 2. Spatial distribution of NQP in China in 2022. Note: This map was produced in accordance with the standard map provided by the National Administration of Surveying, Mapping and Geoinformation, with the map review number GS(2019)1822. The base map has undergone no modification.

4.1.3. Control Variables

The Fiscal Environment Expenditure (*FEE*) is calculated by taking the ratio of environmental spending to fiscal spending within a province. The rise in government funding directed towards environmental protection initiatives and sustainable technologies has had a favorable effect on green economic growth [42,43]. Government expenditure on environmental protection refers to the monetary resources allocated by the state for safeguarding the environment. resources are primarily designated for environmental protection management, environmental monitoring and supervision, pollution control and other aspects. Specifically, pollution control expenditure for environmental protection is directly used to mitigate emissions of environmental pollutants, including greenhouse gases such as carbon dioxide. By investing in advanced pollution control technologies and

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equipment, the government may significantly boost the efficiency of its environmental governance. The Industrial Development Index (*IND*) is measured as the ratio of industrial added value to GDP. Achieving peak carbon emissions in China requires the industrial sector to converge carbon emissions [44]. Industrial production demands substantial energy inputs, predominantly from fossil fuels whose combustion is the reason of significant emissions of greenhouse gases, particularly carbon dioxide. Conversely, industrial growth has driven technological advancement, enhancing production efficiency while fostering the emergence of technologies exhibiting the aim of energy conservation and emission reduction. The implementation of new energy technologies, including solar and wind power, along with energy-efficient systems, can considerably mitigate carbon emissions. *CWF* represents the logarithm of the exhaust gas treatment capacity. The waste gas treatment project directly diminishes greenhouse gas emissions by treating and purifying the waste gas generated in industrial production through a series of technologies and equipment. These greenhouse gases, including carbon dioxide, have an important impact on global climate change. Through waste gas treatment, the intensity of these gases can be effectively reduced against climate change. For instance, numerous studies have been conducted on the emissions from diesel exhaust pollutants and the technologies for controlling these emissions after treatment [45]. *FIN* is the logarithm of the added value of the financial industry. By providing green loan financial services, the financial industry can guide funds to low-carbon, environmental protection and other fields. With the increase of added value in the financial industry, more financial loans are invested in low-carbon areas such as environmental protection, clean energy and green transportation to promote the rapid development of these areas, thus helping to reduce carbon emissions [46]. *GCR* is the green coverage of built up areas in a province. The improvement of green coverage in the built-up areas of a province can promote emission reduction. Firstly, green plants can absorb a large amount of carbon dioxide through photosynthesis, reducing the concentration of pollutants in the air and thus lowering carbon emissions. Secondly, green vegetation can provide shading and ventilation effects, reduce heat accumulation in cities, decrease the demand for air conditioning and other refrigeration equipment, and thereby lower energy consumption and carbon emissions [47,48]. *POP* is the logarithmic value of population. We can observe a close link between the population and carbon emissions in each province. As the population grows, the scope and scale of people's activities correspondingly increase, which will lead to more energy consumption. And energy consumption is a key figure in the greenhouse gas emissions, thus an increase in the global population will cause these emissions to rise [49].

4.1.4. Mediating Variable

The mediating variable, newly applied green patent (*NGP*), is calculated by taking the logarithms of *NGP* in each province. The green patent of a province represents the technological innovation ability and achievements of the province in terms of environmental protection and sustainable development, and is an crucial indicator to evaluate the contribution of environmental protection, industrial transformation and upgrading, policy support and market prospects of the province. Green patents are particularly linked to inventions that lessen their negative effects on the environment or help make better use of available resources[25,50].

All variables' definitions can be found in Table 2.

Table 2. Definition of variables.

Variable type	Variable name	Definition
Explained variable	*CEG*	The ratio of carbon emissions to GDP in a province
Explained variable	*NQP*	The NQP index
Control variables	*FEE*	The ratio of environmental expenditure to fiscal expenditure in the province

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	CWF	The logarithm of the exhaust gas treatment capacity
	GCR	The green coverage of built up areas in a province
	FIN	The logarithm of the added value of the financial industry
	IND	The ratio of industrial added value to GDP
	POP	The logarithmic value of population in a province
Mediating variable	*NGP*	The logarithms of newly applied green patent in a province

4.2. Model

4.2.1. Fixed-Effects Model

Considering a more detailed assessment of the relationships between variables, this study uses a bidirectional fixed effects model to exam the effect of *NQP* on *CEG* as follows:

$$CEG_{it} = \beta_0 + \beta_1 NQP_{it} + \sum_{i=2}^{8} \beta_i \, Control_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{3}$$

CEG_{it} stands the ratio of carbon emissions to GDP for province i in year t. NQP_{it} signifies the corresponding new quality productivity for the province. Controlit comprises a collection of control variables that could potentially impact the *CEG*. μ_i indicates region fixed effects, λ_t denotes time fixed effects, and ε_{it} represents a random error term.

