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Low-Carbon City Pilot Policy and Urban Carbon Productivity: Unveiling the Dual Pathways of Green Innovation and Economic Agglomeration

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Abstract

To advance its green and low-carbon transition, China has implemented the Low-Carbon City Pilot Policy (LCCPP) as a strategic initiative. A critical question remains unanswered on whether this policy effectively improves urban carbon productivity and facilitates the decoupling of economic growth from carbon emissions. Using the phased expansion of the LCCPP across Chinese cities as a quasi-natural experiment, this study constructs a multi-period difference-in-differences (DID) model based on a panel dataset of 276 prefecture-level and above cities from 2007 to 2023. The empirical results show that the LCCPP significantly enhances urban carbon productivity in pilot cities relative to non-pilot counterparts. This finding remains robust across a series of sensitivity checks. Mechanism analysis provides suggestive evidence that the policy may operate through two primary channels: fostering green technological innovation and promoting economic agglomeration. Heterogeneity analysis indicates that the policy's positive effects are more marked in developed cities, innovation-active cities, high-carbon-emission cities, and environmentally prioritized cities. Furthermore, moderation analysis demonstrates that stricter environmental regulations strengthen the policy's effectiveness. These findings provide empirical evidence for optimizing the design of low-carbon policies and offer actionable insights for tailoring green urban transformation strategies to local conditions.

Keywords: low-carbon city pilot policy; urban carbon productivity; green technological innovation; economic agglomeration; environmental regulation; difference-in-differences



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1. Introduction

Since the Industrial Revolution began in the eighteenth century, the large-scale burning of coal, oil, and other fossil fuels has greatly advanced human living standards, while also causing a gradual rise in atmospheric Carbon Dioxide (CO₂) concentrations [1,2]. In the assessment of the Intergovernmental Panel on Climate Change (IPCC), humans are mostly to blame for the abnormal heating of the Earth's surface. According to data released by the World Meteorological Organization (WMO), the global mean near-surface temperature exceeded the pre-industrial level (taking 1850–1900 as the pre-industrial reference period) by nearly 1.55 °C in 2024 [2]. As reported by the International Energy Agency (IEA), by 2025 atmospheric CO₂ concentrations had reached nearly 427 parts per million—about 50% higher than pre-industrial levels—and global CO₂ emissions from fuel combustion had hit a record high of nearly 38.4 gigatons [3]. Consequently, global heating, ecosystem damage, more frequent extreme weather events, and other problems have become much

more serious. In response, various policies have been adopted. One example is the EU Emissions Trading System (EU ETS), which caps industrial emissions and gradually cuts allowance volumes [4]. South Korea and Japan launched their own versions of the Low-Carbon City Pilot Policy (LCCPP) [5,6]. Some American cities began to pay special attention to decarbonizing buildings and transport [7]. Although some progress has been made on each front, in most cases there is still a trade-off between ambitious emission-reduction targets and sustained economic growth. This is why all involved parties now agree that moving toward a lower-carbon world is necessary if humanity is to endure and flourish over the long run.

As both the world's largest developing economy and a leading carbon emitter, China confronts the twin tasks of maintaining rapid urban and industrial growth while reducing Greenhouse Gas (GHG) emissions [8]. As urbanization proceeds quickly, there is also rising anxiety about urban ecological security. The National Development and Reform Commission (NDRC) of China launched the low-carbon city development strategy in selected areas with its July 2010 issuance of the Notice on Launching Low-Carbon Pilot Policies in Provinces, Regions, and Cities. At the Central Urban Work Conference held in 2025, there was reaffirmation of "building beautiful, green, and low-carbon cities." Subsequently, in the Outline of the 15th Five-Year Plan for National Economic and Social Development of China (2026), "urban green and low-carbon transition" appeared among the major strategies outlined in the plan. At its core, green and low-carbon urban development entails a complete decoupling of economic growth from carbon emissions. The amount of economic output generated per unit of carbon emissions—carbon productivity—serves as the key metric for capturing such decoupling [9]; hence, raising carbon productivity has become one of the biggest challenges that cities seeking to develop in a low-carbon and high-quality manner need to address.

