

Article

New Quality Productive Forces, Technological Innovations, and the Carbon Emission Intensity of the Manufacturing Industry: Empirical Evidence from Chinese Provincial Panel Data

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Abstract

Carbon emissions from the manufacturing sector have long been a critical environmental concern. New quality productive forces (*NEP*), which integrate advanced technologies and innovative practices to enhance production efficiency while reducing environmental impact, provide robust support for the green and sustainable development of manufacturing. However, previous studies have not established empirical evidence linking *NEP* to manufacturing carbon emission intensity (*CEI*), nor have they identified the underlying transmission channels. This study makes a methodological innovation by explicitly differentiating technological innovation into disruptive and progressive categories to examine their distinct mediating roles. Using panel data from 30 Chinese provinces from 2012 to 2021, we investigate the direct, heterogeneous, and spatial effects of *NEP* on *CEI*, along with the mediating effects of different innovation types. The results demonstrate that *NEP* significantly reduces *CEI*, and this finding remains robust after addressing endogeneity concerns and conducting comprehensive robustness checks. Mechanism analysis reveals that *NEP* achieves emission reduction primarily through promoting disruptive innovation—fundamental shifts in operational paradigms that substantially reduce environmental footprints. Heterogeneity analysis indicates the strongest emission reduction effect in central China. Based on these findings, we propose targeted policy recommendations: cultivating *NEP* as a fundamental driver, accelerating green technology industrialization, establishing a three-dimensional policy framework integrating innovation incentives, market regulation, and supervisory safeguards, and implementing regionally differentiated strategies. These approaches provide actionable pathways for achieving China's dual-carbon goals and promoting sustainable manufacturing development.

Keywords: new quality productive forces; manufacturing carbon emission intensity; dual-carbon; technological innovation; sustainable development



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1. Introduction

As the world's foremost total and incremental carbon emissions in the international community, China now confronts escalating international pressure to reduce emissions. However, the energy demand characteristics of its current stage of urbanization and economic development make carbon emissions reduction relatively challenging. Therefore, formulating carbon emissions reduction policies at this stage is the most urgent task for the Chinese government [1]. Against this backdrop, General Secretary Xi Jinping declared at the seventy-fifth session of the United Nations General Assembly in September 2020 that

China would strive to culminate its carbon-dioxide emissions prior to 2030 and to accomplish net-zero emissions by 2060, thereby initiating an unprecedented national trajectory of low-carbon development subsequently termed the “dual-carbon” strategy. In January 2024, the Opinions on Comprehensively Promoting the Construction of a Beautiful China further clarified that the “dual-carbon” goals must be embedded in the nation’s overall economic development, mandated the creation of a modern energy system that is clean, low-carbon, secure and highly efficient, and aligned the strategic restructuring of both the energy portfolio and the broader industrial landscape, thereby providing top-level design support for China’s low-carbon transformation. In May 2025, the central government ratified a three-year roadmap for decarbonizing the manufacturing sector (2025–2027), institutionalizing sector-specific mitigation measures and elevating green transition to a national strategic priority.

The manufacturing industry, as a pillar industry of the national economy, faces both crucial missions and severe challenges in implementing the “dual-carbon” strategies [2]. In recent years, China’s manufacturing sector has made marked progress in its low-carbon transition: the stable operation of the national carbon market over multiple years has been accompanied by continuous improvements in carbon accounting systems for key industries, particularly in steel and cement [3]; the application of green technologies such as photovoltaic-based hydrogen production and digital twins has expanded into broader manufacturing scenarios [4]; meanwhile, green manufacturing sectors including new energy vehicles and lithium batteries have maintained a leading global position, driving the low-carbon transformation of upstream and downstream industrial chains. Moreover, given its extensive industrial linkages and strong technological spillover effects, the manufacturing industry serves as a pivotal hub for deploying green innovative technologies and advancing low-carbon development paradigms. Its transformation is not only essential to achieving the dual-carbon goals but also represents a strategic imperative for reshaping global industrial competitiveness.

However, China’s manufacturing low-carbon transition still confronts practical constraints. Mid-to-late industrialization leaves several sub-sectors locked in the low- and mid-end, persistently reliant on natural resources, labor and capital [5]. As a major consumer of resources and emitter of carbon, the sector must urgently deploy technological innovation to shrink the carbon footprint of its processes [6]. Meanwhile, legacy production modes foster low energy efficiency and cleanliness, creating a pronounced high-carbon lock-in. Energy-intensive industries, constrained by complex processes and high costs, sustain elevated carbon intensity. This structural conflict hampers sustainable development and presents a systemic challenge to ecological governance. Furthermore, the high-carbon lock-in directly clashes with the 14th Five-Year Plan target of a 13.5% reduction in energy consumption per unit of industrial added value by 2025 (relative to 2020), underscoring the pressing need to transform conventional production paradigms.

The new quality productive forces is advanced productive capacities generated via technological innovation and industrial upgrading under digitalization and smart technologies. They are characterized by high-skilled labor, technology-intensive means of production, and novel objects of labor. In December 2023, the Central Economic Work Conference incorporated “new quality productive forces” into the core agenda of annual economic work for the first time, clearly proposing to “promote industrial innovation through scientific and technological innovation, especially to foster new industries, new patterns, and new drivers with disruptive and cutting-edge technologies, and develop new quality productive forces” thus providing directional guidance for its practical path. As an intrinsic requirement and pivotal driver for achieving high-quality development, new quality productive forces inherently constitute green productivity, where eco-friendly

development serves as an integral component of high-quality growth [7]. These forces drive transformative shifts in productivity, marked by digitalization, intelligent advancement, and green transition. Their innovation paradigms encompass industrial internet, clean energy substitution, carbon capture and utilization, among others, thereby pioneering pathways to transcend the constraints of conventional economic development models. In recent years, cultivating new quality productive forces has been elevated to a national strategy. It is an objective requirement for emancipating and developing productive forces in the new era, and an inevitable choice for promoting the iterative upgrading of productive forces and realizing modernization [8].

The “dual-carbon” strategies and new quality productive forces have a significant coupling and symbiotic relationship [9]. In essence, new quality productive forces establishes a positive cycle mechanism of “technological innovation—energy efficiency improvement—carbon emissions reduction” through the subversive reorganization of production factors, thereby accelerating the green transition of manufacturing and underpinning the dual-carbon strategies. New quality productive forces can promote technological innovation in manufacturing production, improve production efficiency, and reduce carbon emissions. Specifically, digital-twin technologies enable dynamic optimization of process-level carbon footprints. Similarly, PV-powered hydrogen integrated with carbon-capture systems accelerates the shift of the heavy machinery industry towards near-zero emissions. Concurrently, the development of new quality productive forces also facilitates the transformation of traditional manufacturing human resources into a new type of high-quality workforce. This process enhances personnel quality, promotes the transformation and upgrading of traditional manufacturing, improves management and production efficiency, and reduces carbon emissions levels. These pathways demonstrate that new quality productive forces—embodied in China’s wind-solar-hydrogen-storage revolution and the world’s largest clean-energy innovation-industry-value chain—simultaneously secure energy supply, drive economic growth and cut carbon emissions, thereby translating the “Energy Triangle” synergy into a manufacturing-wide green and low-carbon transformation that accelerates the attainment of the “dual-carbon” goals [10]. New quality productive forces should be explicitly designated as the core policy lever for delivering the manufacturing sector’s dual-carbon targets [11]. Governments at all levels must give priority to the R&D and diffusion of digital and green technologies emblematic of these forces in key emitting industries (e.g., iron and steel, cement, and energy), using technological retrofits and targeted incentives to break the existing high-carbon lock-in [12]. Specifically, they should accelerate the deployment of measurable and traceable digital carbon-footprint management systems across entire value chains, promote large-scale demonstrations of near-zero-emission technologies such as photovoltaic hydrogen production and carbon capture, and simultaneously build a high-caliber workforce equipped with green skills. These interventions will concurrently lower the energy intensity of industrial output, ensure delivery of the 14th Five-Year Plan conservation mandate, and transform emission reduction imperatives into a catalyst for full-spectrum industrial upgrading, thereby providing a scalable and reproducible route to peak CO₂ before 2030 and net-zero by 2060.