4.2.2. Intermediary Effects Model

In order to uncover the mechanism of how the independent variable effects the dependent variable through the mediating variable, the paper employs a mediation model to assess the effect of *NQP* on *CEG* through *NGP*. The specific model is as follows.

$$CEG_{it} = \beta_0 + \beta_1 NQP_{it} + \sum_{i=2}^{8} \beta_i Control_{it} + \epsilon_{it} \tag{4}$$

$$NGP_{it} = \beta_0 + \beta_1 NQP_{it} + \sum_{i=2}^{8} \beta_i Control_{it} + \epsilon_{it} \tag{5}$$

$$CEG_{it} = \beta_0 + \beta_1 NQP_{it} + \beta_2 NGP_{it} + \sum_{i=3}^{9} \beta_i Control_{it} + \epsilon_{it} \tag{6}$$

In model 6, NGP_{it} is the level of the newly applied green patent in the province *i* of year *t*. The NGP_{it} does not have a direct effect on CEG_{it} , but is achieved through the mediating variable NGP_{it} .

4.2.3. Spatial Durbin Model

In accordance to the possible spatial and geographic effects of *NQP* and *CEQ* in each province, the paper examines the spatial spillover impact of *NQP* on *CEQ* utilizing the Dubin model in the following way:

$$CEG_{it} = \alpha + \rho \sum_{\substack{j=1 \\ i \neq j}}^{n} W_{ij} CEG_{it} + \beta NQP_{it} + \gamma \sum_{\substack{j=1 \\ i \neq j}}^{n} W_{ij} NQP_{it} + \eta X_{it} + \theta \sum_{\substack{j=1 \\ i \neq j}}^{n} W_{ij} X_{it} + \mu_i + \varepsilon_i \tag{7}$$

where ρ denotes the spatial autoregressive coefficient, which indicates how the *CEG* of the province is influenced by that of its neighbors. W_{ij} stands for the spatial weight matrix, β stands for the regression coefficient of *NQP* on *CEG*, which shows how *NQP* affects *CEG*. γ denotes the spatial effect of *NQP*, in which may determine the influence of *NQP* in adjacent regions on *CEG* in the province.

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X_{it} is the province i in the t year for each control variable, θ is the spatial effect of control variable. Spatial lag model and spatial error model can be regarded as special forms of spatial Dubin model. When γ = θ =0, the model is a spatial lag model. When ρ = γ = θ =0, the model is a spatial error model.

4.3. Data

Considering the robustness, the study chooses 30 Chinese provinces' panel data with the exclusion of Tibet between 2012 and 2022, totaling 330samples. Raw data for the relevant indicators are the *China Environmental Statistics Yearbook*，the *China Energy Statistics Yearbook*，the *China Science and Technology Statistics Yearbook*，the *China Statistical Yearbook* and the statistical yearbooks of each province between 2013 and 2023. Data on patent applications for green inventions in provinces come from the official website of national intellectual property rights. We utilized interpolation to decrease sample loss because there was only a small amount of missing original data. The descriptive statistics for each variable are displayed in Table 3.

Table 3. Descriptive statistics of variables.

Variables	Observations	Mean	SD	Min	Median	Max
CEG	330	0.643	0.526	0.0620	0.449	2.477
NQP	330	0.285	0.130	0.102	0.253	0.747
FEE	330	0	0.001	0	0	0.019
CWF	330	8.937	0.898	6.316	8.931	10.96
GCR	330	40.16	3.492	29.80	40.50	49.80
FIN	330	7.243	0.940	4.559	7.237	9.355
IND	330	0.328	0.077	0.100	0.330	0.542
POP	330	8.209	0.741	6.345	8.280	9.447
NGP	330	6.478	0.554	4.760	6.615	7.403

5. Empirical Analysis

5.1. Pearson Correlation Test and VIF Test

Correlation analysis is the premise of data regression by analyzing the dependence between the values of variables. Only relevant data can be further regressed for. Table 4 presented that, the correlation coefficient between *CEG* and *NQP* is -0.471, and the two variables are negatively correlated. The correlation coefficient between *CEG* and *NGP* is -0.221, and the two variables are positively correlated.