Since 2010, there have been three phases of pilot programs under this scheme, involving six provinces and eighty-one pilot cities altogether. Participating cities are required to formulate low-carbon development plans tailored to their local resource endowments and economic conditions, establish systems for collecting and managing GHG emissions data, and incorporate emission-reduction targets into local performance assessment mechanisms. This approach is considered one of the most important regulatory instruments because it will help bring about an industrial system and production structure that can make carbon emission reductions compatible with improvements in resource productivity. In other words, the policy ultimately aims to decouple carbon emissions from economic growth, with success measured by rising economic output per unit of carbon emitted. After more than ten years of implementation, three important issues remain to be investigated: first, has the implementation of the LCCPP significantly increased urban carbon productivity? Second, through what transmission routes does the policy take effect? Third, do policy effects vary across different types of cities? Accordingly, treating the phased rollout of the LCCPP as a quasi-natural experiment, we attempt to answer these questions using panel data for 276 prefecture-level and above cities over 2007–2023, and construct a multi-period difference-in-differences (DID) model to investigate the policy's impact on urban carbon productivity and its underlying mechanisms. We also examine heterogeneous effects and the moderating role of environmental regulation intensity. This paper seeks to enrich the existing literature on the green economic consequences of low-carbon policies, and to offer actionable implications for policy optimization and place-based urban sustainability strategies in China.

2. Literature Review

Carbon productivity—the amount of economic output generated per unit of carbon emitted—is commonly used as a core metric for evaluating green economic progress. Improving urban carbon productivity has thus become a major topic of widespread academic interest. Regarding its determinants, the existing literature has conducted valuable discussions from multiple perspectives, including technological progress, industrial agglomeration, digital economy development, and infrastructure construction.

First, in terms of technological progress, industrial new quality productivity significantly enhances urban carbon productivity, with Research and Development (R&D) factor flow serving as a positive mediating channel [10]. Green technology innovation directly enhances carbon productivity while generating positive spillovers for neighboring regions, primarily through structural optimization and factor reallocation [11]. Biased technological progress also works indirectly, operating through energy efficiency improvements and structural upgrades in energy and industry [12]. On industrial agglomeration, high-tech industry concentration boosts local carbon productivity and generates spatial spillover effects [13]. Similarly, green-oriented industrial agglomeration raises carbon productivity, with technological upgrading serving as a partial mediator [14]. Regarding the digital economy, its impact on urban carbon productivity operates via two key mechanisms: boosting green innovation and advancing industrial restructuring [15–17]. On infrastructure, digital infrastructure enhances urban carbon productivity via green technology advancement, industrial optimization, and energy efficiency gains through enhanced innovation capacity [18]. High-speed rail networks contribute by reshaping industrial patterns and generating technological spillovers [19], while network infrastructure reduces CO₂ per unit of Gross Domestic Product (GDP) by encouraging green invention and raising public environmental awareness [20]. Against the backdrop of China's "dual-carbon" strategy, the role of environmental regulations has drawn increasing attention. Development zone upgrading has been found to raise carbon productivity through stricter environmental regulations, improved business environments, and stronger policy support [21]. In achieving the co-reduction in pollutants and carbon emissions, environmental regulations exhibit moderating effects and even nonlinearity—stronger regulations amplify the carbon productivity gains from industrial intelligence [22]. Moreover, environmental regulations directly enhance carbon productivity and additionally foster it indirectly through green innovation [23]. Notably, market-based environmental regulations appear to exert stronger positive incentives than command-and-control approaches, with the former yielding net positive benefits while the latter impose significant adverse effects [24].

The LCCPP thus represents a key institutional initiative in China's pursuit of carbon peaking and carbon neutrality, and has consequently attracted considerable scholarly attention. Existing evaluations of its effects have predominantly focused on two dimensions: pollutant emission reductions and economic outcomes. Studies using spatial DID models find that the LCCPP significantly reduced urban industrial pollution emissions and carbon emissions intensity. Further tests of mediating effects indicate that innovation, industrial structure, and energy consumption effects are the core transmission mechanisms [25], with innovation effects contributing the most [26]. Through various energy-saving and emission-reduction measures, the LCCPP has been shown to reduce urban energy intensity [27], enhance the coordination efficiency of pollution and carbon reduction governance [28], improve urban ecological welfare performance [29], and mitigate urban air pollution—mainly by curbing enterprise pollution discharges and promoting industrial structure upgrading [30]. Beyond environmental benefits, several studies have extended the analysis to economic dimensions. Low-carbon city development has been found to facilitate industrial

restructuring [31,32], generate employment opportunities [33,34], contribute to high-quality development [35–37], and strengthen urban economic resilience [38–40].