In the context of the energy–environment–economy system, the manufacturing industry is a crucial sector that intertwines energy consumption, economic growth, and environmental impact [13]. The transition to low-carbon manufacturing is not only essential for mitigating climate change but also for enhancing energy security and fostering sustainable economic development. The environmental implications of carbon emissions from the manufacturing sector are profound, as they contribute significantly to air pollution, ecosystem degradation, and global warming. By reducing carbon intensity, the manufacturing industry can play a vital role in preserving the environment for future

generations. Therefore, it is imperative to explore the driving forces behind the low-carbon transformation of the manufacturing industry, especially the role of green technological innovation and new quality productive forces—which refer to advanced, knowledge-based, and innovation-driven productive capabilities that integrate digital, intelligent, and sustainable technologies. While green technological innovation represents the technological dimension of decarbonization, new quality productive forces encompass the broader systemic transformation of production modes that embed green innovation into productivity growth [14].

Therefore, this study examines the overall, heterogeneous, and spatial impacts of new quality productive forces (*NEP*) on manufacturing carbon intensity (*CEI*) and investigates the mediating role of technological innovation, with the findings intended to inform evidence-based strategies for sustainable development. The contributions of our work are highlighted as follows: First, it advances the existing literature by systematically linking the emerging concept of *NEP* with manufacturing *CEI*, providing the first empirical evidence bridging macro-level theory and sector-specific realities. Then, it moves beyond the conventional treatment of innovation as a homogeneous driver by identifying disruptive innovation as the pivotal mechanism through which *NEP* triggers a fundamental technological paradigm shift for deep decarbonization. Furthermore, the discovery of the most pronounced emission reduction effects in central China offers a novel perspective on regional late-mover advantages and delivers actionable insights for crafting spatially differentiated policies.

2. Literature Review

2.1. Drivers and Mitigation Policies of Carbon Emissions

With the continuous promotion of the “dual-carbon” goals, the academic community has carried out in-depth research on carbon emissions, with substantial findings, covering carbon emissions trading [15], carbon emissions measurement methods [16], carbon emission impact factors and carbon emission efficiency [17] and other dimensions.

In these studies, carbon trading policies and their emission reduction effect have received extensive attention. The implementation of carbon trading schemes has demonstrated notable efficacy in reducing emissions within pilot regions, thereby enhancing carbon emissions efficiency [18]. The carbon market, by promoting technological advancements [19,20], facilitates a decrease in carbon emissions and encourages businesses to adopt market-incentivized eco-friendly and low-carbon technologies. This outcome stems from a dual approach: restructuring the energy portfolio and elevating energy-use efficiency. Nonetheless, the efficacy of carbon trading policies in reducing emissions varies across different regions [21].

Furthermore, the determinants of carbon emissions constitute pivotal subjects of inquiry. On a macroscopic scale, studies indicate that carbon emissions are affected by multiple factors, including the expansion of urban economies, advancements in information and communication technologies, improvements in the efficiency of energy use, and changes in the composition of energy sources [22–25]. At the industry level, scholars focus on carbon emissions factors in specific fields such as agriculture [26], the cement industry [27] and power industry [28]. Examining the drivers of manufacturing-sector carbon releases reveals multiple mitigation channels, wherein industrial intelligence markedly elevates firm-level carbon performance by lowering both emission intensity and total emissions through a dominant efficiency enhancement mechanism [29]; meanwhile, innovation efficiency of high-tech industry [30], digital finance [31] and supply chain finance [32] have also been confirmed to have significant contributions to emission reduction. These strands of evidence are synthesized in a recent systematic review that identifies three converging

trends in manufacturing-focused carbon studies: a growing urgency in climate-risk assessment, increasing cross-sectoral interactions in mitigation strategies, and the emergence of sustainable-manufacturing pathways [33].

2.2. The Conception, Measurement, and Impacts of New Quality Productive Forces

From the existing research results, the current academic research on *NEP* mainly focuses on the connotation characteristics of *NEP* [34], influencing factors [35], internal logic and realization path [36], theoretical innovation and value implication [37], as well as how to empower the marine economy and promote the sustainable development of ports [38,39], which initially forms the knowledge spectrum of the research on *NEP*. Relevant studies have empirically investigated *NEP* from three perspectives: enterprise, industry, and region [40–42].

At the enterprise level, ESG development [41], digital transformation [43], artificial intelligence policy [44], and financial aggregation [45] have significantly promoted the level of enterprise *NEP*. Enterprise *NEP* has a positive effect on enterprise supply chain resilience by improving enterprise innovation ability, which is characterized by the nonlinear feature of increasing marginal effect [46].

At the industry level, studies have concentrated on the sports equipment manufacturing sector, concluding that the introduction of advanced productive forces can mitigate carbon emissions by fostering sustainable financing mechanisms and concentrating digital expertise [47]. Moreover, the *NEP* can enhance the supply chain resilience of the manufacturing industry chain and exert spatial spillover effects to strengthen the supply chain resilience of neighboring regions' manufacturing industry chains [48]. The development of *NEP* provides an innovative path for the high-quality development of Chinese agriculture and the building of an agricultural powerhouse [49]. The advancement of *NEP* is instrumental in fostering the high-quality development of Chinese agriculture, with regional heterogeneity analyses revealing that Eastern China leads, followed by Western, Central, and Northern China, which outperforms Southern China in this regard [50].

At the regional level, some academic research results have constructed a comprehensive evaluation system of *NEP* from the three aspects of scientific and technological productivity, green productivity and digital productivity to measure the level of *NEP* in 30 provincial-level regions in China from 2012 to 2021 [42], or used the Undesirable-Window-DEA model to measure the level of *NEP* in China from 2012 to 2023 and analyze the spatial differences and dynamic changes in China's *NEP* level by using the Dagum Gini coefficient and Kernel density estimation method [51]. Additionally, scholarly agreement is widespread that the spatial diffusion of *NEP* across China exhibits pronounced heterogeneity. These forces are instrumental in diminishing carbon emissions and improving carbon emissions efficiency, achieved through promoting industrial structural upgrades and catalyzing regional technological advancements [52–57]. Dynamic configuration analysis shows that there are mutual substitution effects of elements within the *NEP* (e.g., resource-saving and industrial digital productivity) and regional heterogeneity of emission reduction paths [58].

2.3. The Relationship Between New Quality Productive Forces and Sectoral Carbon Emissions

While a minority of researchers focus on the manufacturing sector, the majority of scholars tend to select specific industrial fields to investigate the effects of *NEP* on carbon emissions in those particular industries.

A majority of research concentrates on agriculture, proposing that *NEP* can inhibit agricultural carbon emission intensity through mechanisms such as promoting land scale management, agricultural technological progress, rural consumption upgrading, rural

labor productivity, and agricultural land productivity [59–61]. Concurrently, the study indicates that the emergence of *NEP* has significantly advanced the modernization of the agricultural sector, with a notable impact observed particularly in the central and western regions of China and the primary grain-producing zones [60]. In this process, the upgrading of the agricultural industry structure is the key mediating mechanism, exhibiting a single-threshold effect. Despite this, research has shown that external factors like industrial concentration exert a complex influence on agricultural *NEP*, resulting in both globally significant direct and indirect negative effects and region-specific impacts that are beneficial in central economic regions but detrimental in western and eastern regions [61]. Empirical research demonstrates that the introduction of *NEP* in agriculture significantly reduces carbon emission intensity, although this effect is moderated by threshold factors including the urban-rural income disparity and levels of digital financial inclusion [62–64]. Other scholars found an inverted “N”-shaped nonlinear relationship between them, with significant regional differences (inverted N-shaped in the east, N-shaped in the west) [64].

Others have investigated the sports goods manufacturing industry, suggesting that *NEP* can reduce carbon emissions in this sector by driving the development of green credit and fostering digital talent agglomeration [65]. In the marine economy, research confirms that *NEP* significantly promote economic resilience (including the ability to withstand carbon emissions risks), with regional heterogeneity and time-lag effects present [66]. However, research specifically focusing on the manufacturing sector to explore the impact of *NEP* on manufacturing carbon emission intensity and its mechanisms is still very limited.