Table 4. Pearson correlation test.

Variables	*CEG*	*NQP*	*FEE*	*CWF*	*FIN*	*GCR*	*IND*	*POP*	*NGP*
CEG	1								
NQP	-0.471***	1							
FEE	0.085	0.029	1						
CWF	-0.170***	0.586***	-0.015	1					
FIN	-0.597***	0.763***	-0.037	0.718***	1				
GCR	-0.273***	0.461***	-0.008	0.369***	0.560***	1			
IND	0.235***	0.200***	-0.035	0.513***	0.064	-0.035	1		
POP	-0.421***	0.518***	-0.052	0.807***	0.669***	0.346***	0.412***	1	
NGP	0.221***	-0.130**	0.076	-0.190***	-0.246***	-0.198***	-0.172***	-0.229***	1

*** p<0.01,** p<0.05, * p<0.1.

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To prevent multicollinearity of predictive variables, the variance inflation factor(VIF)was used in this study. As Table 4 illustrated, the VIF is 2.90, and the VIF values of all variables are below 10, excluding the possibility of multicollinearity.

Table 4. VIF test.

Variable	VIF	1/VIF
FIN	5.240	0.191
CWF	4.850	0.206
POP	3.090	0.324
NQP	2.620	0.381
IND	2.010	0.498
GCR	1.480	0.677
FEE	1.020	0.981
Mean VIF	2.900	

5.2. Baseline Regression

Table 5 illustrates the baseline regressions outcomes. Particularly, column (1) illustrates the direct regression results between *NQP* and *CEG*, while column (2) shows the regression outcomes after incorporating control variables. The baseline regression findings indicate that *NQP* remains consistently significant in every models at the 1% level, thereby underscoring the robust negative correlation between *NQP* and *CEG*. The findings show that *NQP* exerts a suppressive influence on *CEG*, implying that carbon emission performance is improved and thereby supporting the reliability of Hypothesis 1.

Table 5. Baseline regression.

Variables	(1)	(2)
	CEG	***CEG***
NQP	-0.312**	-0.613***
	(-1.79)	(-2.45)
FEE		5.054
		(1.33)
CWF		0.0584*
		(1.80)
GCR		-0.011**
		(-1.86)
FIN		-0.110**
		(-1.79)
IND		-1.090***
		(-3.31)
POP		0.540***
		(2.96)
Constant	0.732***	-2.530**
	(14.74)	(-1.78)
Observations	330	330

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Variables	(1) CEG	(2) CEG
R^2	0.987	0.991
Number of id	30	30
Area	YES	YES
Year	YES	YES

t statistics in parentheses* p < 0.1, ** p < 0.05, *** p < 0.01.

According to Zhang et al.[41], the level of coupling coordination between *NPQ* and manufacturing carbon emission efficiency has shown an ongoing rising tendency. Additionally, the *NQP* of provinces in China has exhibited an increase over the year, as has the efficiency of manufacturing carbon emissions. Manufacturing is only an integral part of all industries, it is a key source of carbon emissions, highlighting the essential role of *NQP* in driving improvements in carbon emission performance. Plus, the control variable coefficients shown in Table 5 indicate that *CWF* exerts a positive yet modest influence on *CEG*, aligning with the conclusions drawn by Zhang et al.[51].Human activities significantly contribute to the rise CO_2 level in atmosphere , with approximately two-thirds of the greenhouse effect attributed to such activities. *GCR* coefficient is notably negative at a 5% significance level, corroborating the results of Chen et al.[52] . There exists a beneficial link between the *CEG* and the growth of both urban areas and ecological green spaces. Consistent with what Xu and Liu found, the FIN coefficient is negative at the 5% significance level as well[53] . As GDP per capita increase, the interplay between the real economy and financial industries has promoted the carbon emissions incline across different regions. The *IND* coefficient is negative at a 1% significance level, supporting the research conducted by Zhang et al.[54]. High-carbon industries greatly contribute to the escalation of carbon emissions, at the same time, the medium and low carbon industries tend to have a more favorable impact on carbon emissions. The *POP* coefficient , which is positive at the significant level of 1%, contrasts with the findings of Zhu and Peng[55], possibly due to the fact that changes in population structure on carbon emission performance. Furthermore, the impact of control variables on *CEG* underscores the complex nature of *CEG* performance, which is shaped by a variety of indicators.