Existing studies have made commendable progress in identifying determinants of urban carbon productivity and evaluating low-carbon city development, yet several gaps remain. First, most studies examine carbon productivity from a single-factor perspective—whether technological progress, industrial agglomeration, or otherwise—with few adopting the holistic logic embedded in the LCCPP framework. Second, policy-effectiveness research is limited; the literature largely evaluates emission-reduction and economic-growth effects in isolation, rarely using carbon productivity as a composite indicator of decoupling between economic growth and carbon emissions. Third, regarding transmission mechanisms, most attention has been paid to general effects, while systematic tests of both green technology innovation and economic agglomeration channels are lacking. Furthermore, how environmental regulation intensity moderates these effects, along with the heterogeneous impacts of innovative city pilots and key environmental protection city status, has yet to be examined. To fill these gaps, this paper draws on panel data covering 276 prefecture-level and above cities in China from 2007 to 2023, and treats the phased rollout of the LCCPP as a quasi-natural experiment, constructing a multi-period DID model. Our marginal contributions are threefold. On mechanisms: unlike most studies that consider only a single channel, we simultaneously examine green technology innovation and economic agglomeration as mediating pathways. On moderation: we investigate how environmental regulation intensity moderates policy effectiveness, highlighting the institutional constraints on policy transmission and offering a new lens for understanding heterogeneous policy outcomes. On methodology: we apply the debiased machine-learning (DML) method as a robustness check to address potential functional-form misspecification in conventional linear models, thereby strengthening causal inference. Collectively, the evidence presented here contributes to the refinement of the LCCPP and informs regionally adapted green transition strategies.

3. Theoretical Framework and Research Hypotheses

3.1. *The Direct Impact of the LCCPP on Urban Carbon Productivity*

The LCCPP is an integrated environmental regulation instrument that directly affects urban carbon productivity by alleviating the burdens associated with carbon reduction. Although environmental regulations entail certain institutional costs during implementation, the key issue is not emission reduction per se, but whether they enhance economic output and thus reconcile the tension between regulatory stringency and economic growth. This reasoning yields three theoretical mechanisms through which the LCCPP exerts its direct effects.

First, the innovation-compensation effect originates from the Porter Hypothesis, according to which well-designed environmental regulations encourage firms to pursue innovation, enabling them to offset compliance burdens and boost productivity. Under the LCCPP, establishing GHG emission accounting systems enables the allocation of reduction targets across major industries and enterprises. Facing stringent carbon constraints, firms are compelled to upgrade production technologies to maximize profits at lower cost—achieving the same output with substantially lower energy consumption [41,42]. This mechanism reduces carbon intensity while increasing output per ton of CO₂ emitted, i.e., raising carbon productivity.

Second, the industrial optimization effect builds on the structural dividends theory, which holds that reallocating productive factors from less to more productive sectors enhances aggregate productivity [29]. Accordingly, the LCCPP requires pilot areas to adjust their industrial structures, curb excessive expansion of high-emission, energy-intensive

sectors, and facilitate the reallocation of factors toward low-energy, high-output services and emerging strategic industries. Through such restructuring, resources shift from industries with high marginal carbon emissions to those with lower marginal emissions, reducing carbon intensity while maintaining output and yielding structural dividends [30], thereby enhancing urban carbon productivity.

Third, the factor optimization effect follows from resource allocation theory. Through subsidies, tax incentives, and preferential green loans provided under the LCCPP, capital and technology flow toward green and low-carbon sectors, directing R&D efforts toward low-carbon technology development and application [43]. These emerging technologies reshape production functions and ultimately decouple economic growth from CO₂ emissions. Market-based environmental regulations outperform command-and-control approaches in improving carbon productivity [24], justifying the LCCPP's reliance on market-oriented instruments. Moreover, evidence shows that the LCCPP not only reduces urban carbon intensity but also enhances total-factor carbon productivity without compromising local economic growth [44]. Based on the preceding discussion, we put forward our first research hypothesis.