In summary, current research on carbon emissions is relatively comprehensive, yet studies examining the impact mechanisms between *NEP* and carbon emissions remain limited. Existing research on the interaction between *NEP* and carbon emissions has primarily concentrated on the agricultural sector, with a notable lack of studies targeting the manufacturing industry. However, traditional manufacturing industries are significant contributors to national carbon emissions [67], and given the severe emission challenges in this sector, manufacturing plays a pivotal role in energy conservation and emission reduction [68], thus urgently requiring a green transformation.

Despite the expanding body of research on new quality productive forces (*NEP*), their carbon reduction effect within the manufacturing sector—the largest industrial source of emissions—has not been rigorously examined. Three significant research gaps remain: (1) Existing empirical studies have predominantly focused on agriculture or niche industries, leaving economy-wide evidence on manufacturing notably absent. (2) The micro-level innovation pathways through which *NEP* influence carbon emissions remain under-explored, particularly the distinction between disruptive and incremental innovation, leaving key mechanisms in a “black box”. (3) Although regional heterogeneity is widely acknowledged, the spatial patterns and underlying determinants of how *NEP* reduce manufacturing carbon intensity remain unclear, which limits the design of spatially targeted policies. To address these shortcomings, this study focuses specifically on the manufacturing sector, disentangling the dual innovation mechanisms, and systematically mapping regional heterogeneity using panel data from 30 Chinese provinces, thereby providing new theoretical and policy-relevant insights into the decarbonization potential of *NEP*.

3. Theoretical Analysis and Research Hypotheses

With the introduction of the “dual-carbon” theory, reducing carbon emissions has increasingly become a vital direction for economic development [8]. *NEP* manifest salient eco-oriented attributes [69], simultaneously elevating economic efficiency and advancing coordinated, high-quality development across the economic, social and environmental nexus [52].

NEP initially aggregate production-factor information through advanced digital infrastructures that encompass large-scale data analytics, IoT ecosystems and cognate technologies, thereby dissolving information silos and facilitating real-time dissemination and accurate pairing of factor data. Leveraging these integrated data [70], new quality productive forces dynamically adjusts and optimally allocates production factors—adjusting energy supply structures to meet production needs, refining raw-material procurement plans, and scheduling production equipment rationally—thereby improving factor-utilization efficiency. This efficiency gain directly reduces energy consumption and resource waste during production, lowering the carbon-emission intensity of manufacturing.

Furthermore, through market-demand insights and resource-integration capabilities [9], *NEP* redirect social resources into sectors characterized by low-carbon profiles and elevated value creation, thereby imposing resource constraints and competitive pressures on high-carbon industries. Under these pressures, high-carbon industries transform themselves by upgrading product structures and optimizing industrial layouts, thereby reducing their own carbon emission intensity. Simultaneously, *NEP* promotes integration between manufacturing and other low-carbon sectors, giving rise to emerging low-carbon industries and increasing their share within manufacturing. Ultimately, the dual processes of high-carbon-industry transformation and low-carbon-industry expansion upgrade the overall industrial structure of manufacturing and cut carbon-emission intensity.

Finally, the supply chain collaboration platforms built by *NEP* facilitate carbon-emission information sharing and coordinated governance among upstream and downstream firms, driving the adoption of low-carbon production and logistics throughout the entire supply chain. Through production-process optimization, flexible manufacturing, and supply chain coordination, low-carbon control is achieved across the entire production flow, ultimately reducing the carbon-emission intensity of manufacturing. Accordingly, Hypothesis 1 is advanced. The specific transmission mechanism is illustrated in Figure 1.

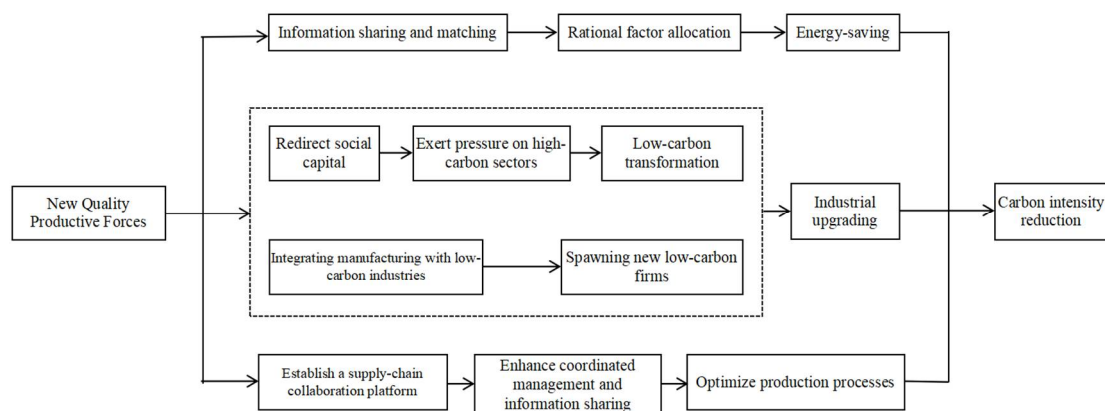


Figure 1. Transmission Mechanism Diagram.

Hypothesis 1. *The development of new quality productive forces has a significant inhibitory effect on the carbon emission intensity in the manufacturing industry.*

NEP can promote technological innovation. First, at the micro level, new quality productive forces can drive technological innovation within manufacturing enterprises. New quality productive forces represents an advanced form of productivity characterized by digitalization, intelligence, and greening [71]. Building on this, the development of new quality productive forces significantly drives cutting-edge technological innovation and empowers the transformation of traditional manufacturing industry [28]. Consequently, the advancement of *NEP* in the manufacturing sector necessitates that enterprises, as in-

novation drivers, augment their R&D investments and reinforce the deep integration of industry-academia-research collaboration under their leadership, thereby bolstering their technological innovation capabilities. Furthermore, streamlining the institutional environment for private manufacturers by removing entry barriers, allowing market mechanisms to govern resource flows and instituting targeted public innovation funds will furnish robust safeguards for firm level innovation. Second, at the macro level, *NEP* can facilitate technological advancement across the manufacturing industry as a whole. Specifically, they encourage manufacturing enterprises to form collaborative innovation networks to jointly tackle technological challenges. In the context of *NEP*, manufacturing enterprises need to strengthen cooperation and establish closely integrated innovation consortiums across industrial chains, enabling resource sharing and complementary advantages. For instance, automated production lines and intelligent robots in the manufacturing industry have increased efficiency, and AI predictive maintenance technology in the high-tech manufacturing sectors has reduced equipment downtime by 30 per cent [28]. Within the convergence of global economic restructuring and sustainability imperatives, eco-innovation has evolved into a decisive engine for elevating national competitive advantage while countering environmental threats, and *NEP* have emerged as a key driving force for such green technological innovation in manufacturing [72]. Ultimately, by fostering collaborative innovation among manufacturing enterprises, *NEP* promotes technological innovation at the industry-wide level within manufacturing.

Technological innovation can optimize manufacturing enterprises' production processes and reduce carbon emissions. First, it drives manufacturing enterprises to develop and adopt more environmentally friendly and efficient production techniques. For example, in manufacturing, the application of precision machining technology reduces raw material waste while enhancing product quality and performance, thereby decreasing resource consumption and carbon emissions throughout the production cycle. Second, technological innovation facilitates intelligent modeling and optimization of production processes. Through in-depth analysis and mining of production data, manufacturing enterprises can achieve precise regulation and optimal allocation of production systems, identify bottlenecks and inefficiencies, and implement automated, intelligent scheduling and control of production processes [1]. Disruptive innovation promotes manufacturing industrial upgrading, and *NEP* promote the transformation of the manufacturing economic structure towards quality enhancement [73]. This optimization reduces carbon emissions by developing new quality productive forces to enhance technological innovation capabilities of manufacturing enterprises, rationalizes production processes and consequently reduces carbon emissions. Informed by this analysis, Hypothesis 2 is advanced.

