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ARTICLE

Carbon Reduction Effect of Digital New Quality Productivity: Theoretical Analysis and Empirical Evidence

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ABSTRACT

The continuous innovation and widespread application of digital technology have expedited the transformation of productivity and presented an opportunity to achieve carbon peak and carbon neutrality. Digital new quality productivity, characterized by the integration of advanced technologies, innovative business models, a new economic framework, and ongoing innovation, stands as a superior production factor. It plays a crucial role in fostering high-quality economic growth and leading efforts to meet the "dual carbon" objectives. Using panel data from Chinese prefecture-level cities from 2011 to 2022, this study employs various econometric models to empirically examine the impact and underlying mechanisms of digital new quality productivity on carbon emission reduction. The findings reveal that: (1) There exists a significant U-shaped nonlinear relationship between digital new quality productivity and carbon emission performance, with an inflection point at 0.2750. (2) Dual objective constraints significantly moderate the relationship between digital new productivity and carbon emission performance. Setting moderate economic growth targets positively influences the effect of digital new quality productivity on carbon emission performance. (3) The impact of digital new quality productivity on carbon emission performance varies considerably based on factors such as urban location, city size, resource endowment, and specific city characteristics. It is essential to focus on nurturing digital new quality productivity, exploring the integration of balanced economic growth objectives with environmental goals, and effectively leveraging the environmental benefits derived from the advancement of digital new quality productivity tailored to local contexts.

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1. Introduction

Since the reform and opening-up policy's implementation, China has experienced significant economic development. However, this rapid growth, marked by substantial energy consumption and high emissions, has led to considerable environmental challenges [1]. According to the "World Energy Statistical Yearbook 2021", China's carbon emissions increased from 8.83 billion tons in 2011 to 9.894 billion tons in 2020, representing 30.90% of global carbon emissions and underscoring the formidable task of reduction. As a responsible global power and dedicated developing nation, China pledged at the United Nations General Assembly in September 2020 to peak carbon dioxide emissions by 2030 and achieve carbon neutrality by 2060 [2]. These "dual carbon" goals illustrate China's commitment to global climate governance and are essential for the nation's high-quality development [3].

In September 2023, during his inspection tour of Northeast China, General Secretary Xi Jinping introduced the concept of "new quality productivity". He emphasized the need to integrate scientific and technological innovation to advance strategic emerging industries and future industries, thereby accelerating the formation of new quality productivity. Digital new quality productivity represents a novel paradigm in the digital economy era, defined by the seamless integration of digital technology with high-quality productivity [4, 5]. This emerging model is essential to the broader concept of new quality productivity. The rapid growth of the digital economy is profoundly transforming production methods, lifestyles, and governance practices [6]. According to the "Blue Book of Digital Economy: China's Digital Economy Frontier (2021)", during the "14th Five-Year Plan" period, China's digital economy is expected to continue its rapid expansion, with an estimated average annual nominal growth rate of 11.30%, significantly outpacing the nominal GDP growth rate for the same period. Consequently, the digital economy's share of GDP is projected to exceed one-third. Digital technology has the potential to deeply integrate and innovate in the sectors of energy, resources, and the environment. Therefore, a critical question arises: Can the continually evolving digital new qualitative productivity become a driving force in the low-carbon transformation of the economy, achieving the dual benefits of reduced carbon emissions and enhanced carbon efficiency? If digital new qualitative productivity improves carbon emission outcomes, what are the underlying mechanisms? Is there a spatial spillover effect influenced by regional disparities? How effective is digital new quality productivity in balancing economic growth with environmental sustainability? Examining the logical and operational mechanisms behind these interactions is crucial.

In reviewing the existing literature on the factors influencing carbon emissions, early research primarily concentrated on the interplay between economic growth and environmental protection. The seminal Environmental Kuznets Curve (EKC) postulates an inverted U-shaped relationship between environmental pollution levels and per capita income [7]. Conversely, some scholars suggest the existence of a U-shaped relationship between environmental pollution and economic growth [8]. With the escalating processes of globalization, increased scholarly attention has been directed towards the environmental impacts of foreign direct investment, encapsulated in theoretical frameworks such as the "Pollution Haven Hypothesis" [9–11] and the "Pollution Halo Hypothesis" [12–14]. Recent domestic studies have extensively examined the effects of transportation infrastructure on emission reduction. Investments in transportation infrastructure are noted for their potential to enhance environmental quality, particularly through the expansion of road networks, which has demonstrated substantial efficacy in pollution abatement [15]. Furthermore, the development of urban rail transit stands out as a pivotal measure for mitigating congestion and managing environmental issues, particularly in highly populated urban areas [16]. The introduction of high-speed rail has been identified as significantly reducing urban industrial carbon emissions and fostering positive technological spillovers to small and medium-sized cities along its routes [17]. Moreover, the literature has explored various other dimensions, including environmental regulation [18, 19], fiscal decentralization [20, 21], economic agglomeration [22, 23], technological innovation [24, 25], and technological transformation [26]. A burgeoning niche within the literature investigates the measurement, impact mechanisms, and spatial effects of digital technological innovation and the digital economy on carbon emissions [27], contributing valuable practical insights. Despite the breadth of existing research, a notable gap persists in understanding the complex interactions between transportation infrastructure and carbon emissions, especially considering regional disparities and advancements in technology.

Examining existing literature on the influential factors of carbon emissions, early studies primarily focused on the relationship between economic growth and environmental protection. For instance, the famous Environmental Kuznets Curve (EKC) posits an inverted U-shaped relationship between environmental pollution levels and per capita income [7]. Some scholars argue that there is a U-shaped relationship between environmental pollution and economic growth [8]. With the deepening process of globalization, increasing attention has been given to the impact of foreign direct investment on the environment, including theoretical perspectives like the "Pollution Haven Hypothesis" [9–11] and the "Pollution Halo Hypothesis" [12–14]. In recent years, numerous domestic research papers have focused on exploring the impact of transportation infrastructure on emission reduction effects. Investments in transportation infrastructure can improve environmental quality, and the effect of increasing road area on pollution reduction is relatively effective [15]. Specifically, the construction of urban rail transit is an important measure for alleviating congestion and managing the environment, with notably significant effects in densely populated cities [16]. The opening of high-speed rail significantly reduces urban industrial carbon emissions and has a positive technological spillover effect on the industrial carbon reduction of small and medium-sized cities along the route [17]. Additionally, literature has analyzed perspectives from environmental regulation [18, 19], fiscal decentralization [20, 21], economic agglomeration [22, 23], technological innovation [24, 25], and technological transformation [26]. A few studies have also explored the measurement, impact mechanisms, and spatial effects of digital technological innovation and the digital economy on carbon emissions [27], yielding many conclusions of significant practical value. Despite extensive studies, there is a notable gap in both theoretical and empirical investigations concerning the influence of digital, high-quality productivity on carbon emissions. Furthermore, much of the current scholarly work has not accounted for the significant interplay between digital high-quality productivity and low-carbon transformation, especially within China, where such dynamics are inherently influenced by the pursuit of economic growth and environmental objectives. This interplay is critical for developing tailored carbon reduction strategies for major economies. Based on a thorough derivation of the theoretical model addressing the impact of digital new quality productivity on carbon emissions, this paper empirically examines the effect and underlying mechanisms of digital new quality productivity on carbon emissions. This analysis is conducted within the framework of dual objectives, utilizing panel data from 278 prefecture-level and above cities in China, spanning the years 2011 to 2022.