Hypothesis 1. *Policies for the LCCPP can significantly improve a city's carbon productivity.*

3.2. *The Mechanism Through Which the LCCPP Affects Urban Carbon Productivity*

The LCCPP may generate a synergistic amplification effect through the mutual reinforcement between green technological innovation and economic agglomeration. On the one hand, economic agglomeration creates favorable spatial and factor conditions for green technological innovation. The geographical concentration of enterprises, research institutions, and skilled labor facilitates knowledge spillovers and technology diffusion, thereby reducing R&D and information-seeking costs and stimulating more green innovation [45]. On the other hand, green technological progress helps economic agglomeration reduce emissions and improve efficiency. By saving resources and protecting the environment, new technologies enhance urban attractiveness, attracting more high-quality factors and further promoting spatial concentration of economic activities [46]. Thus, rather than simply adding up these two effects, it is their interaction—mutually conditioning and reinforcing each other in practice—that ultimately underpins the LCCPP's impact on carbon productivity. This study examines green technological innovation and economic agglomeration as two separate channels. Although we do not quantify their interaction, this clearly warrants further investigation.

3.2.1. Green Technology Innovation

It is believed that the LCCPP will affect urban green technological innovation along two main pathways: regulation and resources. In terms of regulation, innovation incentives arise from regulatory pressure exerted by regulators. Under the LCCPP, experimental zones are required to establish carbon-emission-control goals within their jurisdictions, allocate carbon-reduction tasks among major industries, and thereby provide market players with clear expectations and guidance regarding the carbon reductions they must achieve, as well as direction on where to innovate. According to the Porter Hypothesis, well-designed environmental regulation may partly or fully offset its compliance costs by stimulating “innovation compensation” among regulated firms. This is because regulatory signals resolve part of the uncertainty surrounding corporate environmental investment, compelling firms to reassess their resource efficiency, and thereby shifting their focus from end-of-pipe measures toward source-based technological innovation [47,48]. Given carbon emission constraints, enterprises must lower their emission intensity through improved production processes and the development of clean energy sources [41]; consequently,

they face additional demand for investment in green technology R&D. Second, this type of innovation requires certain enabling conditions. Beyond target-setting itself, various supporting resources are available. The policy package includes subsidies for green R&D, the development of low-carbon industrial parks, improvements to the green finance system, and talent attraction and cultivation programs. Government subsidies alleviate funding constraints and financial bottlenecks faced by enterprises in green R&D, and send positive signals regarding the future prospects of such investment through their demonstration effect, thereby helping firms secure external resources [49]; talent introduction policies directly increase the local supply of science and technology professionals, providing intellectual support for regional green technology R&D [50]; institutional improvements—such as those to the green finance system—reduce transaction and coordination costs for innovative activities, thereby stimulating market participants' willingness to engage in green R&D [51].

Green technological innovation will continuously drive carbon productivity improvements, with substantial theoretical and empirical support. The effect operates through two aspects: first, a direct reduction in carbon emissions attributable to innovation itself; second, an indirect influence. Regarding the former, green technology R&D focuses on energy conservation and low-carbon technologies, so its progress lowers both energy consumption and CO₂ emissions per unit of output. Empirical evidence shows that, partly due to green innovation, clean energy shares in total energy consumption have increased and the energy supply structure has become more rational, resulting in significant reductions in carbon intensity [52]. In addition, progress in renewable resources has reduced dependence on carbon-rich fossil fuels such as coal; meanwhile, the promotion of new energy vehicles and other energy-saving technologies has curbed carbon emissions from final energy consumption [44]. International experience similarly suggests that technology-oriented changes driven by environmental regulations form an important micro-level foundation for carbon productivity improvements [53]. Second, there is the structural optimization effect. Green technological innovation not only directly affects the production process but also indirectly raises carbon productivity by facilitating industrial upgrading and improving factor allocation efficiency [54]. Research indicates that green innovation can redirect funds and labor from low-efficiency, energy-intensive sectors toward high-efficiency, low-emission sectors, thereby improving aggregate factor utilization [17]. Moreover, green innovation enhances traditional industries' capacity for equipment and technology upgrading, phasing out backward production capacity and fostering emerging industries with high-value-added and low-carbon emissions [23]. After all, industrial structure upgrading essentially entails reallocating production factors from low-value-added to high-value-added activities. Only through such reallocation can the economy reduce CO₂ emissions while maintaining output growth. Green technology R&D thus acts as both a “push” factor (eliminating obsolete capacity) and a “pull” factor (generating new industries), and it is through this combined push–pull dynamic that two-way adjustment occurs [55]. On this theoretical basis, green technological innovation can be considered a testable channel through which the LCCPP affects carbon productivity. Accordingly, this paper proposes the following hypotheses.