Hypothesis 2. *New quality productive forces reduce carbon emission intensity in the manufacturing industry by promoting technological innovation.*

The theory of regional economic development gradient transfer posits that regional economic disparities stem from differences in industrial structure quality [74]. High-gradient regions drive development through innovation and transfer declining industries to low-gradient regions, thereby forming a dynamic economic equilibrium. Regional variations in resource endowments, industrial compositions, and technological bases can give rise to spatial heterogeneity in the carbon emissions reduction impact of *NEP*. From the perspective of regional development gradients, eastern China, benefiting from higher economic levels and innovation resource agglomeration advantages, completed the intelligent transformation of traditional industries earlier. Their technology spillover effects approach threshold levels [75], resulting in weakened marginal substitution effects between *NEP* and existing technological systems and relatively limited emission reduction potential.

In contrast, the central and western regions still predominantly rely on energy-intensive manufacturing and exhibit significant efficiency gaps in production processes [76]. The technological penetration of *NEP* demonstrates greater marginal improvement potential in these areas. Meanwhile, eastern regions' higher stringency of environmental regulations and marketization degree impose multiple policy constraints on corporate emission reduction behaviors, whereas central and western regions exhibit tendencies of "race to the bottom" in environmental governance [77]. *NEP* could create stronger emission reduction incentives by breaking traditional path dependencies. Furthermore, regional disparities in digital infrastructure amplify spatial heterogeneity. While digital technology applications in eastern China have entered a mature phase, central and western regions remain in the digital dividend release period [52], where energy efficiency improvements from digital transformation demonstrate more significant effects. Due to differences in regional factor allocation efficiency, technology diffusion speed, and institutional environments, the inhibitory effect of *NEP* on manufacturing carbon emission intensity manifests a gradient characteristic of "central > western > eastern regions". Therefore, Hypothesis 3 is proposed.

Hypothesis 3. *The carbon emission intensity-reducing effect of new quality productive forces in manufacturing demonstrates regional disparities.*

4. Research Design

4.1. Selection of Variables

4.1.1. Explained Variable

In this study, we select the carbon emission intensity of manufacturing (*CEI*) as the explained variable of this study [78]. Owing to differences in both total carbon emissions and manufacturing output across Chinese provinces, *CEI* is calculated as total carbon emissions from the manufacturing sector divided by the sector's gross output value in each province, serving as the measurement indicator for carbon emission intensity. The carbon emission intensity of the manufacturing sector is computed as follows [78]:

$$CEI = \frac{E}{GDP} \quad (1)$$

where *E* represents provincial-level manufacturing carbon emissions sourced from the Carbon Emission Accounts and Datasets (CEADs), and *GDP* denotes the provincial manufacturing output. This metric measures regional emission efficiency by adjusting for provincial differences in both emissions and economic output.

4.1.2. Explanatory Variable

This paper employs the development level of new quality productive forces (*NEP*) as the explanatory variable. In line with the concept of *NEP* and guided by the criteria of data availability, scientific validity, and systematic completeness, an indicator system is developed based on Lu et al.'s research [42] (Table 1). This framework assesses *NEP* across three core dimensions: technological productivity (as reflected by innovation capacity and R&D efficiency), green productivity (indicated by energy conservation and emission reduction outcomes), and digital productivity (gauged by digital infrastructure and industrial integration). To ensure objectivity, the entropy weight method is applied to calculate the weights for the *NEP* indicators. This data-driven method assigns weights according to the degree of variation within each indicator, thereby providing a more accurate representation of regional differences in *NEP*. The detailed calculation steps follow.

Table 1. Evaluation indicator system of new quality productive forces.

Primary	Secondary	Code	Tertiary Indicators	Interpretation	Direction
Technological Productivity	Innovative Productivity	A1	Innovation R&D	Number of domestic patent grants	+
		A2	Innovative Industry	Revenue from high-tech industries	+
		A3	Innovation Products	Industrial innovation expenditure of large-scale enterprises	+
	Technological Productivity	A4	Technical Efficiency	Labor productivity of large-scale industrial enterprises [Calculated as: (Total profit + Number of employees × average wage)/Number of employees, following Lu and Guo's methodology]	+
		A5	Technical R&D	Full-time equivalent of R&D personnel in large-scale industrial enterprises	+
		A6	Technical Production	Raw density of robot installations	+
Green Productivity	Resource-conserving Productivity	B1	Energy Intensity	Energy consumption/ <i>GDP</i>	−
		B2	Energy Structure	Fossil energy consumption/ <i>GDP</i> [Fossil energy = Coal + Crude oil + Natural gas]	−
		B3	Water Intensity	Industrial water use/ <i>GDP</i>	−
	Environment-friendly Productivity	B4	Waste Utilization	Comprehensive utilization rate of industrial solid waste	+
		B5	Wastewater Emissions	Industrial wastewater discharge/ <i>GDP</i>	−
		B6	Waste Gas Emission	Industrial SO ₂ emissions/ <i>GDP</i>	−
Digital Productivity	Digital Industry Productivity	C1	Electronics Manufacturing	Integrated circuit production	+
		C2	Telecom Services	Total telecom business volume	+
		C3	Network Penetration	Number of internet broadband access ports	+
	Digital Industry Productivity	C4	Software Services	Software business revenue	+
		C5	Digital Infrastructure	Optical cable line length/Regional area	+
		C6	E-commerce	E-commerce sales	+

Note: “+” indicates a positive indicator; “−” indicates a negative indicator.

Step 1: Standardization

Positive indicators:

$$X_{ij} = \frac{X_{ij} - \min(X_{ij})}{\max(X_{ij}) - \min(X_{ij})} \quad (2)$$

Negative indicators:

$$X_{ij} = \frac{\max(X_{ij}) - X_{ij}}{\max(X_{ij}) - \min(X_{ij})} \quad (3)$$

where X_{ij} represents the level of *NEP* in the i -th province/municipality in the j -th year, and $i = 1, 2, \dots, m$ (number of evaluated objects), $j = 1, 2, \dots, n$ (number of indicators).

Step 2: Calculate the characteristic proportion of the i -th evaluated object under the j -th indicator:

$$P_{ij} = \frac{X_{ij}}{\sum_{i=1}^m X_{ij}} \quad (4)$$

Step 3: Calculate the information entropy of each indicator:

$$e_j = -K \sum_{i=1}^m (P_{ij} \times \ln P_{ij}) \quad (5)$$

$$K = \frac{1}{\ln m} \quad (6)$$

Step 4: Calculate the weight of each indicator:

$$W_j = \frac{1 - e_j}{\sum_{j=1}^n (1 - e_j)} \quad (7)$$

Specific indicators and calculation formulas are provided in Table 1.

4.1.3. Control Variables

To mitigate potential confounding effects of provincial characteristics on manufacturing carbon emissions, we incorporate four control variables following prior studies [69,79,80]: economic development level (pGDP) (measured as the natural logarithm of per capita gross regional product), urbanization level (UL) (expressed as the urban population share of total population), environmental regulation (REG) (measured by the proportion of industrial pollution abatement investment relative to industrial value added), and trade openness (OPEN) (defined as the proportion of total imports and exports to regional GDP).

4.1.4. Intermediary Variables

In this study, technological innovation is divided into disruptive technological innovation (D_innov) and progressive technological innovation (P_innov). Referring to Sun et al.'s study [81], invention patents possess high technological content and are difficult to obtain, representing a form of high-level technological innovation. Therefore, to measure disruptive technological innovation, we use the number of invention patent applications, applying a logarithmic transformation after adding 1. Utility model patents and design patents have lower technological content and lower barriers, so the number of green utility model and design patents filed plus 1 and then take the logarithm as an indicator of P_innov.

4.2. Data Source

Given the availability of data, this study conducts an empirical analysis using panel data from 30 Chinese provinces (excluding Hong Kong, Macao, Taiwan, and Tibet Autonomous Region) during 2012–2021. The data were obtained from multiple authoritative channels, including Carbon Emission Accounts and Datasets (CEADS) [82], CSMAR database [83], China Statistical Yearbook [84], China Energy Statistical Yearbook [85], China Statistical Yearbook on Science and Technology [86], China Statistical Yearbook on Environment [87]. To preserve sample size and ensure consistency, all variables were standardized, missing values were interpolated, and selected variables were log-transformed. Table 2 presents the descriptive statistics of key variables.

Table 2. Descriptive statistics of main variables.