This paper contributes significantly to the existing literature in four key areas. First, it investigates the nonlinear dynamics between emerging digital new quality productivity and carbon emission performance, along with their spatial spillover effects. This research broadens the scope of environmental impact studies related to digital new quality productivity and enriches the existing literature on the role of data technology in environmental management. By thoroughly exploring this relationship, the study addresses the limitations of prior research, which often result in inadequate policy recommendations. Second, the paper develops a theoretical model within a dual-sector framework to analyze how digital new quality productivity influences carbon emission performance through various channels. This model clarifies the theoretical mechanisms by which digital new quality productivity affects carbon emissions and employs an enhanced mediating effect model to confirm the presence and significance of structural optimization and technological innovation effects. Third, the study takes into account the constraints of economic growth and environmental goals specific to China. It examines the intensity of these constraints to gain deeper insights into the mechanisms and unique characteristics of digital new quality productivity in promoting urban low-carbon transitions. Lastly, the paper considers the external impacts of nationwide initiatives such as the "Broadband China" strategy and the "Low-Carbon Pilot Cities" policy, as well as internal variations like city location, resource endowments, and specific urban characteristics. Through this comprehensive analysis, the paper systematically examines the heterogeneous effects of digital new quality productivity on carbon emission performance.

2. Theoretical Analysis and Research Assumptions

2.1. The Direct Impact of Digital New Quality Productivity on Carbon Emission Performance

The digital economy has engendered new forms of digital new quality productivity, closely associated with the digitization of various productivity factors. Investigating the relationship between this digital new quality productivity and carbon emission performance is essential for a comprehensive understanding of the digital economy. Digital and intelligent technologies significantly contribute to low-carbon transitions by providing unmatched efficiency and cost advantages. Consequently, the digital economy emerges as a crucial driver of urban low-carbon transformations [28]. From the perspective of governmental governance, digital new quality productivity enhances the capacity for managing low-carbon initiatives. Utilizing digital technology enables precise tracking of energy market trends and price fluctuations, fostering the development of a carbon trading data platform grounded in market mechanisms. This approach substantially lowers the costs associated with carbon information search and matching. Moreover, it facilitates proactive governmental interventions to balance energy supply and demand through pricing strategies and cross-subsidies. Additionally, digital new quality productivity supports uncovering the "carbon background", implementing "carbon plans", promoting "carbon trading", and achieving "carbon emission reduction". These measures significantly improve the government's capability to monitor and regulate carbon emissions [29]. In the context of industrial structural transformation and enhancement, leveraging Metcalfe's Law, which pertains to digital networks, enables the intricate integration of digital technologies into carbon-intensive industries—thereby disseminating the benefits of digital emission reduction [30]. Firstly, it facilitates the reallocation of production resources from less efficient to more efficient sectors, unrestricted by temporal or spatial constraints, allowing enterprises to adopt smart and intensive management practices and drive sustainable innovation. Secondly, it significantly reduces energy consumption across the industrial landscape [31]. By examining these dynamics, we gain insights into how digital new quality productivity not only fuels economic advancement but also fosters sustainable and low-carbon growth across various sectors [32].

In the domain of digital new quality productivity, not all effects are conducive to reducing carbon emissions; some induce negative environmental consequences, known as "green blind spots," which impair carbon emission performance. Particularly, the extensive application of digital technology in the mining sector significantly amplifies the scale and speed of non-ferrous metal and mineral resource extraction, leading to excessive resource consumption and subsequent environmental externalities [2]. Moreover, critical industries such as telecommunications, software development, and the Internet necessitate a robust power supply to sustain digital new quality productivity [33]. Given that China, the world's second-largest digital economy, primarily relies on coal for power generation, this dependence can lead to increased coal consumption and carbon emissions [34]. Further research indicates that digital technology drives equipment renewal during the early stages of enterprise development. This renewal demands substantial energy extraction and usage to maintain production efficiency, thereby inevitably increasing carbon emissions. However, as companies mature, the application of digital technologies can significantly reduce pollution control costs, subsequently decreasing carbon emissions [35]. Consequently, the following research hypothesis is proposed:

Hypothesis 1. *A nonlinear relationship exists between digital new quality productivity and carbon emission performance.*

2.2. The Mechanism of the Impact of Digital New Quality Productivity on Carbon Emission Performance

The digital economy, an emerging economic paradigm, leverages technological advancements to enhance carbon emissions performance through technological innovation and industrial transformation [36]. The development of green technology is crucial for improving carbon emissions performance. At a macro level, digital technologies synergize with energy technologies, integrating the digital and traditional economies. This integration promotes novel low-carbon technologies and supports the transition toward environmentally sustainable production methods, leading to intelligent manufacturing. As a result, carbon emissions are inherently reduced, improving overall carbon performance. From a micro perspective, digital capabilities enhance the dissemination of low-carbon technologies, accelerating their adoption across various sectors and driving industries toward digital and low-carbon advancements. This transformation alters traditional energy consumption patterns through efficient resource allocation and promotes the widespread adoption of clean technologies, significantly reducing corporate carbon emissions [37]. The upgrading of industrial structures driven by digital advancements enables technological dissemination and industrial integration. Technologies such as cloud computing and artificial intelligence help identify informational advantages and technological gaps when integrated with traditional industrial processes. This seamless flow of factors within industries leverages the scale and competitive advantages of data platforms to facilitate cross-industry factor allocation [38, 39].

This paper develops a theoretical model to analyze the multi-channel impacts on carbon emission performance and elucidates how digital advancements in productivity influence carbon emission metrics. Building on the Cobb-Douglas production function, an energy-inclusive production function is formulated:

$$\mathrm{Y} = AL^{\alpha}K^{\beta}E^{1-\alpha-\beta} \tag{1}$$

$$\mathrm{CP} = \frac{Y}{E^{1-\alpha-\beta}V} = \frac{AL^{\alpha}K^{\beta}}{V} \tag{2}$$

$$\mathrm{A} = \mathrm{f}(\theta) \tag{3}$$

Among them, Y, A, L, K, E, CP, Vrepresent economic output, technological innovation, labor quantity, capital stock, energy consumption, carbon emission performance, and carbon emission conversion coefficient, respectively. It is assumed that technological innovation is positively correlated with digital new quality productivity θ. Simplifying the above equation yields:

$$\mathrm{CP} = \mathrm{f}(\theta)\,\frac{L^{\alpha}K^{\beta}}{V} \tag{4}$$

From Equation (4), it can be seen that the larger the digital new quality productivity θ and the higher the technological innovation A, the higher the carbon emission performance of a single sector.