5.3. Robustness Tests and Endogenous Treatment

The baseline regression analysis outlined previously indicates that *NQP* plays a significant role in constraining *CEG*. To assess the model's reliability, additional methodologies will be employed for robustness assessment.

5.3.1. Substitution of the Explained Variable

For the purpose of robustness testing, this paper utilizes the proxy variable approach to reduce the impact of the explained variable selection bias on the regression results. Table 6 details the outcomes of a new regression analysis that used the ratio of CO_2 emissions to industrial value added as the principal explained variable instead of *CEG*. According to the results in Column (1), the *NQP* is still statistically significant at the 5% level even after controlling for the explanatory variable.

Table 6. Robustness tests and endogeneity treatment.

Variables	(1) CEG	(2) CEG	(3) CEG	(4) CEG	(5) CEG
NQP	-2.220**	-0.617*	-0.395*		-0.698***
	(0.024)	(0.058)	(0.099)		(0.008)
FEE	27.002**	4.979	0.766	-4.979***	25.290***
	(0.047)	(0.298)	(0.817)	(0.000)	(0.000)
CWF	0.163	0.067*	0.056	0.049	0.482***

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	(1)	(2)	(3)	(4)	(5)
Variables	***CEG***	***CEG***	***CEG***	***CEG***	***CEG***
	(0.151)	(0.095)	(0.118)	(0.148)	(0.000)
GCR	-0.029	-0.012	-0.012**	-0.011*	0.019**
	(0.174)	(0.112)	(0.048)	(0.060)	(0.012)
FIN	-0.706***	-0.122*	-0.147*	-0.162**	-0.404***
	(0.003)	(0.089)	(0.064)	(0.042)	(0.000)
IND	-10.864***	-1.152***	-1.110***	-1.158***	1.052***
	(0.000)	(0.002)	(0.003)	(0.002)	(0.001)
POP	1.079	0.518**	0.473**	0.426**	-0.439***
	(0.274)	(0.017)	(0.022)	(0.043)	(0.000)
L.NQP			-0.278**	-0.342**	
			(0.040)	(0.039)	
Constant	2.146	-2.288	-1.666	-1.205	1.945***
	(0.775)	(0.155)	(0.263)	(0.439)	(0.000)
Observations	330	286	260	260	330
Number of id	30	30	30	30	30
Area	YES	YES	YES	YES	
Year	YES	YES	YES	YES	

t-values in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5.3.2. Excluding Special Samples

In addressing the issue of special samples, the study excludes data from municipalities such as Beijing, Tianjin, Shanghai, and Chongqing, which operate under a distinct policy framework compared to other provinces[56]. This exclusion is intended to enhance the generalizability of the findings and minimize the impact of atypical samples. The outcomes presented in Column (2) of Table 6 ensure that the coefficients on *NQP* continue to be significant at the 10% level.

5.3.3. Lag Treatment

To address potential endogeneity arising from bidirectional causality, the study used first-order and second-order lags for the core explanatory variables, and to further find out the lag time length of *NQP* on *CEG*. Specifically, *L. NQP* denotes the corresponding variable lagged by one period. The regression outcomes for these lags are provided in columns (3)and (4) of Table 6, revealing that the coefficient on *NQP* remains significant, with both *NQP* and *L.NQP* significant at the 5% level, which denotes that *NQ*P has a one-year time lag effect on CEG. This temporal relationship implies that productivity may initially develop, subsequently leading to improvements in carbon performance.

5.3.4. Endogenous Treatment

In order to solve the possibility of endogeneity in the regression model, the research uses a two-stage least squares (2SLS) approach. Based on previous studies[57], this research selects the full-time equivalent of R&D Personnel and the installation density of robots as instrumental variables. The instrumental variables selected for this study satisfy relevance and exclusivity. These instrumental variables are related to the endogenous variable *NQP*, and are independent of the latent regression results. According to Table 6, column (5), after accounting for the influence of instrumental variables, *NQP* has a significant effect on *CEG*, supporting the results of the previous study.