Variable Type	Variable Name	Observations	Mean	Standard Deviation	Minimum	Maximum
Dependent Variable	CEI	300	0.563	0.435	0.019	2.215
Explanatory Variable	NEP	300	0.121	0.116	0.014	0.765
Mediating Variables	D_innov	300	8.352	1.413	4.522	11.541
	P_innov	300	10.167	1.427	6.021	13.553
Control Variables	pGDP	300	10.912	0.429	9.889	12.123
	UL	300	61.742	40.2	36.41	725.328
	REG	300	0.003	0.004	0	0.031
	OPEN	300	0.041	0.042	0.001	0.215

4.3. Model Construction

4.3.1. Benchmark Regression Model

To assess the influence of NEP on CEI within the manufacturing sector, the subsequent econometric model is formulated:

$$CEI = \beta_0 + \beta_1 NEP_{it} + \beta_2 Controls_{it} + \mu_i + \lambda_i + \varepsilon_i \quad (8)$$

where CEI represents the carbon emission intensity of the manufacturing sector in each province; NEP_{it} denotes the comprehensive index of new quality productive forces for each province; $Controls_{it}$ represents the control variables for each province, including economic development level (pGDP), urbanization level (UL), environmental regulation (REG), and trade dependency (OPEN); i and t indicate province and year, respectively; μ_i represents province fixed effects; λ_t represents time fixed effects; β_0 , β_1 , and β_2 are constant terms; and ε_{it} is the random error term.

4.3.2. Mediation Effect Test Model

To investigate the mediating roles of technological innovation and industrial structure upgrading, a mediation effect model was established following the analytical framework of Li et al. [47]. The validation procedure entails three sequential steps. Initially, the baseline relationship is scrutinized to confirm a significantly negative coefficient of NEP on manufacturing carbon emissions. Subsequently, the analysis assesses the effect of NEP on the hypothesized mediator, technological innovation, where a significant positive relationship is required. Provided these conditions are satisfied, the final step examines the correlation between the mediator and carbon emissions to ascertain the significance of the mediation pathway. The measurement of technological innovation aligns with the methodology of Li et al. [47], as defined by the following equation:

$$TC_{it} = \beta_0 + \beta_1 NEP_{it} + \beta_2 Controls_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (9)$$

$$CEI_{it} = \beta_0 + \beta_1 NEP_{it} + \beta_n TC_{it} + \beta_2 Controls_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (10)$$

where TC_{it} represents the technological innovation of each province, which serves as a mediating variable. Specifically, TC_{it} denotes two types of technological innovation in the manufacturing sector: Disruptive technological innovation (D_innov) and Progressive technological innovation (P_innov).

Within the mediation analysis framework, Equation (3) measures the driving effect of NEP on manufacturing technological innovation, thereby providing the necessary precondition for the establishment of the mediating pathway. Equation (4) subsequently incorporates technological innovation into the baseline model to quantify its mediating contribution along the causal chain linking NEP to carbon emissions reduction.

5. Analysis of Empirical Results

5.1. Benchmark Regression Results

Table 3 reports the estimated impacts of NEP on CEI across five nested specifications. As control variables are progressively introduced, the NEP coefficient remains negative and significant at the 1% level throughout, rising from -0.152 in the baseline model to -0.293 in the full specification. This persistent and increasing negative association, robust to a wide set of socioeconomic controls, offers strong empirical support for Hypothesis 1: the development of NEP significantly lowers manufacturing carbon emission intensity. The inclusion of control variables amplifies the absolute magnitude of the NEP coefficient, suggesting that the carbon reduction effect of NEP is both substantial and robust. Furthermore, the models exhibit high explanatory power, with R^2 values between 0.931 and 0.949, and both province- and year-fixed effects are statistically significant, underscoring the appropriateness of the empirical strategy. Regarding control variables, per capita GDP (pGDP) shows a consistently positive and highly significant influence (coefficients between 0.664 and 0.672, significant at the 1% level), confirming a short-term “scale effect” of economic growth on carbon emissions. Urbanization level (UL) is consistently signed positive and hovers around 0.050–0.051 (significant at the 5% level), mirroring the extra energy demand

triggered by urban expansion. In contrast, neither environmental regulation (REG) nor trade openness (OPEN) shows statistical significance, which may be attributed to the time lag in the implementation of environmental policies and the complex role of processing trade in shaping carbon intensity.

Table 3. Benchmark regression results.

Variable	(1)	(2)	CEI (3)	(4)	(5)
NEP	−0.152 *** (−2.973)	−0.268 *** (−4.168)	−0.273 *** (−4.183)	−0.287 *** (−4.323)	−0.293 *** (−4.067)
pGDP		0.664 *** (7.938)	0.675 *** (7.889)	0.671 *** (7.779)	0.672 *** (7.758)
UL			0.050 ** (2.220)	0.051 ** (2.272)	0.051 ** (2.238)
REG				0.042 (0.779)	0.042 (0.778)
OPEN					−0.015 (−0.303)
Constant	0.774 *** (93.437)	0.486 *** (13.177)	0.433 *** (8.452)	0.431 *** (8.411)	0.435 *** (8.266)
Province fixed effects	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES
Sample size	300	300	300	300	300
R ²	0.931	0.949	0.949	0.949	0.949

Note: **, and *** indicate statistical significance at the 5%, and 1% levels, respectively; standard errors are reported in parentheses.

5.2. Robustness Tests

5.2.1. Substitution of Explanatory Variables

Given significant disparities in economic growth and population distribution across provinces, directly using carbon emission intensity (defined as carbon emissions per unit of GDP) as the dependent variable may introduce estimation biases due to inherent differences in regional economic scales. To verify the reliability of the findings, this study conducts a robustness test by replacing the dependent variable: carbon emission intensity is adjusted to the logarithm of total manufacturing carbon emissions, followed by data standardization based on inverse indicators. This alternative metric offers two advantages: First, it directly measures the absolute scale of emissions from the production side, avoiding measurement errors in carbon intensity caused by fluctuations in GDP across regions. Second, logarithmic transformation compresses the variable scale to mitigate the influence of outliers and aligns with the interpretation of elasticity coefficients (e.g., percentage change effects) in economic models. The regression results in column (1) of Table 4 show that after replacing the dependent variable, the estimated coefficient of NEP is −0.106 and remains statistically significant at the 1% level with a negative sign, consistent with its inhibitory effect on carbon intensity in the baseline regressions. Further comparisons reveal that the signs and significance levels of control variables (e.g., per capita GDP, energy structure) remain highly consistent with the baseline model. The model exhibits high explanatory power with an R² of 0.982 and a sample size of 300. These findings indicate that regardless of whether “carbon emission intensity” or “the logarithm of total manufacturing carbon emissions” is used as the regional carbon emission indicator, NEP significantly reduce per capita carbon emissions, and its emissions reduction effect is robust to differences in the economic implications of the metrics. This evidence validates the robustness of the conclusion from an operationalization perspective, demonstrating that the research outcomes do not depend on specific measurement approaches, thereby effectively addressing potential endogeneity concerns arising from regional heterogeneity.

Table 4. Robustness test results.

Variable	(1) Substitution of Explanatory Variables	(2) Excluding Certain Regions	(3) Excluding Certain Years	(4) Lagging by One Period	(5) 1% Trimming
<i>NEP</i>	−0.106 *** (−3.441)	−0.291 *** (0.0715)	−0.318 *** (0.0810)	−0.314 *** (−3.491)	−0.341 *** (−4.976)
Constant	0.347 *** (12.432)	0.542 *** (0.0843)	3.800 * (2.107)	0.450 *** (8.335)	0.529 *** (8.360)
Control Variables	YES	YES	YES	YES	YES
Province Fixed Effects	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES
Sample Size	300	290	270	270	300
R^2	0.982	0.951	0.955	0.951	0.953

Note: * and *** indicate statistical significance at the 10% and 1% levels, respectively; standard errors are reported in parentheses.

5.2.2. Excluding Some Areas

To further validate the robustness of the results, we re-estimate all models after systematically varying the sample composition. Given that Liaoning Province underwent substantial industrial restructuring and policy pilot reforms (e.g., revitalization of old industrial bases) during 2012–2021, its economic development path and carbon emission characteristics may systematically differ from those of other provinces. To mitigate potential bias caused by regional heterogeneity, the sample data of Liaoning Province from 2012 to 2021 were excluded for re-estimation. As shown in Column (2) of Table 4, the core explanatory variable *NEP* continues to exhibit a statistically significant inhibitory effect on *CEI* at the 1% level, with a coefficient of −0.291, which is highly consistent with the benchmark regression results. The signs and significance of the control variables remain largely unchanged, and the model fit ($R^2 = 0.951$) is comparable to that of the baseline model, further confirming the reliability of the estimates. These findings indicate that the research conclusions are not distorted by unique regional development stages or policy shocks, demonstrating a high degree of robustness.