Extending the model again to the two-sector model, and distinguishing between the two sectors with high and low carbon emission performance, i.e., $CP_1 > CP_2$, then:

$$\frac{CP_1}{CP_2} = \tau > 1 \tag{5}$$

Given the theoretical framework, it is evident that regional digital new quality productivity substantially impacts the upgrading of industrial structures. The model investigates the following dimensions:

$$\mathrm{UIS} = \frac{Y_1}{Y_2} = g(\theta) \tag{6}$$

$$\mathrm{CP} = \frac{Y}{VE} = \frac{Y_1+Y_2}{V\left({Y_1}/{CP_1V} + {Y_2}/{CP_2V}\right)} \tag{7}$$

Integrating Equations (5), (6), and (7) yields:

$$\begin{aligned}\mathrm{CP} = \frac{Y}{VE} &= \frac{Y_1+Y_2}{V\left({Y_1}/{CP_1V} + {Y_2}/{CP_2V}\right)} \\ &= \frac{UIS+1}{{Y_1}/{CP_1} + {Y_2}/{CP_2}} = \left(\frac{UIS+1}{UIS+\tau}\right)CP_1 \\ &= \left[\frac{g(\theta)+1}{g(\theta)+\tau}\right] f(\theta)\,\frac{L_1^{\alpha}K_1^{\beta}}{V}\end{aligned} \tag{8}$$

Increased digital new quality productivity clearly optimizes industrial structures and enhances carbon emission performance. This indicates that a higher percentage of high-performing departments regarding carbon emissions can improve the region's overall carbon emission performance.

In summary, the second research hypothesis is formulated as follows:

Hypothesis 2. *The improvement of digital news quality primarily enhances carbon emission performance through technological innovation and the upgrading of industrial structures.*

2.3. The Moderating Effect of Dual Objective Constraints on the Impact of Digital New Quality Productivity on Carbon Emission Performance

Formulating economic development policies in China necessitates accounting for the constraints posed by economic growth and environmental targets. Effective low-carbon governance requires optimal market resource allocation and proactive government intervention[40]. Both economic growth and environmental objectives are essential policy instruments for achieving efficient low-carbon governance, with balanced dual-target constraints being critical for realizing the "dual carbon" goal[41]. Promotion competition theory suggests that local governments are incentivized to meet economic growth targets. When the central government establishes provincial targets, local authorities often amplify these goals, creating a scenario of "competition for growth" and "competition for investment". This competitive model has historically spurred China's rapid economic growth but has also resulted in a "zero-sum game," skewing the investment structure toward infrastructure rather than services, and consequently, contributing to high carbon emissions. Persistent investment in traditional sectors has entrenched a path dependence characterized by "high energy consumption, high emissions, and high pollution", further aggravating carbon emissions. Thus, excessively high economic growth targets undermine technological innovation and industrial upgrading driven by new digital new quality productivity, impeding the transition to low-carbon development[42]. In contrast, the 14th Five-Year Plan addresses these challenges by imposing constraints on energy consumption and carbon emissions through a combination of environmental regulations and oversight mechanisms[43, 44]. Based on this, the research hypothesis 3 is proposed:

Hypothesis 3. *Setting excessively high economic growth targets undermines the effectiveness of digital innovation in enhancing low-carbon governance. Conversely, imposing stringent environmental targets enhances the performance of digital innovations in low-carbon governance.*

3. Research Design

3.1. Model Building

3.1.1. Static Panel Model

In this paper, we develop a model grounded in the STIRPAT framework, which systematically assesses the influence of key socio-economic factors on environmental outcomes. This model is particularly effective for analyzing the determinants of carbon emission performance[45]. The benchmark model is presented as follows:

$$\begin{aligned} \ln CEP_{it} = \alpha_0 + \alpha_1 lnNQP_{it} + \alpha_2 lnSNQP_{it} \\ + \alpha_3 lnC_{it} + \mu_i + \sigma_t + \delta_{it} \end{aligned} \tag{9}$$

Among them, CEP_{it} represents the carbon emission performance of city i in the t year; NQP_{it} and $SNQP_{it}$ are the level of digital new quality productivity and its square term, respectively; C_{it} represents the group of control variables that affect carbon emission performance, including economic development level, urbanization level, population size, fixed asset investment, foreign direct investment and other variables. μ_i, σ_t, δ_{it} represent the regional effect, the temporal effect, and the stochastic perturbation term, respectively.

3.1.2. Mechanism Test Model

To investigate the existence and contribution of two primary mechanisms—the technological innovation effect and the industrial structure upgrading effect—this study adopts the methodology outlined by Cutler and Lleras-Muney[46]. Specifically, mechanism variables are incorporated into equation (9), including the measurement of the technological innovation effect per 10,000 green patent applications (ETI) and the ratio of the added value of secondary and tertiary industries to capture the industrial structure upgrading effect (IUS), while controlling for all other variables. The test steps are outlined as follows: (1)Directly assess the impact of digital new quality productivity on technological innovation and the upgrading of industrial structures to verify the presence of these two mechanisms. (2) Based on regression Equation (11), further quantify the explanatory power of the two mechanisms. This calculation involves obtaining the coefficients $\widehat{\alpha}$ and $\widehat{\phi}$ representing the development level of new digital productive forces from regression Equations (9) and (11), respectively, and then calculating $1 - \widehat{\alpha} / \widehat{\phi}$ to determine the contribution of the mechanistic variables. The relevant regression equation is provided below:

$$\ln\gamma_{it} = \beta_0 + \beta_1 lnNQP_{it} + \mu_i + \sigma_t + \delta_{it} \tag{10}$$

$$\begin{aligned} \ln CEP_{it} = \phi_0 + \phi_1 lnNQP_{it} + \phi_2 lnSNQP_{it} \\ + \phi_3 ln\gamma_{it} + \phi_4 lnC_{it} + \mu_i + \sigma_t + \delta_{it} \end{aligned} \tag{11}$$

3.1.3. Spatial Econometric Model

The Spatial Durbin Model (SDM) marks a pivotal advancement in the realm of spatial econometrics. This model not only integrates the advantages of the Spatial Autoregressive Model (SAR) and the Spatial Error Model (SEM), but also mitigates their limitations by thoroughly accounting for the spatial effects of random shocks [47]. Additionally, the model utilizes the Wald statistic to determine the specific spatial panel form with a significance level of 1%, thereby substantiating the appropriateness of the SDM. Consequently, this study employs the SDM framework to formulate a spatial econometric model aimed at assessing the influence of digital new quality productivity on carbon emission performance. The corresponding equation is as follows:

$$\begin{gathered}\ln CEP_{it} = \alpha_0 + \rho WlnCEP_{it} + \alpha_1 lnNQP_{it} \\ +\alpha_2 lnSNQP_{it} + \alpha_3 lnC_{it} + \varepsilon_1 WlnNQP_{it} \\ +\varepsilon_2 WlnSNQP_{it} + \mu_i + \sigma_t + \delta_{it}\end{gathered} \tag{12}$$

Where: all variables are consistent with (1), ρ is the spatial autoregressive coefficient, and W is the spatial weight matrix. In this paper, two spatial weight representation methods are mainly adopted, one is the geographical distance weight matrix, which is measured by the reciprocal (distance_{ij}) of the geographical distance between the two cities, in which the geographical distance between the two cities is calculated by latitude and longitude, and this weight matrix is mainly used in the benchmark regression of the SDM spatial model. As shown in Equation (13):

$$W_{jdl} = \begin{cases} 1/\text{distance}_{ij}, i \neq j \\ 0, i = j \end{cases} \tag{13}$$

The second is the spatial weight matrix of economic distance, which is constructed based on the reciprocal of the gap between the per capita GDP of the two cities, and is used in the robustness test. As shown in Equation (14), where $pGDP$ denotes GDP per capita:

$$W_{jjl} = \begin{cases} \frac{1}{|pGDP_i - pGDP_j|}, i \neq j \\ 0, \ i = j \end{cases} \tag{14}$$