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5.4. Heterogeneity Test

5.4.1. Heterogeneity of Geographic Location

The 30 provinces in the sample were put into 3 categories including eastern, central, and western regions in accordance to their geographical locations to investigate potential disparities between *NQP* and *CEG* across these areas. As indicated in Table 7, a significant association between *NQP* and *CEG* was observed in both the eastern and western provinces, whereas the central provinces exhibited minimal influence from *NQP*. This discrepancy can link to variations in resource availability and levels of economic development.

Table 7. Heterogeneity of geographic location.

Variable	**EAST *CEG***	**CENT *CEG***	**WEST *CEG***
NQP	-0.470*	0.152	-0.903*
	(0.071)	(0.807)	(0.078)
FEE	-22.255	18.774	9.411
	(0.604)	(0.873)	(0.174)
CWF	0.036	0.030	0.102*
	(0.189)	(0.361)	(0.089)
GCR	-0.004	-0.001	-0.022
	(0.597)	(0.910)	(0.108)
FIN	0.055	0.123***	-0.259***
	(0.585)	(0.003)	(0.007)
IND	0.841	-1.775***	-1.298***
	(0.168)	(0.004)	(0.002)
POP	0.969*	-2.355**	0.849**
	(0.095)	(0.030)	(0.049)
Constant	-8.342**	20.432**	-3.531
	(0.048)	(0.030)	(0.353)
Observations	110	66	121
R^2	0.977	0.994	0.992
Number of id	10	6	11
Area FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

t-values in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5.4.2. Heterogeneity of Different NQP Levels

The study acknowledged the heterogeneity in *NQP* levels across provinces, leading to the classification of the sample into three distinct groups: high, medium, and low. If you look at Table 8, in provinces categorized as high and low, *CEG* demonstrated with a 10% significance level, as presented in NQP-High group. In contrast, the medium group showed a statistically insignificant effect of *NQP*, as indicated in NQP-Mid group.

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Table 8. Heterogeneity of different NQP levels.

Variable	NQP-High	NQP-Mid	NQP-Low
	CEG	*CEG*	*CEG*
NQP	-1.065*	-0.055	-0.200*
	(0.069)	(0.901)	(0.055)
FEE	11.342	40.333	26.397
	(0.149)	(0.629)	(0.386)
CWF	0.053	0.063	0.016
	(0.276)	(0.195)	(0.217)
GCR	-0.021*	0.006	0.005*
	(0.081)	(0.378)	(0.055)
FIN	-0.430*	-0.093	0.076*
	(0.050)	(0.363)	(0.062)
IND	-1.136***	-1.429***	0.755**
	(0.006)	(0.009)	(0.032)
POP	0.694**	0.329	0.523**
	(0.016)	(0.484)	(0.015)
Constant	-1.070	-1.489	-5.349**
	(0.636)	(0.634)	(0.012)
Observations	110	143	77
R^2	0.988	0.993	0.980
Number of id	10	13	8
Area FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

t-values in parentheses * p < 0.1, ** p < 0.05, *** p < 0.01.

6. Impact Mechanism Test

6.1. Mediating Effect Test

According to Table 9, the *NQP* coefficient in column (1) to (3) was statistically significant at the 5% , 1% and 1% level, respectively, thereby confirming that *NGP* had a positively effect on *CEG* and serves as a mediator between *NQP* and *CEG*. The hypothesis2 is confirmed. However, in column (2), the regression coefficient sign of the main explanatory variable *NGP* was inverted, suggesting a masking effect.

Table 9. Mediating effect test.

	(1)	(2)	(3)
Variable	*CEG*	*NGP*	*CEG*
NQP	-0.693**	0.966**	-0.781***
	(-3.16)	(2.71)	(-3.56)
FEE	25.25	20.89	23.35
	(1.46)	(0.74)	(1.36)
CWF	0.482***	0.194**	0.465***
	(11.17)	(2.75)	(10.74)