5.2.3. Excluding Selected Years

To mitigate potential confounding effects of significant exogenous shocks—such as the COVID-19 pandemic in 2020, which caused abrupt economic disruptions and anomalous energy consumption patterns—this study excludes all annual data from 2020 to ensure that estimation reflects periods of relatively stable economic operation. After removing these anomalous observations, the effective sample size decreases from 300 to 270, while the temporal coverage remains continuous apart from the omitted year. The re-estimated results, as shown in Column (3) of Table 4, reveal that the coefficient of *NEP* remains significantly negative (−0.318) at the 1% level ($p < 0.01$), which aligns closely in sign, magnitude, and statistical significance with the benchmark estimates. Although the reduced sample size might marginally affect estimation precision, the core findings regarding the carbon reduction effect of *NEP* remain highly consistent. Notably, the model fit remains strong with an R^2 of 0.955. This confirms that the inverse relationship between new quality productive forces and carbon emission intensity is not driven by extreme events or transient policy shocks, thereby underscoring the robustness and data-level reliability of the main conclusions.

5.2.4. Lag One Period Behind

To further investigate the dynamic impact of *NEP* on *CEI*, the core explanatory variable was lagged by one period. The regression results demonstrate that the one-period lagged term of *NEP* remains negatively signed and highly statistically significant, with a coefficient

of -0.314 ($t = -3.491$) at the 1% level. Notably, the magnitude of this lagged effect is even larger than that observed in the contemporaneous model, reinforcing the persistent inhibitory influence of *NEP* on carbon emission intensity. The signs and significance of the control variables remain largely consistent, indicating stable model structure and variable relationships. Moreover, the model continues to exhibit strong explanatory power, with an R^2 value of 0.951, based on a sample of 270 observations. These findings provide robust empirical evidence that the carbon reduction effect of *NEP* is not merely contemporaneous but persists over time, effectively mitigating concerns regarding reverse causality and further validating the reliability of the main conclusions.

5.2.5. 1% Trimming

To effectively mitigate the potential distortion caused by extreme values and ensure the accuracy and reliability of the estimates, all variables were winsorized at the 1% level. After this procedure, the absolute value of the *NEP* coefficient rose to -0.341 ($t = -4.976$), revealing that outliers in the raw data previously masked part of the carbon-reduction benefit attributable to *NEP*. The model maintains a high goodness-of-fit, with an R^2 of 0.953. Both province and year fixed effects remain statistically significant, and the signs and significance of the control variables are consistent with those in the baseline regressions. This confirms that the core findings are robust to extreme observations and alternative data treatments. Furthermore, across multiple robustness checks—including explanatory variable replacement, regional and temporal sample exclusion, lagged treatment, and winsorization—the coefficient of *NEP* remains consistently negative and significant at the 1% level, affirming the reliability and generalizability of the main conclusion.

5.3. Endogeneity Test

To address potential endogeneity concerns, particularly reverse causality, this study uses the one period lagged value of the core explanatory variable, denoted as *L.NEP*, as an instrumental variable. The instrumental variable regression results in Column (2) of Table 5 indicate that the coefficient of *L.NEP* is -0.298 and remains statistically significant at the 1% level. This result confirms that the negative impact of *NEP* on carbon emission intensity persists after controlling for potential endogeneity, which is consistent with the baseline estimates in both sign and significance. The lagged variable is economically justified given the time required for technology diffusion and emission reduction effects, where previous technological capabilities rather than concurrent factors are more likely to affect current emission levels. Additionally, control variables including *UL* and *pGDP* maintain their expected signs and significance, with coefficients of 0.053 (significant at 5%) and 0.648 (significant at 1%), respectively, supporting the validity of the instrumental variable approach. Overall, the test demonstrates that the carbon reduction effect of *NEP* is not driven by reverse causality, strengthening the reliability of the conclusions.

Table 5. Endogeneity test results.

Variable	(1) <i>NEP</i>	(2) <i>CEI</i>
<i>L.NEP</i>	1.054 *** (24.850)	
<i>UL</i>	0.000 (−0.042)	0.053 ** (2.451)
<i>pGDP</i>	0.004 (0.248)	0.648 *** (7.884)

Table 5. Cont.

Variable	(1) <i>NEP</i>	(2) <i>CEI</i>
OPEN	−0.045 ** (−2.287)	−0.074 (−1.157)
REG	0.008 (1.179)	0.032 (0.582)
<i>NEP</i>	(−3.148)	(−6.390) −0.298 *** (−3.997)
Constant	0.046 *** (2.681)	0.511 *** (5.619)
Sample Size	270	270
R^2	0.995	0.950

Note: **, and *** indicate statistical significance at the 5%, and 1% levels, respectively; standard errors are reported in parentheses.

5.4. Mediation Effect Test

The mediating effect analysis, as presented in Table 6, provides empirical evidence supporting the hypothesized mechanisms through which new quality productive forces influence carbon emission intensity. Column (1) reproduces the benchmark estimate: *NEP* enters with a highly significant coefficient of -0.293 , corroborating its direct dampening impact on *CEI*. In column (2), *NEP* exhibits a positive and highly significant impact on disruptive innovation (*D_innov*) with a coefficient of 0.120 , indicating that a one-unit increase in *NEP* is associated with a 0.120 -unit rise in disruptive innovation. When both *NEP* and *D_innov* are included in column (3), the coefficient of *D_innov* is significantly negative (-0.313 , $t = -1.891$), while the coefficient of *NEP* remains significant at -0.256 ($t = -3.673$), suggesting that disruptive innovation acts as a partial mediator. This result implies that *NEP* not only directly reduces carbon emissions but also fosters disruptive technological innovations—such as industry-academia-research integration and increased R&D investment—which further contribute to lowering *CEI*. In contrast, columns (4) and (5) examine the role of progressive innovation (*P_innov*). While *NEP* shows a significantly negative influence on *P_innov* in column (4) (-0.108 , $t = -2.137$), the coefficient of *P_innov* in column (5) is insignificant (0.009 , $t = 0.074$), indicating the absence of a mediating effect through progressive innovation pathways. These findings robustly confirm Hypothesis 2, highlighting that the carbon reduction effect of *NEP* is primarily channeled through disruptive technological innovation rather than progressive improvements. As reported in Table 6, the mediating roles of disruptive and progressive innovation differ markedly. *NEP* exerts a significant indirect effect on *CEI* via the promotion of disruptive innovation, thereby establishing a partial mediation pathway. Conversely, the policy pressure appears to crowd out resources devoted to incremental innovation, as evidenced by the negative coefficient of *NEP* on the latter; moreover, the marginal abatement effect of progressive innovation is statistically negligible. Consequently, the progressive-innovation channel remains inactive. These findings underscore that the principal emission reduction mechanism of environmental policy lies in incentivizing fundamental technological breakthroughs rather than in the progressive refinement of existing techniques, thereby deepening our understanding of how policy drives emission reductions through innovation.

Table 6. Results of the mediation effect test.

Variable	(1) <i>CEI</i>	(2) <i>D_innov</i>	(3) <i>CEI</i>	(4) <i>P_innov</i>	(5) <i>CEI</i>
<i>NEP</i>	−0.293 *** (−4.067)	0.120 *** (4.836)	−0.256 *** (−3.673)	−0.108 ** (−2.137)	−0.293 *** (−3.937)
<i>D_innov</i>			−0.313 * (−1.891)		
<i>P_innov</i>					0.009 (0.074)
Constant	0.435 *** (8.266)	0.394 *** (19.465)	0.558 *** (7.063)	0.554 *** (22.095)	0.430 *** (4.843)
Control Variables	YES	YES	YES	YES	YES
Province Fixed Effects	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES
Sample Size	300	300	300	300	300
<i>R</i> ²	0.949	0.991	0.950	0.980	0.949

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively; standard errors are reported in parentheses.