Hypothesis 2. *There is a positive correlation between the LCCPP and improvements in urban green technology innovation.*

3.2.2. Economic Agglomeration

The LCCPP is expected to influence urban economic agglomeration through two channels: enhancing the attractiveness of production factors and optimizing the industrial ecosystem. Improving the attraction of various production factors means that once a city is approved as a low-carbon pilot site, it can receive supportive policies from both central and

local governments. These supportive policies mainly include preferential arrangements in fiscal subsidies, tax incentives, and green finance. With such policy support, local operational and production costs for enterprises decrease to some extent, generating a “policy haven” effect to a certain degree. Consequently, productive resources such as capital, human capital, and technology gravitate to these pilot cities [56]. Regarding talent mobility, some studies suggest that, through the wage premium, improved urban living comfort, and innovation-driven development stimulated by the LCCPP, there is a considerable promotion of the purposeful agglomeration of scientific and technological talent [57]; meanwhile, from the perspective of new economic geography theory, policy-induced factor flows also expand market size, generating more “forward linkages” and “backward linkages,” and the agglomeration cycle continues until spatial economic agglomeration stabilizes [58]. Second, there is the optimization of the industrial ecosystem. According to the LCCPP’s guidance for pilot cities on constructing low-carbon industrial systems, pilot cities are expected to steer industrial development planning toward energy-efficient, environmentally friendly modern service industries and strategic emerging industries. These emerging industries are characterized by long industrial chains and strong forward and backward linkages, and their development requires coordinated support from upstream suppliers and downstream service providers, which will drive many firms to locate nearby [59]. In addition, pilot policies also promote the development of low-carbon industrial parks that offer firms access to shared facilities and public services, reducing location-related concerns and supporting costs for firms, thereby promoting more pronounced spatial agglomeration through this sharing effect [60].

Increased levels of economic agglomeration will further drive growth in carbon productivity, and existing theoretical and empirical research provides supporting evidence on three levels. First, economies of scale. When economic activities are spatially concentrated, firms can share infrastructure and public services, thus lowering both energy use and carbon intensity per unit of output. Theoretically, economies of scale rely on the joint construction and sharing of infrastructure to reduce market transaction and administrative regulatory costs and improve overall energy efficiency, thereby achieving co-benefits for growth and emissions reduction [61]. Second, the market-driven convergence of micro-enterprises toward market centers, along with diversified agglomeration patterns, can significantly enhance carbon productivity at the urban level [62,63]. More generally, the positive relationship between economic activity density and energy efficiency has been confirmed by numerous studies—cities with higher density tend to have lower per capita infrastructure costs and more efficient public transportation systems, which constitute the spatial foundation for carbon emissions reduction [64]. Second, knowledge spillover effects. Within agglomeration areas, technological exchange and knowledge sharing among firms are facilitated, promoting the rapid dissemination and diffusion of low-carbon technologies. Through close interaction with competitors and upstream and downstream suppliers, firms can more promptly acquire knowledge regarding product characteristics, environmental protection technologies, and clean production processes. When integrated with firms’ existing knowledge systems, this new knowledge helps drive technological transformation and green innovation [56]. In agglomeration economics theory, knowledge spillovers constitute a primary source of externalities arising from the spatial clustering of economic activities—personal interactions, labor migration, and tacit knowledge flows all display strong distance-decay properties; therefore, geographic proximity itself constitutes a key condition for knowledge transfer [65]. The spatial agglomeration effects formed by high-tech industries can accelerate the diffusion of heterogeneous knowledge and technologies across sectors, helping enterprises and other innovation actors acquire external knowledge and stimulate low-carbon innovation activities, which is crucial for improving carbon pro-

ductivity [66]. Third, the effects of specialized division of labor. Economic agglomeration has driven a specialized division of labor in pollution control and emissions reduction, giving rise to service-oriented enterprises dedicated to environmental pollution prevention and control. These specialized environmental service firms can provide pollution control at lower cost and higher efficiency, curbing carbon emissions while promoting economic growth. Under the division-of-labor perspective, agglomeration-driven market growth fosters greater functional specialization among firms, spinning off pollution control as an independent, scale-efficient industry. This development boosts treatment efficiency and simultaneously enhances the productive capacity available for firms' core businesses [67]. Synthesizing the above theoretical logic, economic agglomeration constitutes the second testable mechanism through which the LCCPP influences carbon productivity.