Variable	(1) CEG	(2) NGP	(3) CEG
GCR	0.0189**	-0.0193	0.0207***
	(3.08)	(-1.93)	(3.38)
FIN	-0.404***	-0.286***	-0.378***
	(-9.42)	(-4.08)	(-8.67)
IND	1.050**	-2.198***	1.251***
	(3.25)	(-4.17)	(3.81)
POP	-0.439***	-0.0796	-0.432***
	(-10.51)	(-1.17)	(-10.41)
NGP			0.0912**
			(2.69)
Constant	1.948***	8.681***	1.156**
	(6.89)	(18.86)	(2.85)
Observations	330	330	330
R^2	0.638	0.134	0.646

t-values in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

To elucidate above complex mechanism of play and to ascertain the direct and indirect effects of *NGP* on *CEG*, the study employed mediation decomposition techniques, referencing existing literature and utilizing the Sobel-goodman test[58]. The findings presented in Table 10 confirmed the results of the Sobel test. The results showed that *NGP* indeed functions as a mediator, , with an estimated indirect effect value of 0.088 and a Z value of 1.91, which was significant at the 10% level. The *acoefficient* showed that the regression coefficient for the mediating variable *NGP* on the explanatory variable *CEG* was 0.966, significant at the 1% level. While the *bcoefficient* showed that the regression coefficient of the explanatory variable *CEG* on the mediator *NGP* was 0.091, which was significant at the 1% level. However, the coefficient of the indirect effect(0.088) failed to exceed the direct effect estimate (-0.781), and the total effect estimate (-0.693) was significantly negative. According to Arshad and Gulzar's research [59], the results of Sobel-goodman test demonstrated that there was a masking effect, meaning that *NGP* did not directly promote the improvement of *CEG*. Rather, it facilitated the improvement of *CEG* indirectly by enhancing *NQP*.

Table10. Sobel-goodman mediation tests.

Variable	Coefficient	Std Error	Z	P>∣Z∣
Sobel	0.088	0.046	1.910	0.056
Goodman-1 (Aroian)	0.088	0.047	1.847	0.064
Goodman-2	0.088	0.044	1.979	0.048
a coefficient	0.966	0.356	2.707	0.006
b coefficient	0.091	0.034	2.693	0.007
Indirect effect	0.088	0.046	1.909	0.056
Direct effect	-0.781	0.219	-3.561	0.000
Total effect	-0.693	0.219	-3.164	0.001
Proportion of total effect that is mediated	-0.127			
Ratio of indirect to direct effect	-0.112			
Ratio of total to direct effect	0.887			

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6.2. Spatial-Spillover Effects Test

6.2.1. Spatial Autocorrelation Analysis

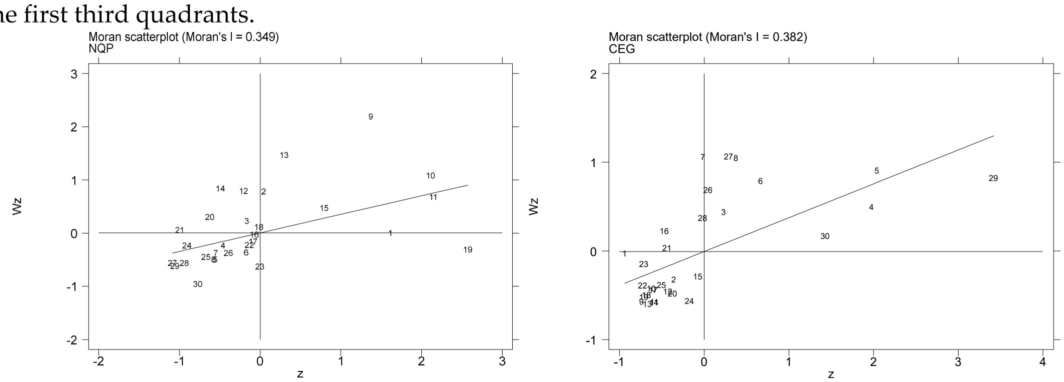
To assess whether a variable is spatially correlated, we utilized the global Moran index to analyze spatial autocorrelation. Table 11 shows the results of our annual global Moran's index calculation, as well as our *CEG* and *NQP* Moran's index calculations. The global Moran's index showed a positive value from 2012 to 2022, indicating that the two variables were clustered either high-high or low-low throughout the observation period. There was also a substantial spatial autocorrelation between *CEG* and *NEP* among provinces within this timeframe, as the Z-value for each year was greater than 1.96. These results demonstrate that *CEG* and *NEP* are positively correlated with one another in space and that a spatial-clustering phenomenon does in fact exist.

Table 11. Annual global spatial autocorrelation analysis.