3.2. Variable Measures and Descriptions

3.2.1. Explanatory Variables

The dependent variable in this study is urban carbon emission performance (CEP), primarily represented by urban carbon emission intensity. To illustrate the positive impact of digital new quality productivity on urban carbon emission performance, the study uses the reciprocal of urban carbon emission intensity and subsequently standardizes it for analytical purposes. Urban carbon emission intensity is defined as the ratio of urban carbon emissions to GDP. Due to the lack of detailed city-level energy consumption data, this study leverages DMSP-OLS and NPP-VIIRS nighttime light data, as referenced in previous research [48, 49], to estimate carbon emissions in Chinese prefecture-level cities. This method assumes that increased economic activity, indicative of better economic development, correlates with higher energy consumption. Deng Rongrong and Zhang Aoxiang (2021) adopted this measurement method in their study [50] and confirmed its high inversion accuracy, validity, and scientific reliability. The methodology follows these stages: Initially, two nighttime light remote sensing datasets (DMSP-OLS and NPP-VIIRS) are integrated. These datasets undergo continuous correction and logarithmic transformation to extract total nighttime light values at the city scale. Subsequently, particle swarm optimization, combined with a back propagation algorithm, is employed to standardize the scales of various spatial metrics. A matching control analysis is then conducted to investigate the relationship between urban carbon emissions and nighttime light brightness. Based on this analysis, a fitting relationship and a carbon emission inversion model are developed to derive urban carbon emission data. In the final step, the accuracy of the data is verified to enhance its applicability [51].

3.2.2. Explanatory Variables

The explanatory variable in this paper is the level of development of digital new quality productivity (NQP). In the realm of political economy, the assessment of digital new quality productivity hinges on three fundamental components: digital workers, digital labor objects, and digital labor materials. Additionally, a comprehensive evaluation index system has been established to measure new digital new quality productivity, which includes dimensions such as digital infrastructure, digital data input, and digital output [52]. This paper extends prior research by proposing a detailed evaluation framework (see **Table 1**) that comprises three primary indicators, six secondary indicators, and sixteen tertiary indicators, centered on digital workers, labor objects, and digital labor data. The coefficient of variation method is applied to assign weights to these indicators [53], facilitating the evaluation of the development level of new digital new quality productivity at the municipal level.

Table 1. Evaluation index system of the development level of digital new quality productivity.

Target Layer	Criterion Layer	Indicator Layer	Measurement Method	Attribute
Digital workers	Number of digital workers	Science inputs	The government spends annually on science	+
		Invest in education	The government's annual financial expenditure on education	+
		Number of R&D personnel	Full-time equivalent of R&D personnel in industrial enterprises above designated size	+
	Digital Workforce Quality	Innovative R&D	Number of domestic patents granted	+
		Innovative industries	Number of new product development projects in high-tech industries	+
		Output per capita	GDP per capita	+
		Employment philosophy	The proportion of persons employed in the tertiary industry in total employment	+
Digital Labor Objects	Emerging industries	Strategic emerging industries	The output value of high-tech industries of industrial enterprises above designated size	+
			The number of patents in high-tech industries	+
		Emerging industry activity	Total import and export trade	+
	Digital business	Proportion of telecommunications services	The total telecommunication business accounts for the proportion of regional GDP	+
		Proportion of software business	The total volume of software business accounts for the proportion of regional GDP	+
Digital labor data	Tangible means of production	Digital infrastructure	Fiber length	+
			Number of Internet broadband access ports	+
		Mobile phone penetration	Mobile calls per 100 people	+
	Intangible means of production	R&D input	R&D expenditure	+
		Digital innovation	Digital Financial Inclusion Index	+
		Development of the digital economy	Frequency of digital economy policy	+

3.2.3. Control Variables

In reviewing the literature on the determinants of carbon emission performance, it has been identified that economic development, population size, and technological progress are the primary factors. Additionally, investments in fixed assets and the degree of openness to international markets are considered control variables (**Table 2**)[54, 55].

3.3. Data Sources

In light of the digital economy's recent advancements and the accessibility of relevant data, this study investigates the period from 2011 to 2022. Prefecture-level cities with substantial data gaps are excluded, resulting in a sample consisting of 278 Chinese cities at or above the prefecture level. The primary data sources comprise the "China City Statistical Yearbook", "China Energy Statistical Yearbook", various statistical annual reports of prefecture-level cities, the China Carbon Emission Database, the Green Patent Database, and the EPS Database. Missing values are addressed using the proximity mean method and linear interpolation. Data on economic growth and environmental targets are sourced from local municipal government work reports. Additionally, gray value data of nighttime lights is obtained from the global nighttime light database, adjusted to accurately reflect urban lighting data for China[56]. **Table 3** provides descriptive

Table 2. Description of the control variable.

The Variable Name	Variable Symbol	Calculation Method
Level of industrial development	DLI	The logarithm of the number of units of industrial enterprises above designated size
Level of urbanization	UR	Urbanization rate
Population size	POP	Urban resident population
Investment in fixed assets	IFA	Investment in fixed assets per capita
OFDI	FDI	Outward FDI as a share of GDP

Table 3. Variable descriptive statistics.

The Variable Type	The Variable Name	Variable Symbol	Mean	Standard Deviation	Min	Max
Explanatory variables	Carbon performance	CEP	0.2611	0.1302	0.0731	1.6591
Explanatory variables	The level of development of digital new quality productivity	NQP	0.1337	0.0679	0.0268	0.6529
	Digital New Qualitative Productivity Level Squared	SNQP	0.0226	0.0357	0.0005	0.4263
Mechanism variables	Technological innovation effect	ETI	0.6652	1.6173	0.0033	7.8815
	The effect of industrial structure upgrading	ISU	1.7732	1.3081	0.7266	3.8891
Control variables	Level of industrial development	DLI	4.1198	2.7911	3.6577	9.6689
	Level of urbanization	UR	0.6712	0.4491	0.1022	1.8823
	Population size	POP	4.8854	1.0977	2.2981	7.6928
	Investment in fixed assets	IFA	3.0166	1.7633	2.3015	6.6671
	OFDI	FDI	1.8933	1.6642	0.2711	5.0172

Note: Observed value N = 336.

statistics for the variables.

4. Empirical Results

4.1. The Impact of Digital New Quality Productivity on Carbon Emission Performance under Static Panel Model

4.1.1. Benchmark Regression Analysis

Columns (1) and (2) of **Table 4** display the regression outcomes for the level of development of digital new quality productivity and its squared term, respectively. The regression result in Column (1) presents a coefficient of 0.0185 for the impact of digital new quality productivity on carbon emission performance. However, this coefficient lacks statistical significance, indicating an absence of conclusive statistical evidence to support a positive effect of digital new quality productivity on carbon emission performance. In contrast, the results in Column (2) demonstrate that the linear term of digital new quality productivity is significantly positive at the 1% level, while the squared term is significantly negative at the 5% level. This pattern remains consistent even after controlling for other pertinent factors influencing carbon emission performance, suggesting a significant U-shaped nonlinear relationship between digital new quality productivity and carbon emission performance. These findings corroborate Hypothesis 1.