Hypothesis 3. *There is a positive correlation between the LCCPP and increases in economic agglomeration.*

3.3. The Moderating Effects of Environmental Regulation

Environmental regulation is an important moderator affecting the effectiveness of the LCCPP. Drawing on the Porter Hypothesis, well-designed environmental regulations generate an “innovation-as-compensation” effect: compliance-driven technological innovation helps reduce abatement costs while generating additional competitive benefits [68]. This theory provides a key theoretical foundation for analyzing the moderating role of environmental regulation in LCCPP implementation. Under this policy, regulatory stringency reflects the extent to which local governments restrict emissions and prioritize environmental enforcement. Thus, stricter regulation compels firms to pay greater attention to emission reduction, generating stronger innovation incentives stimulated by low-carbon policy demands, thereby exerting a stronger influence on carbon productivity improvement. The moderating mechanism operates primarily through three channels.

First, the policy's binding effect is reinforced. Stricter environmental regulations imply that local governments have established more stringent carbon and pollution emission limits with corresponding supervision and penalties. Consequently, non-compliance becomes more costly for firms in pilot cities, creating strong incentives for emission reduction. At this point, the LCCPP's requirements align with firms' interests—they strive to meet regulatory demands through technological innovation and process optimization, thereby complying while containing costs and even reaping benefits, ultimately raising carbon productivity. Second, the policy's incentive effect is strengthened. Drawing on the Porter Hypothesis, properly designed environmental rules can trigger an “innovation-offset” effect: compliance-oriented technological innovation partially or fully offsets the cost burden of regulation. Some scholars suggest that technological innovation mediates the LCCPP's contribution to high-quality urban development, but the magnitude of this mediating effect depends largely on environmental regulation stringency [69]. When regulatory stringency reaches a high level, firms face stronger compliance pressure, yet the marginal return on investment in environmentally friendly technologies also increases, thereby strengthening the policy's role in improving carbon productivity. Empirically, a survey of advanced manufacturing firms identifies another pathway: the synergistic effect of regional environmental regulations and firm-level environmental strategies in promoting green innovation [70]. Third, the resource-reallocation effect under policy fine-tuning. Environmental regulation significantly amplifies the LCCPP's contributions to both carbon mitigation and energy-saving [71]. This implies that in regions with stricter environmental regulations, local authorities tend to allocate more public funds to green sectors, steer private investment into clean industries, and hasten the exit of high-energy-use and heavy-polluting firms. This encourages the movement of resources from less productive uses toward more advanced

and efficient activities, thereby improving the overall allocation of resources. Accordingly, environmental regulation stringency is another key moderator influencing the LCCPP's effect on carbon productivity. Drawing on the above discussion, this paper puts forward the following hypothesis:

Hypothesis 4. *Environmental regulation intensity positively moderates the effect of the LCCPP on urban carbon productivity, such that the policy's effectiveness increases with the stringency of local environmental regulations.*

4. Empirical Design

4.1. Variable Selection and Data Sources

Because the LCCPP was carried out in three stages—launched in certain prefecture-level and above cities in 2010, 2012, and 2017—this study adopts a multi-period incremental DID model. Considering the start dates of this pilot program and its associated time-lag effect, the three pilot batches take 2010, 2013, and 2017 as their implementation years. It then assesses the actual policy influence on carbon productivity in the pilot cities since policy implementation. This study uses data from 2007 to 2023 for Chinese cities at or above the prefectural level. The preprocessing routine involves: (1) excluding cities with severe data deficiencies; (2) for the few cities with minor data gaps in certain years, applying linear interpolation to fill them; (3) standardizing the years with relatively complete data for each prefecture-level and above city as the baseline. This procedure yielded balanced panel data for 276 prefecture-level and above cities, comprising 123 pilot cities and 153 non-pilot cities, totaling 4692 observations. Our sample does not cover the Tibet Autonomous Region, Hong Kong, Macao, or Taiwan. In addition, based on data availability, several prefecture-level cities—including Laiwu, Tongren, Bijie, Haidong, Danzhou, Sansha, Zhongwei, Turpan, and Hami—were also excluded. The basic data for this study come mainly from three sources. First, city-level macroeconomic indicators—population, employment, industrial composition, and local government spending—are obtained from the China Urban Statistical Yearbook (2007–2023), provincial and municipal yearbooks, and prefectural government work reports (2007–2023). Second, we draw carbon emission figures from the Carbon Emission Accounts and Datasets (CEADs). Third, we obtain green patent application data from the China National Intellectual Property Administration (CNIPA) Patent Search and Analysis System, and classify relevant indicators following the World Intellectual Property Organization (WIPO) International Green Patent Classification.