Year	CEG		NQP	
	I	z	I	z
2012	0.461***	4.260	0.361***	3.332
2013	0.436***	4.051	0.283***	2.722
2014	0.438***	4.072	0.268***	2.586
2015	0.424***	3.965	0.297***	2.840
2016	0.426***	3.943	0.294***	2.814
2017	0.406***	3.843	0.304***	2.929
2018	0.396***	3.782	0.191**	1.938
2019	0.395***	3.784	0.316***	3.069
2020	0.402***	3.833	0.366***	3.466
2021	0.394***	3.803	0.371***	3.509
2022	0.395***	3.828	0.335***	3.186

t statistics in parentheses ** $p < 0.05$, *** $p < 0.01$.

For the purpose of investigating the local spatial correlation more thoroughly, we applied the local Moran's I method to examine the spatial autocorrelation of *NQP* and *CEG* at a local level. Figure 3 illustrates Moran's I scatter plots for *CEG* and *NQP* across each province for 2022, demonstrating a strong positive spatial association at the local level, as the majority of provinces are concentrated in the first third quadrants.



(**a**) (**b**)

Figure 3. Annual Local spatial autocorrelation analysis. (**a**) Moran's index of *NQP* in 2022; (**b**) Moran's index of *CEG* in 2022.

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6.2.2. Spatial Model Suitability Tests

In order to comprehend the features of spatial correlation, particularly its presence in either the error term or the lag term, the assessment of the Lagrange Multiplier (LM) is important prior to moving forward with model estimation. Decisions between SEM and SLM (Spatial Linear Modeling) must be based on this evaluation. Table 12 shows that every single LM test result is statistically significant. Results from both the Wald and LR tests indicate that the null hypothesis, which states that SDM can be reduced to SLM or SEM, is still not challenged. For this reason, we will be conducting our spatial regression analysis using the SDM model.

Table 12. Spatial model comparison tests.

Method	Statistical Value	prob
LM-spatial error	17.30	0.0000
LM-spatial lag	40.16	0.0000
LR-spatial error	29.32	0.0006
LR-spatial lag	266.58	0.0000
Wald-spatial lag 1	17.03	0.0092
Wald-spatial lag 2	54.35	0.0000
Wald-spatial error 1	13.41	0.0370
Wald-spatial error 2	15.20	0.0336

6.2.3. Space Spillovers and Decomposition

This study investigates the relationship between *NQP* and *CEG* across neighboring provinces. As shown in the Table 13, the results of column(1) present the baseline regression indicating a significantly negative coefficient for *NQP*'s impact on *CEG*. An analysis of columns (2) shows that a province's *NQP* positively influences the *CEG* of adjacent provinces, enhancing the carbon emission performance of those neighboring province. This indicates a spatial interconnectedness in the overall network of carbon emission performance, which exhibits significant local clustering[60]. To further understand this phenomenon, the spatial effect is divided into three components: direct, indirect and total effect, utilizing the spatial regression partial differentiation method. In columns(5), population leads changes in productive and consumptive activities, which significantly affect the spatial relocation of carbon emissions[61] . The spatial autocorrelation coefficient, denoted as rho, was 0.277,which was statistically significant at the 1% level. The findings indicated that the advancement of *NQP* in local area has the potential to significantly lower *CEG* while simultaneously enhancing *CEG* in the adjacent areas, thereby corroborating the outcomes of earlier analyses. A closer examination of columns (3), (4), and (5) reveals a positive spatial-spillover effect of *NQP* on *CEG*, lending empirical support to Hypothesis 3. In Column(2), the spatial autocorrelation coefficient of *NQP* of 0.695 is significant at the 1% level, indicating the presence of spatial autocorrelation in the development of *NQP*. From the analysis of columns(3)-(5), the total effect of *NQP* on *CEG* was -0.135, significant level of 10%, which means that for every 1 unit increase in *NQP* level, *CEG* decreases by 0.138 units. The direct effect of *NQP* on *CEG* was -0.508, while the indirect effect of *NQP* on *CEG* was 0.373. The direct and indirect effects were in opposite directions, indicating that the development of *NQP* may be that carbon leaked to the surrounding areas through supply chains, industrial chains and other channels, leading to an increase in carbon emissions in neighboring provinces. The fact that *FIN* significantly reduces CO_2 emissions in the area proves that green finance has a domino effect[62]. IND also has the significant inhibitory effect on local CO_2 emissions. At the 1% significance level, *FEE* and *FIN* exhibit a spatial spillover total effect in controlled variables.

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Table 13. Spatial-spillover effects.