The initial inefficiencies of digital technologies, combined with substantial investments and resource consumption during digitalization and industrial digitalization, lead to elevated carbon emission intensity. This escalation is further exacerbated when companies must invest in green research and development (R&D), resulting in cumulative energy consumption that impairs carbon emission performance. Conversely, as digital technology evolves, the enhanced productivity and efficiency of input factors foster industrial transformation and upgrading. This progression reduces carbon emission intensity and subsequently improves carbon emission performance.

4.1.2. Instrumental Variable Regression

In considering the influence of urban institutional environments, government governance capabilities, and scientific and technological innovation on the development of digital

Table 4. Regression results of the static panel model.

Variables	(1)	(2)	Instrumental Variable Regression Phase 1	Phase 2
NQP	0.0185 (0.2142)	−0.7627** (0.3613)	/	−0.8123*** (0.3732)
SNQP	/	1.3868*** (0.5167)	/	1.4109*** (0.5695)
Control variables	YES	YES	YES	YES
Constant terms	1.8636*** (0.6135)	1.8862*** (0.6210)	0.0381** (0.0378)	0.2233** (0.0916)
Tool variables	/	/	0.0079*** (0.0086)	/
Time fixation effect	YES	YES	YES	YES
Regional fixed effects	YES	YES	YES	YES
R^2	0.4132	0.4187	0.7655	0.6633
Observations	3336	3336	3336	3336

Note: *, **, and *** represent significant at the 1%, 5%, and 10% levels, respectively; In parentheses are robust standard errors. The same applies hereinafter.

productivity and carbon emission performance, an inherent relationship exists between digital productivity and carbon emission performance. To address potential endogeneity, this study adopts established instrumental variable construction methods. Specifically, an instrumental variable is devised by combining terrain undulation with an annual dummy variable, leveraging the natural factor of topographic relief. The rationale for this choice is twofold: first, topographic relief originates from natural factors and is theoretically independent of other economic variables, thus meeting the erogeneity requirement. Second, topographic relief encapsulates the complexity of urban topography, which affects the difficulty and costs of digital infrastructure construction, thereby satisfying the relevance criterion.

Table 4 displays the findings from the regression analysis. Initially, the significant positive correlation between the instrumental variable and the endogenous variables corroborates the correlation hypothesis. In the subsequent stage, the primary term coefficient for digital new quality productivity is statistically significant and negative at the 1% level, while the squared term coefficient is significantly positive at the same level. These results indicate that appropriate instrumental variables can effectively mitigate potential endogeneity issues, thereby accurately elucidating the impact of digital new quality productivity on carbon emission performance. Furthermore, a stable U-shaped nonlinear relationship is evident between digital new quality productivity and carbon emission performance.

4.2. The Impact of Digital New Quality Productivity on Carbon Emission Performance under the Spatial Panel Model

4.2.1. Spatial Correlation Analysis

In preparation for spatial econometric regression, it is essential to perform a spatial correlation analysis on the core variables. The Moran's I index is frequently employed to assess the spatial correlation characteristics among these variables. In this study, we computed the global Moran's I index using a geographical distance matrix for 278 prefecture-level cities in China spanning from 2011 to 2022. The results reveal that the Moran's I index for the core variable is significantly greater than zero at the 1% significance level throughout the observation period. This indicates a significant spatial autocorrelation between digital new quality productivity and carbon emission performance across Chinese cities. Therefore, the distribution of digital new quality productivity and carbon emission performance is not random but demonstrates spatial dependence.

4.2.2. Spatial Effect Test Results

The results demonstrated in **Table 5** indicate the use of the Spatial Durbin Model (SDM) for spatial econometric regression analysis. Column (1) reveals a significant negative coefficient for the linear term of digital new quality productivity at the 1% significance level, while the squared term is significantly positive at the same level, suggesting a U-shaped nonlinear relationship between digital new quality productivity and carbon emission performance, which aligns with previous empirical findings. In Column (2), the coefficient for the spatial lag term of digital new quality productivity does not demonstrate a significant U-shaped nonlinear relationship. This signifies that the spatial spillover effect of digital new quality productivity on the carbon emission performance of neighboring Chinese cities is negligible during the study period. Columns (3) through (5) decompose the spatial effects of digital new quality productivity on carbon emission performance. The direct and total effects for both the linear and squared terms are significant at the 5% level, underscoring the existence of a U-shaped nonlinear relationship within individual regions and in the overall context.

In analyzing indirect effects, only the squared term of digital new quality productivity is significant at the 10% level, indicating that the spatial spillover effect on carbon emission performance is negligible. This minimal impact can be attributed to the siphoning effect caused by disparities in urban economic development levels, which diminishes the positive spillover effect of digital new quality productivity in central cities.

4.3. Robustness Test

To further assess the robustness of the impact of digital new quality productivity on carbon emission performance, this paper conducts robustness tests from four perspectives: substituting explanatory variables, incorporating the interaction term of the time trend with control variables, excluding the impact of other policies, and replacing the spatial weight matrix.

4.3.1. Replace the Explanatory Variable

Incorporating energy consumption and carbon emissions into the traditional Total Factor Productivity (TFP) framework, we use Total Fuel Consumption (TFC) as an indicator of carbon performance. The selected input factors include labor, capital, and energy, while the outputs consist of gross domestic product (GDP) and carbon emissions, with the latter regarded as an undesirable output. Detailed calculations employ the non-radial, non-angular Slack-Based Measure Data Envelopment Analysis (SBM-DEA) method. As indicated in **Table 6**, even after substituting the explanatory variables, digital new quality productivity demonstrates a significant U-shaped nonlinear relationship with carbon emission performance, corroborating the benchmark regression results.

4.3.2. Added Control Variables to Interact with Time Trends

Incorporating interaction terms between the time trend and control variables in the empirical model significantly mitigates estimation bias. This mitigation is attributable to the stabilization of the time trend of the influencing factors of the explanatory variable upon their inclusion [57]. Column (2) of **Table 6** illustrates that the significance and direction of the impact coefficient of digital new quality productivity on carbon emission performance remain largely consistent, thereby affirming the robustness of the benchmark regression results.

4.3.3. Exclude Other Policy Implications

In this paper, we examine the “Broadband China” and “Low-carbon Pilot Cities” policies, given their considerable influence on the development of digital new quality productivity and low-carbon transformation in urban areas. The “Broadband China” strategy was implemented in stages from 2014 to 2016, assigning a value of 1 to pilot cities and 0 to non-pilot cities. The “Low-carbon Pilot Cities” initiative began in 2010, initially including 5 provinces and 8 cities, with further expansions in 2012 and 2017. Similar value assignments were made: 1 for pilot cities and 0 for non-pilot cities. Column (3) of Table 6 presents regression results excluding the effects of these two policies. The analysis reveals no significant differences in the coefficients related to the impact of digital new quality productivity on carbon emission performance when these policies are omitted. This underscores the robustness of the regression results discussed earlier.

4.3.4. Replace the Spatial Weights Matrix

Selecting appropriate spatial weight matrices is crucial for the outcomes of spatial regression analyses. This study adopts an economic geography matrix instead of the traditional geographic distance matrix to re-estimate the Spatial Durbin Model (SDM). The results, as shown in column

Table 5. Regression results of spatial SDM model.