5.5. Heterogeneity Analysis

Owing to differences in industrial structure, resource endowments and development priorities, both *CEI* and the level of *NEP* differ markedly across regions. To depict these disparities, we map manufacturing carbon emission intensity and new quality productive forces for 30 provinces using the 2012–2021 means of all underlying indicators. Figure 2 shows that intensity is universally high; coastal provinces exceed inland provinces and eastern regions systematically surpass western regions, reflecting the national distribution of resources and industry in which coastal areas host the most developed, and therefore most carbon-intensive, manufacturing bases. Figure 3 reveals pronounced heterogeneity in new quality productive forces. High values are concentrated in a small number of coastal provinces with stronger economic fundamentals; average *NEP* is higher in the east than in the west and higher in the south than in the north.

The significant regional disparities evident in the initial analysis warrant a further examination of the heterogeneous impact of *NEP* on *CEI*. Following the standard tripartite regional classification of China [88], the provinces are grouped into eastern (Beijing, Tianjin, Shanghai, Hebei, Liaoning, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Hainan), central (Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, Hunan), and western (Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang) regions. The regression results in Table 7 demonstrate pronounced spatial heterogeneity. The impact of *NEP* is most potent in the central region, with a coefficient of −2.399 ($p < 0.01$). A substantial, though moderately weaker, effect is observed in the western region (coefficient = −1.037, $p < 0.01$). In contrast, the effect in the eastern region is statistically marginal and negligible in magnitude (coefficient = −0.090, $p < 0.10$), indicating its minimal contribution to decarbonization efforts there.

This spatial gradient—most effective in central China, followed by western China, and weakest in eastern China—aligns with theoretical expectations relating to regional disparities in industrial structure, technological maturity, and policy stringency. Eastern China, already ahead in both growth momentum and industrial transformation, now faces diminishing marginal returns from additional *NEP* uptake; technology frontiers are largely tapped and layered environmental mandates leave little room for further efficiency gains. In contrast, central China benefits from considerable potential for technological marginal

improvement, especially given its reliance on energy-intensive industries and less stringent environmental governance, allowing *NEP* to break path dependency and induce significant emission reductions. Similarly, western China shows meaningful responsiveness to *NEP*, supported by latecomer advantages in digitization and energy efficiency enhancements, despite a lower baseline economic development level.

These findings, grounded in robust empirical evidence across 110 observations in eastern China, 80 in central China, and 110 in western China—with all models controlled for province and year fixed effects and showing high goodness-of-fit (R^2 ranging from 0.921 to 0.974)—provide strong support for Hypothesis 3, confirming that the carbon reduction effect of *NEP* is spatially heterogeneous. Accordingly, policy interventions should account for these regional distinctions to effectively harness the decarbonization potential of *NEP*.

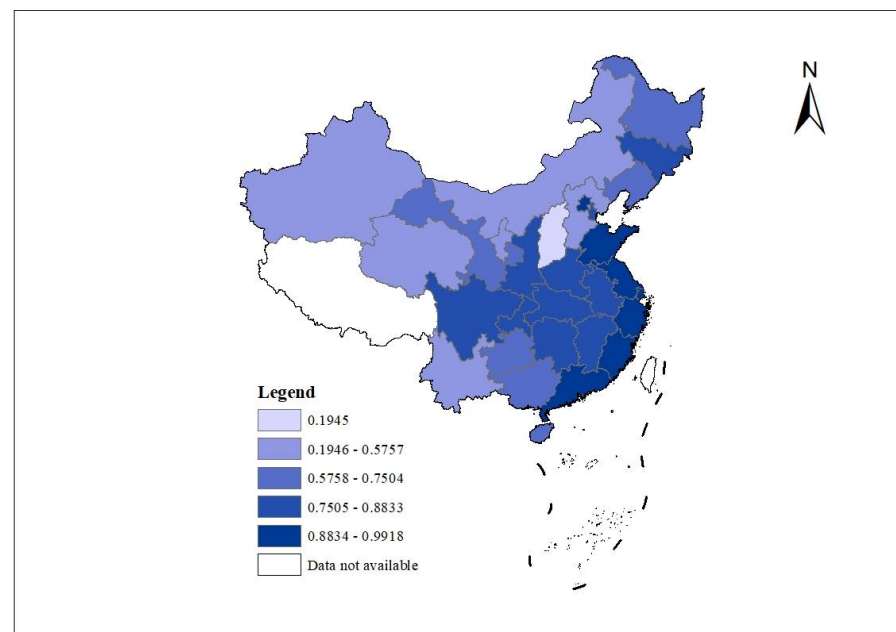


Figure 2. Distribution of Carbon Emission Intensity by Region.

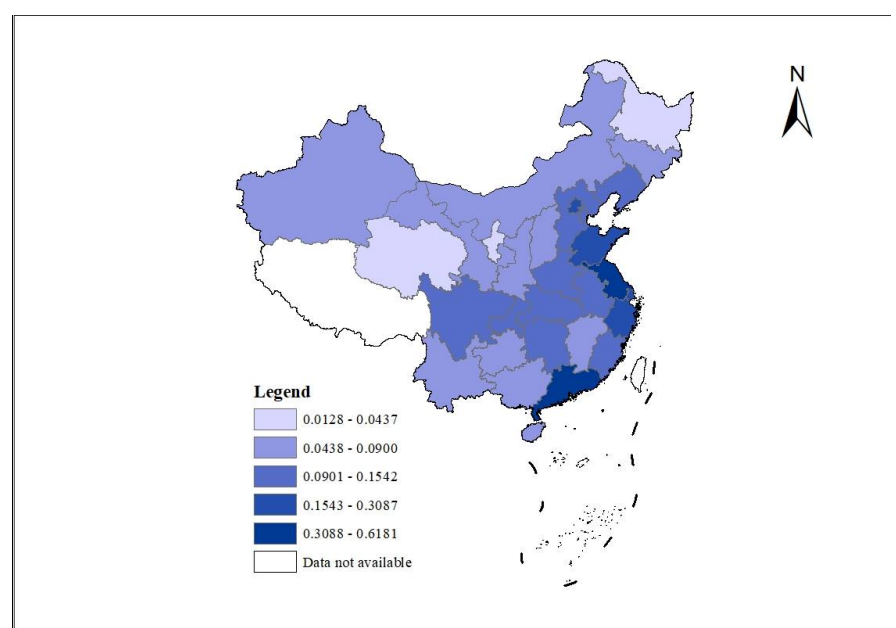


Figure 3. Regional Distribution of New Quality Productive Forces.

Table 7. Regional heterogeneity regression results.

Variable	CEI		
	(1) The Eastern Region of China	(2) The Central Region of China	(3) The Western Region of China
<i>NEP</i>	−0.090 * (−1.72)	−2.399 *** (−3.11)	−1.037 *** (−2.98)
Constant	1.221 (0.69)	−6.855 (−1.59)	0.185 ** (2.44)
Control Variables	Yes	Yes	Yes
Province Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Sample Size	110	80	110
R^2	0.964	0.974	0.921

Note: *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively; standard errors are reported in parentheses.

6. Discussion

The empirical results of this study resonate with and extend the burgeoning literature on the environmental implications of new quality productive forces (*NEP*) across various sectors in China. The consensus that *NEP* are a significant driver of green transition is strongly supported by the findings at the manufacturing level presented here. Specifically, the significant negative impact of *NEP* on manufacturing carbon emission intensity aligns with the conclusions of Xu et al. [89], who found that *NEP* significantly promote green development at the provincial level through technological advancement and industrial structure optimization. This is further corroborated by Wang and Kang [90], who demonstrated that the digital economy, a core element of *NEP*, directly facilitates the green transformation of the manufacturing industry in Chinese cities. This growing body of evidence confirms that the decarbonization effect of *NEP* is not sector-specific but a pervasive force across the economic system.