	(1)	(2)	(3)	(4)	(5)
Varible	**Main**	**Wx**	**Direct Effect**	**Indirect Effect**	**Total Effect**
NQP	-0.552**	0.695***	-0.508**	0.373***	-0.135*
	(-2.162)	(2.619)	(-1.993)	(2.662)	(-1.938)
FEE	3.577	-10.54***	2.815	-11.92***	-9.109***
	(1.123)	(-3.199)	(0.856)	(-4.189)	(-3.065)
CWF	0.0486	0.00159	0.0524	0.0186	0.0710
	(1.327)	(0.046)	(1.481)	(0.477)	(1.504)
FIN	-0.264***	0.0161	-0.268***	-0.0762	-0.344***
	(-4.042)	(0.238)	(-4.322)	(-1.137)	(-5.433)
GCR	-0.0117*	0.00208	-0.0119**	-0.0003	-0.0122
	(-1.934)	(0.262)	(-2.047)	(-0.034)	(-1.320)
IND	-1.014***	0.509*	-0.987***	0.274	-0.713
	(-3.298)	(1.847)	(-3.267)	(0.820)	(-1.459)
POP	0.312	0.338	0.339	0.566	0.905**
	(1.130)	(0.759)	(1.350)	(1.109)	(2.081)
Spatial	0.277***				
rho	(3.256)				
Variance	0.003***				
sigma2_e	((4.745))				
N	330				

t statistics in parentheses ** $p < 0.05$, *** $p < 0.01$.

7. Conclusions and Policy Implications

CO_2 emissions are a primary driver of climate change and is greatly threatening global sustainable development. One possible way for sustainable economic growth is to reduce CO_2 emissions by increasing productivity levels, especially NQP level.

This study evaluates the level of NQP utilizing panel data from 30 Chinese provinces between 2012 and 2022, exploring the mechanism and spillover effect of NQP on carbon emission performance. The conclusions are as follows: (1) NQP significantly decreases carbon emissions per unit of GDP and improves carbon emission performance which remains valid after the robustness test applying the instrumental variable method. (2) The NQP has made a significant contribution to enhancing carbon emission performance by fostering advancements in green innovation. (3) The influence of NQP extends beyond the local region, positively affecting the carbon emission performance levels of adjacent provinces through a spatial spillover effect. (4) The eastern, non-resource-based and innovative regions experience a greater impact from the NQP in terms of carbon emission performance.

Drawing from the theoretical analyses and empirical findings presented, we propose such policy measures.

At first, to drive the advancement of NQP. When it comes to labor, people are the most active and significant contributor to productivity. Talent is the most critical and core element of innovation, and it is the leading force of scientific and technological innovation. The NQP puts forward higher requirements for the knowledge and skills of workers. The talent working mechanism and talent training model need to be optimized for the development of NQP. Improving NQP is also inseparable from the subject of labor, which is the foundation of NQP. The scope and fields of labor subjects already have been greatly expanded, such as digital and intelligent facilities, new materials, new

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energy, driven by scientific and technological innovation. Carbon emission reduction should actively embrace and use new labor subjects to improve performance. In terms of labor tools, they are the source of power for NQP. Carbon reduction relies on new, smarter, more efficient, lower-carbon, and safer production tools that weaken the constraints of natural conditions on production activities. Therefore, improving NQP should be a top priority when developing carbon emission policies.

Secondly, to better adopt the innovation and application of green technology and improve the incentives of green systems. To further enhance the advancement and implementation of environmentally-friendly technology, it is crucial to bolster the innovation and implementation of green technology. This entails not only developing cutting-edge solutions but also improving the incentives and support systems for the adoption of green systems. Promoting sustainable practices is essential in creating a greener future. By raising awareness and providing incentives, we may promote people and businesses to act in environmentally-friendly ways and help the reduction of carbon emissions.

Thirdly, to strengthen cross-regional policy coordination to promote overall carbon emission reduction in different regions. It is imperative to foster effective cross-regional policy coordination. By promoting collaboration and synchronization among different regions, we can collectively work towards achieving a significant cut in carbon emissions on a larger scale. This approach will ensure a thorough and holistic approach to solve world-wide problem of climate change. Collaborating with international organizations will enable us to leverage their expertise and resources in combating climate change. By establishing partnerships, we can promote knowledge sharing and facilitate the transfer of green technology, allowing us to accelerate progress in combating environmental challenges globally.

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