Variables	(1) CEP	(2) Spatial Lag Items	(3) Direct Effects	(4) Indirect Effects	(5) Total Effect
NQP	−0.6391*** (0.3317)	−0.5913 (0.3016)	−0.6503** (0.3433)	−0.6364 (0.3275)	−1.2867** (0.5139)
SNQP	1.1959*** (0.0378)	1.0375 (0.0097)	1.2002** (0.0467)	1.1936* (0.0263)	2.3938** (0.1615)
Control variables	YES	YES	YES	YES	YES
rho	0.1302*** (0.0287)	/	/	/	/
Sigma2_e	0.0098*** (0.0003)	/	/	/	/
R^2	0.2399	0.2378	0.2377	0.2402	0.2588
Observations	3336	3336	3336	3336	3336

(4) of **Table 6**, indicate that the regression coefficients and the directions of both linear and quadratic terms of digital new quality productivity are largely consistent with previous findings. Additionally, the significance of these results has increased, further affirming the robustness of the original regression outcomes.

4.4. Mechanism of Action Analysis

The empirical findings of the referenced study reveal a significant U-shaped non-linear relationship between advancements in digital new quality productivity and carbon emission performance. Specifically, the research identifies two primary mechanisms through which digital new quality productivity impacts urban carbon emissions: the technological innovation effect and the industrial structure upgrading effect. This paper examines and quantifies the presence and significance of these mechanisms, extending the previous mechanistic model.

Table 7 presents the impact mechanisms of digital new quality productivity on carbon emission performance, alongside the existence and contribution test results. Columns (1) and (2) display the regression analyses used to identify the mechanisms. The findings indicate that digital new quality productivity exerts a significant positive influence on both technological innovation and industrial structure upgrading, with a more pronounced effect on technological innovation. This confirms the substantial role of digital new quality productivity in enhancing these mechanisms.

Columns (3), (4), and (5) present the regression results concerning the contributions of these mechanisms. The analysis shows that the combined effect of these two mechanisms on the impact of digital innovation on carbon emission performance exceeds 50%. Specifically, the technological innovation effect is the most significant, contributing 38.1120%, followed by the industrial structure upgrading effect at 19.3362%. These findings substantiate Hypothesis 2.

4.5. Heterogeneity Analysis

4.5.1. Urban Location Heterogeneity

The Qinling-Huaihe River line functions as a crucial geographical boundary between northern and southern China, distinctly separating these regions in terms of topography, climate, economic development, and ecological environment. Column (1) of **Table 8** presents regression results related to urban location heterogeneity, revealing that the impact of digital new quality productivity on carbon emission efficiency varies significantly across these regions. Notably, in northern cities, the inflection point where digital new quality productivity begins to affect carbon emission efficiency occurs at a markedly lower value than in southern cities. This shift from a negative to a positive effect over a broader spectrum indicates that the efficacy of digital new quality productivity in enhancing low-carbon governance is more pronounced in the north. This difference is likely due to the predominantly secondary industry-based, lower-end industrial structure of northern cities, which face severe environmental pollution and thus exhibit a stronger need for pollution control and emission reduction measures.

Table 6. Regression results of robustness test.

Variables	(1) Replace the Explanatory Variable	(2) Control Variable * Time Trend Item	(3) Exclude Other Policy Implications		(4) Economic Distance Matrix Regression		
			Broadband China	Low-Carbon Pilots	Direct Effects	Indirect Effects	Total Effect
NQP	−0.7631** (0.3617)	−0.7512** (0.3583)	−0.7003** (0.3167)	−0.7015** (0.3193)	−0.5633*** (0.3326)	−0.6175 (0.3105)	−1.1808*** (0.5016)
SNQP	1.3873*** (0.5168)	1.3667*** (0.5076)	1.3045*** (0.4703)	1.3167*** (0.4789)	1.2110*** (0.0571)	1.2084* (0.0368)	2.4194*** (0.1802)
T* Control variables	/	YES	/	/	/	/	/
Control variables	YES	YES	YES	YES	YES	YES	YES
R^2	0.3016	0.3263	0.3637	0.3705	0.3313	0.3015	0.3366
Observations	3336	3336	3336	3336	3336	3336	3336

4.5.2. Heterogeneity in City Scale

In the realm of low-carbon governance, city size plays a crucial role, particularly in the context of digital new quality productivity. According to the 2014 directive from the State Council, cities with a permanent urban population below 1 million are classified as small and medium-sized, while those with a population exceeding 1 million are labeled large cities. Column (2) of **Table 8** presents regression results that investigate the differential impacts of digital new quality productivity on low-carbon governance across various city sizes. The findings indicate that large cities experience more pronounced effects compared to their smaller counterparts. This pattern suggests that the rapid advancement of digital new quality productivity in large cities fosters urban green transformation by enhancing the agglomeration effect and mitigating the negative consequences of congestion.

4.5.3. Heterogeneity of Urban Resource Endowment

The phenomenon of the "resource curse" in resource-based cities has been extensively documented by scholars. This leads to the pertinent query: will the low-carbon governance of emerging digital new quality productivity face analogous challenges inherent to the "resource curse"? In accordance with the classification criteria set forth in the National Sustainable Development Plan for Resource-based Cities (2013–2020) by the State Council, we have categorized the cities in our sample as either resource-based or non-resource-based. Column (1) of **Table 9** presents the regression results that address the heterogeneity of urban resource endowments. The findings indicate that, over the sample period, the impact of low-carbon governance catalyzed by digital new quality productivity is not significant in resource-based cities. In contrast, the effect is pronounced in non-resource-based cities. These results suggest that digital new quality productivity holds considerable potential to mitigate the "resource curse." Therefore, resource-based cities should focus on a top-level design for digital new quality productivity that is both scientific and orderly, thereby strategically planning for the city's low-carbon transformation. Such an approach would promote high-quality regional development.

4.5.4. Heterogeneity of the City's Own Characteristics

Adapting measures to local conditions is crucial for improving the efficacy of low-carbon governance via urban digital productivity. This study leverages the Digital Inclusive Finance Index from Peking University's Internet Finance Research Center to assess urban inclusive finance levels. Cities in the sample are categorized into two groups: those with high financial inclusion and those with low financial inclusion. Additionally, urban fiscal expenditure levels are evaluated by the proportion of fiscal expenditure to GDP, using data from the China Urban Statistical Yearbook, to further classify cities into high and low fiscal expenditure groups.

Column (2) of **Table 9** presents the regression results analyzing heterogeneity in urban characteristics. The findings indicate that cities with higher levels of digital financial inclusion more effectively harness digital new quality pro-

Table 7. The mechanism, existence and contribution of the imp act of digital new quality productivity on carbon emission performance, and the regression results of the test.