However, this study delves deeper into the mechanisms, revealing a critical nuance: the emission reduction effect is primarily mediated by disruptive green innovation rather than incremental improvements. This finding refines the broader technological mechanism proposed by Xu et al. [89] and others, suggesting that for manufacturing decarbonization, it is the groundbreaking, qualitative technological leaps embedded within *NEP*—such as digital twins or AI-driven process optimization—that are most effective in breaking high-carbon lock-ins. This insight carries significant theoretical implications for innovation and environmental economics. It demonstrates that the quality of innovation matters more than its mere quantity in achieving deep decarbonization. Consequently, policy must undergo a paradigm shift: from providing broad-based incentives for general technological progress to strategically fostering an ecosystem conducive to transformative, disruptive innovations. This emphasis on the quality of innovation echoes the findings of Liang and Hu [90], who highlighted that digital economy development promotes green technology innovation in manufacturing, underscoring the complexity of the technological leap. Thus, the current analysis adds a new layer to the understanding of how *NEP* drive environmental gains by highlighting the primacy of disruptive innovation.

Furthermore, the pronounced regional heterogeneity observed—where the central region exhibits the strongest effect, followed by the western and eastern regions—offers a crucial empirical contribution to the spatial analysis of *NEP*. This gradient pattern of “central > western > eastern” in manufacturing decarbonization complements and contrasts with the findings of other regional studies. For instance, Gao et al. [91] observed the highest coupling coordination between *NEP* and carbon total factor productivity in the eastern region, while studies in agriculture noted a leadership role for the eastern region [50].

Similarly, Wang and Kang [92] found the digital economy's impact on manufacturing green transformation was significant in the eastern and central regions but not the west, partially aligning with the observed gradient and highlighting the role of regional readiness. This discrepancy underscores that the effectiveness of *NEP* is highly context-dependent. The stronger effect in central China, a traditional manufacturing hub with greater potential for technological upgrading, suggests that *NEP* yield the highest marginal abatement benefits in transition economies locked into high-carbon structures, precisely where the need for transformative change is most acute. This finding provides a novel perspective on the theory of “late-mover advantage” in green technological catch-up, challenging the conventional assumption of a linear positive correlation between economic development level and decarbonization capacity. For policymakers, this implies a need to reconceptualize central China not as a passive recipient of eastern technology transfer, but as a strategic pilot zone for the industrialization of disruptive green technologies, where targeted investments and policy innovations can unlock its disproportionate potential for emission reduction.

Finally, a significant spatial spillover effect was detected, which echoes the findings of studies in other economic domains. Gao et al. [63] identified significant spatial spillovers in the coordination between *NEP* and forestry economic resilience, while Gao et al. [66] found that marine *NEP* enhance the economic resilience of coastal areas, with implications that likely transcend provincial boundaries. The foundational enabler of these spillovers may be the large-scale, integrated new energy systems discussed by Zou et al. [10], whose “Energy Triangle” theory frames the synergy between energy security, economic growth, and environmental sustainability underpinning *NEP*. This collective evidence from manufacturing, forestry, and marine sectors [63,66], supported by the infrastructural basis of the green energy revolution [10], reinforces the concept that the benefits of *NEP* are not confined by administrative borders but generate positive externalities, necessitating inter-regional cooperation in policy design to fully harness their decarbonization potential.

In summary, the principal theoretical contribution of this study lies in advancing the understanding of *NEP*'s environmental effects from “whether it works” to “how it works best.” By identifying disruptive innovation as the core mechanism and the central region as the pivotal spatial context, we reveal the dynamic engine and optimal pathway for deep decarbonization. Within the context of China and other emerging industrial economies striving to achieve dual-carbon goals, our conclusions provide fresh knowledge: success hinges on a strategic reorientation from “flood-irrigation”-style innovation incentives to “drip-irrigation”-style cultivation of disruptive technologies, and from “one-size-fits-all” emission reduction mandates to differentiated regional strategies that leverage comparative advantages. These insights generate a new, actionable framework for steering innovation-driven green transitions.

7. Conclusions and Recommendations

7.1. Conclusions

The urgent imperative to reconcile China's “dual-carbon” goals with sustainable development underscores the challenge of achieving carbon–economic decoupling in the manufacturing sector. This study proposes that new quality productive forces (*NEP*), which integrate green and intelligent technologies, serve as a viable pathway for promoting high-quality and sustainable transition. Drawing on a 2012–2021 provincial-level panel that covers 30 jurisdictions, we build an “*NEP* → technological innovation → *CEI*” typology and evaluate it with province- and year-double fixed-effects estimation. Baseline estimates show that *NEP* significantly lowers manufacturing carbon emission intensity, with coefficients ranging from -0.152 to -0.293 (all significant at the 1% level); this negative effect survives robustness checks that replace variables, drop regions or years, lag regressors, and winsorize

at 1%. An IV strategy using the one-period lag of *NEP* yields an almost identical coefficient (-0.298 , 1% significance), mitigating endogeneity concerns. Mediation analysis reveals that disruptive—rather than incremental—innovation accounts for most of the emission reduction channel. Regional heterogeneity is pronounced: the reduction effect is strongest in central China (-2.399), moderate in the west (-1.037), and weaker in the east (-0.090 , significant at 10%), reflecting differences in industrial structure, technological maturity and policy implementation. These findings confirm that *NEP* is a robust, economically meaningful driver of manufacturing decarbonization in China, but they also highlight the need for region-specific policies to unlock its full potential.

Despite these insights, this study has certain limitations. The measurement of *NEP* may not fully capture its multidimensional nature, and endogeneity concerns, though mitigated, may not be completely eliminated. Future research could adopt more comprehensive indicators for *NEP*, explore additional transmission mechanisms such as structural effect and governance effect, and extend the analysis to intra-regional or firm-level data for more granular policy implications.

7.2. Recommendations

Building on the empirical findings discussed earlier, several targeted policy directions can be proposed to harness the potential of new quality productive forces (*NEP*) in driving a green and low-carbon transformation of the manufacturing sector.

First, accelerating the development of *NEP* is essential to catalyze the green transition in manufacturing. The strong negative correlation observed between *NEP* advancement and carbon emission intensity underscores their significant potential in reducing industrial emissions. As a representation of advanced productivity, *NEP* not only stimulates technological innovation but also fosters the emergence of new business models that align with eco-friendly development. Therefore, enhancing the innovation capacity within the manufacturing sector is critical. This can be achieved by promoting technological breakthroughs and optimizing industrial structures to guide manufacturing toward sustainable transformation and upgrading.

Second, efforts should be directed toward promoting green and low-carbon technologies to improve energy efficiency across the manufacturing industry. Enterprises are encouraged to increase their investment in research and development of such technologies, which are pivotal in achieving green transformation. To support this, the government could establish dedicated R&D funds and create incentives for collaboration among businesses, universities, and research institutes. Such partnerships would not only accelerate innovation but also facilitate the commercialization of green technologies. Additionally, manufacturers should adopt advanced energy-saving technologies and equipment, refine production processes, and continuously improve energy utilization efficiency.

Third, it is imperative to refine the policy framework that underpins the development of *NEP*. A comprehensive, multi-dimensional policy system should be constructed, incorporating innovation incentives, market regulation, and institutional oversight. For instance, expanding the super-deduction ratio for green technology R&D expenses can stimulate corporate innovation. Meanwhile, implementing a tiered carbon tax system and establishing an annual emission reduction incentive fund could create market-driven motivation for decarbonization. Furthermore, introducing a carbon budget management system for key industries and developing a digital platform for environmental performance monitoring would enhance regulatory efficiency and transparency. Through the dual mechanism of policy guidance and institutional constraints, enterprises can be encouraged to increase R&D investment, accelerate technological iteration, and elevate their position in the global

value chain. At the same time, stronger environmental supervision and law enforcement are necessary to ensure the widespread adoption of green and low-carbon technologies.

Finally, regional strategies for developing *NEP* must be tailored to local conditions to maximize their effectiveness. In eastern China, where technological maturity is relatively high, the focus should be on exploring the integration of *NEP* with emerging industries. This includes increasing investment in cutting-edge R&D and building cross-sector innovation platforms. Central China, characterized by energy-intensive industries with low efficiency, should prioritize the deep integration of *NEP* into these sectors. Leveraging industrial transfers from the east can further amplify emission reduction outcomes. In western China, where the potential for technological diffusion remains underexploited, greater investment in digital infrastructure is needed. Encouraging pilot programs for digital transformation in local enterprises can help expand the application of *NEP* and foster inclusive green growth.

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