Variables	**(1) ETI**	**(2) ISU**	**(3) Baseline Regression**	**(4) Mechanism 1: Technological Innovation Effect**	**(5) Mechanism 2: The Effect of Industrial Structure Upgrading**
				ETI	**ISU**
NQP	0.0465*** (0.0379)	0.0022*** (0.0016)	−0.7627** (0.3613)	−1.2323*** (0.4021)	−0.9455** (0.3826)
SNQP	/	/	1.3868*** (0.5167)	1.8537*** (0.5235)	1.5672** (0.5196)
ETI	/	/	/	0.0483*** (0.0392)	/
ISU	/	/	/	/	0.0027*** (0.0023)
$1-\widehat{\alpha}/\widehat{\phi}$	/	/	/	38.1120%	19.3362%
Control variables	YES	YES	YES	YES	YES
Time fixation effect	YES	YES	YES	YES	YES
Regional fixed effects	YES	YES	YES	YES	YES
Observations	3336	3336	3336	3336	3336
Adjusted R^2	0.8729	0.8751	0.4187	0.3688	0.3119

ductivity for low-carbon governance. Conversely, cities with lower fiscal expenditure levels exhibit a more pronounced impact of digital new quality productivity on low-carbon governance. This trend may be due to cities with high fiscal expenditure possessing diverse methods of pollution control and emission reduction, which can dilute the specific contributions of digital new quality productivity. In contrast, cities with limited fiscal expenditure tend to rely more heavily on digital new quality productivity for pollution control and emission reduction, thereby maximizing its impact.

5. Further Exploration: A Dual-Objective Constraint Perspective

Based on the preceding theoretical analysis, the influence of excessively high economic growth targets and stringent environmental objectives on the relationship between digital new quality productivity (NQP) and carbon emission performance exhibits significant divergence. This paper empirically examines the moderating effects of these dual-objective constraints on said relationship.

Economic growth target constraints (EGCs) are quantified based on the economic growth targets articulated by each prefecture-level city in their annual government work reports. Interaction terms between these targets and non-qualified performance (NQP) measures are subsequently constructed. Moreover, EGCs are categorized into hard economic growth constraints (HEGCs) and soft economic growth constraints (SEGCs). HEGCs are characterized by terminology such as "strive," "above," and "ensure," while SEGCs are denoted by expressions like "up and down" or "around" [58].

In the evaluation of Environmental Objective Constraints (EOCs), we examine the presence of explicit energy consumption targets in municipal government work reports. The analysis includes deriving interaction terms between these targets and the distributional quality parameter (NQP) [59]. EOCs are classified into Direct Environmental Goal Constraints (DEGCs) and Indirect Environmental Goal Constraints (IEOCs). DEGCs are considered fulfilled when a city meets specific emission reduction targets detailed in its government work report, with the achievements being publicly disclosed in the report of the following year. If these criteria are not met, IEOCs are deemed to be in effect [60]. The data utilized for assessing the interplay between economic growth and environmental constraints is drawn from municipal government work reports of prefecture-level cities

Table 8. Heterogeneity test regression results I.

Variables	(1) Urban Location Heterogeneity		(2) Heterogeneity in City Scale	
	South of the Qinling-Huaihe Line	North of the Qinling-Huaihe Line	Metropolis	Small and Medium-Sized Cities
NQP	−0.6238* (0.0383)	−0.5036** (0.1989)	−0.5115*** (0.2193)	−0.7012** (0.3192)
SNQP	1.3013* (0.3365)	1.1973** (0.2026)	1.1767*** (0.2769)	1.3167** (0.4789)
Control variables	YES	YES	YES	YES
R^2	0.3828	0.3913	0.3827	0.3703
Observations	3336	3336	3336	3336

Table 9. Heterogeneity test regression results II.

Variables	(1) Heterogeneity of Urban Resource Endowment		(2) Heterogeneity of the City's Own Characteristics			
	Resource-Basedn Cities	Non-Resource-Based Cities	The Level of Digital Financial Inclusion		The Level of Fiscal Expenditure	
			High	Low	High	Low
NQP	−0.6415 (0.0393)	−0.5013** (0.1967)	−0.5143** (0.2192)	−0.7013* (0.3192)	−0.7363* (0.3253)	−0.5007*** (0.1146)
SNQP	1.3766 (0.3393)	1.1943** (0.2006)	1.1767*** (0.2769)	1.3167* (0.4789)	1.3746* (0.4819)	1.1643*** (0.2469)
Control variables	YES	YES	YES	YES	YES	YES
R^2	0.2637	0.3178	0.3818	0.3706	0.3829	0.4077
Observations	3336	3336	3336	3336	3336	3336

over multiple years.

Table 10 presents regression results examining the impact of economic growth target constraints on digital new quality productivity and carbon emission performance. The interaction coefficient between economic growth target constraints and digital new quality productivity is significantly negative at the 10% level, indicating that such constraints adversely affect carbon emission performance and thereby hinder digital new quality productivity. When these growth targets are further divided into hard and soft constraints, it is observed that hard constraints have a pronounced negative moderating effect, while soft constraints exhibit positive moderating effects. This suggests that overly ambitious economic growth targets can undermine the efficiency of digital new quality productivity in promoting low-carbon governance. In contrast, moderate economic growth targets facilitate the optimal utilization of digital new quality productivity, thereby enhancing low-carbon governance efficiency.

Column (2) of Table 10 presents regression results under the constraints of environmental objectives. The findings indicate that the interaction coefficient between environmental objective constraints and digital new quality productivity is significantly positive at the 5% level. This suggests that environmental objectives positively moderate the impact of digital new quality productivity on carbon emission performance. Furthermore, a comparison between direct and indirect environmental objectives reveals that the positive moderating effect is significantly stronger for direct environmental constraints. This implies that stringent environmental targets enhance the low-carbon governance performance of digital new quality productivity. Hence, Hypothesis 3 is fully supported.

6. Conclusions and Policy Implications

6.1. Conclusions

In the context of dual objective constraints, this study investigates the impact mechanism of digital new quality productivity on carbon emission performance. Using comprehensive evaluation and coefficient of variation methods, we assess the development level of digital new quality productivity in 278 prefecture-level cities from 2011 to 2022. NPP-VIIRS night light data is used to estimate carbon emission performance inversely in these cities. To analyze the

Table 10. Dual-objective constrained regression results.

Variables	(1) Adjustment of Economic Growth Target Constraints			(2) Adjustment of Environmental Target Constraints		
NQP	−0.9811** (0.3762)	−0.8366** (0.3477)	−0.5022** (0.2133)	−0.4101** (0.1502)	−0.5166** (0.2033)	−0.6122** (0.0375)
SNQP	1.5366*** (0.5313)	1.4625* (0.5188)	1.3911** (0.3628)	1.0833*** (0.1601)	1.1966** (0.2014)	1.3033** (0.3371)
NQP*EGC	−0.0266* (0.0131)	/	/	/	/	/
NQP*HEGC	/	−0.0211* (0.0081)	/	/	/	/
NQP*SEGC	/	/	0.0277** (0.0139)	/	/	/
NQP*EOC	/	/	/	0.0611** (0.0722)	/	/
NQP*DEGC	/	/	/	/	0.0433*** (0.0579)	/
NQP*IEOC	/	/	/	/	/	0.0201* (0.0100)
Control variables	YES	YES	YES	YES	YES	YES
Time fixation effect	YES	YES	YES	YES	YES	YES
Regional fixed effects	YES	YES	YES	YES	YES	YES
R^2	0.3001	0.3103	0.3466	0.3371	0.3811	0.3702
Observations	3336	3336	3336	3336	3336	3336

nonlinear impact and spatial spillover effects of digital new quality productivity on carbon emission performance, we implement both a static panel model and an SDM spatial econometric model. Furthermore, enhanced mediation and moderation effect models are employed to elucidate the mechanisms driving this relationship, with a particular emphasis on the moderating effects of economic growth and environmental targets. The main findings are as follows:

(1) In the specified field, a significant U-shaped nonlinear relationship is observed between digital new quality productivity and carbon emission performance. The analysis of static panel data reveals that at development levels below 0.2750, digital new quality productivity hinders carbon emission performance. Nevertheless, this inhibitory effect weakens as digital new quality productivity increases. Beyond the threshold of 0.2750, the influence transitions from inhibition to promotion, and this promotive effect becomes more pronounced as the digital economy progresses. The Spatial Durbin Model (SDM) spatial effect analysis demonstrates a minimal spatial spillover effect of digital new quality productivity on carbon emission performance, with a more substantial impact on local carbon emissions. These findings are robust across various sensitivity analyses.

(2) In assessing the impact of digital new quality productivity on carbon emission performance, technological innovation and industrial structure upgrading emerge as predominant mechanisms. Mechanism testing reveals that these two factors collectively account for over 50% of the observed effect, with technological innovation contributing the most at 38.11%, followed by industrial structure upgrading at 19.34%. However, additional mechanisms, such as resource allocation, improvements in energy efficiency, and economic growth effects, may also influence the overall impact.

In the field of environmental economics, dual objective constraints are instrumental in influencing the relationship between digital new quality productivity and carbon emission performance. A moderate economic growth target positively affects this association. Specifically, under such a target, the inflection point at which further increases in digital new quality productivity enhance carbon emission performance shifts from 0.2750 to 0.1805. This shift accelerates the achievement of the necessary digital new quality productivity level to improve carbon emission performance, thereby enhancing the efficiency of low-carbon governance. Conversely, an overly ambitious economic growth target imposes restrictive effects, hindering the beneficial impact of digital new quality productivity on carbon emission performance. In this scenario, the inflection point is delayed from 0.2750 to 0.3911, thus reducing the effectiveness of low-carbon governance.

Environmental objectives generally enhance the impact of digital new quality productivity on carbon emission performance. Furthermore, the inflection point for digital new quality productivity has decreased from 0.2750 to 0.1893, thus lowering the threshold for improving carbon emission performance. This progression increases the efficiency of low-carbon governance associated with digital new quality productivity.

(4) The impact of digital new quality productivity on carbon emission performance exhibits substantial heterogeneity. Notably, the efficacy of low-carbon governance driven by digital new quality productivity is significantly higher in cities located north of the Qinling-Huaihe River compared to those in the south. In contrast to small and medium-sized or resource-dependent cities, larger and non-resource-dependent cities are more inclined towards green development, leveraging digital new quality productivity for pollution control and emission reduction. Furthermore, cities with high levels of financial inclusion and low fiscal expenditure can significantly enhance the low-carbon management capabilities of digital new quality productivity.

6.2. Policy Implications

Based on the aforementioned conclusions, the following policy implications are recommended:

(1) Local and municipal governments should recognize digital productivity as a crucial driver of economic growth. It plays a key role in enhancing industrial frameworks, advancing green and low-carbon transitions, and promoting high-quality development. To capitalize on these benefits, governments must invest significantly in digital infrastructure, particularly in 5G, artificial intelligence, and big data. Priority should be placed on integrating these technologies within the energy sector to stimulate innovation and develop new low-carbon technologies, business models, and industries.

Fortification of the "Broadband China" strategy, coupled with policies promoting "smart cities" and "low-carbon pilot cities," is necessary. Continuous enhancements in urban network infrastructure will facilitate the integration of green and low-carbon principles through digital technology. This approach ensures optimal preparedness for capitalizing on the environmental benefits of enhanced digital productivity.

Enhancing digital governance capabilities is crucial. Adopting a coordinated strategy for digital industry development and industrial digitalization will foster advanced industrial structures and expedite the transformation of the energy sector. This approach will facilitate large-scale utilization of clean energy and improve energy efficiency, particularly by optimizing spatial spillover effects in major central cities.

(2) To effectively integrate scientific and economically viable growth objectives with environmental goals, it is crucial to harness the benefits of dual-goal constraints in promoting low-carbon governance through digital innovation in quality productivity. Local governments, when establishing annual targets, should implement flexible constraints on economic growth objectives to prevent undue pressure. This strategy can alleviate the expansion of government debt financing, curb overinvestment, and enhance the efficiency of low-carbon governance driven by digital new quality productivity, thereby reducing urban carbon emissions.

Local governments should concurrently enforce stringent environmental targets. By implementing robust regulatory measures, they can maximize the innovative, complementary, and quality-enhancing effects of these constraints. This approach fosters synergy between the digital economy and environmental regulations.

After thorough investigation and technical simulations, governments should formulate an optimally differentiated strategy that balances dual objectives. This approach will enable the heterogeneous management of targets within urban jurisdictions, leveraging varying administrative levels and city scales to guide policy measures effectively. By implementing tailored, specialized policies, local governments can enhance low-carbon governance performance and fully capitalize on the benefits of digital productivity advancements.

(3) Given the significant variation in urban characteristics, it is crucial to scientifically evaluate and implement the environmental welfare impacts of digital new quality productivity tailored to specific local conditions. Variations in resource endowment, levels of digital inclusive finance

and fiscal expenditure intensity contribute to the diverse environmental welfare outcomes associated with digital new quality productivity across cities. Consequently, government policies must be localized, considering factors such as resource dependence, the degree of inclusive financial development, and fiscal spending intensity. Policies and plans should be crafted to effectively integrate digital new quality productivity with low-carbon initiatives.

In accordance with developmental principles, it is essential to address the dynamic interplay between the catch-up phase and balanced growth of regional digital technology. This interplay is particularly evident in the left half of the U-shaped curve, which encapsulates the influence of digital innovation on carbon emission performance. The goal is to advance both the overall development and quality of digital technology to maximize environmental benefits. For cities situated on the right half of the U-shaped curve, the focus should be on pioneering advancements in disruptive technologies. Efforts should target expanding and deepening the environmental benefits of digital technology and utilizing it to transform traditional industries throughout their lifecycle. This strategy aims to enhance the adaptability of the digital economy and industrial structure while improving the efficiency of low-carbon governance driven by new digital innovations.

6.3. Research Deficiencies and Prospects

This paper investigates the relationship between digital new quality productivity and carbon emission performance at the city level. Given the rapid advancement of digital technology and the increasing segmentation of the digital industry, further exploration is essential. In particular, there is a requirement for methods to objectively measure the impact of digital productivity quality on carbon emissions within the digital economy sector. Additionally, significant disparities in CO_2 emissions may exist even within the same province or prefecture-level city. Therefore, county-level studies are vital to capture regional heterogeneity and devise effective policies for CO_2 emission reduction.

Author Contributions

Conceptualization, data curation, formal analysis, investigation, methodology, project administration, resources, supervision, validation, visualization, writing—original draft, writing—review & editing, S.Y.; conceptualization, investigation, project administration, resources, software, visualization, writing—original draft, writing—review & editing, Z.Q.Y.; data curation, formal analysis, formal analysis, methodology, software, supervision, validation, writing—original draft, writing—review & editing, W.Z.

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Data will be available on request from the author.

Conflicts of Interest

The authors declare no conflict of interest.

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