4.2. Specification of the Measurement Model

4.2.1. Baseline Model Configuration

The following Equation (1) specifies the multi-period DID model we use to estimate the effect of the LCCPP on urban carbon productivity.

$$carbonprod_{it} = \alpha + \beta did_{it} + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (1)$$

where $carbonprod_{it}$ denotes the carbon productivity of city i in year t ; $did_{it} = treat_i \times post_t$ is the main explanatory variable, indicating LCCPP coverage for city i in year t . Its coefficient β estimates the average treatment effect on carbon productivity. Specifically, a significantly positive β implies that the policy effectively raises carbon productivity in pilot cities on average, whereas a significantly negative β would suggest that the policy reduces carbon productivity instead. α is the estimated constant; X_{it} is the vector of city-level control variables mentioned above; μ_i represents the city fixed effects (FE); λ_t represents the year FE; and ε_{it} is the error term. We cluster standard errors at the city level throughout to address potential serial correlation and within-group dependence.

4.2.2. Setting up the Impact Mechanism Model

To further examine the impact of the LCCPP on urban carbon productivity and the pathways through which it works, we follow [72] and construct a mechanism testing model based on the baseline regression specification. The specific formula is shown in Equation (2).

$$M_{it} = \alpha + \beta did_{it} + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (2)$$

where M_{it} denotes mechanism variables, including green technology innovation (app_{it}) and economic agglomeration (eag_{it}); a significant β indicates that the policy operates through the corresponding mechanism; the remaining variables are defined as previously.

4.3. Variable Definition

4.3.1. Dependent Variable

Carbon productivity is a core indicator of green economic development, capturing the amount of GDP produced per unit of carbon dioxide released. Following [73], we measure it as the ratio of regional GDP to CO₂ emissions:

$$carbonprod_{it} = \frac{GDP_{it}}{CO_{2it}} \quad (3)$$

where CO_{2it} denotes CO₂ emissions (in tons) of city i in year t , obtained from CEADs; and GDP_{it} denotes the real local GDP (in ten thousand yuan) of city i in period t . To remove the influence of price fluctuations, we set 2007 as the base period and obtained real GDP by adjusting nominal GDP with the Consumer Price Index (CPI). For cities without published CPI figures, the CPI of their corresponding provinces serves as a substitute. Thus, according to the above Equation, a larger ratio indicates higher carbon productivity in that city, implying greater room for further emission reductions. Consequently, lower carbon intensity reflects a higher level of low-carbon development in those cases.

4.3.2. Key Explanatory Variable

The main policy indicator in this study is the dummy variable did_{it} , indicating the LCCPP. For the later two rounds of pilot implementation—where the relevant provinces had already applied for and obtained approval for low-carbon pilots before the selection of the eleven pilot cities—this paper, following [74], also defines the start date of provincial-level pilot policies as the policy implementation date for each affected city. Accordingly, the specification is $did_{it} = treat_i \times post_t$, where $treat_i$ is a group dummy taking the value 1 for cities included in any of the three NDRC pilot cohorts, and 0 otherwise; $post_t$ is a treatment-timing dummy taking the value 1 if city i had implemented the LCCPP by year t , and 0 otherwise. With the pilot staggered across three cohorts—launched in 2010, 2013, and 2017—and treatment timing varying by city, our analysis adopts a multi-period DID specification.

4.3.3. Control Variables

To reduce the risk of omitted-variable bias, and drawing on prior work, we include several city-level factors as controls in the regression: Population Size (logarithm of year-end permanent resident population), Economic Development Level (log per capita GDP), Financial Development Level (deposit-plus-loan balances of financial institutions scaled by regional GDP), Industrial Structure (secondary industry value-added as a share of regional GDP), Urbanization Level (proportion of non-agricultural population to registered population), and Science and Technology Innovation Capacity (science and technology outlays as a share of local government spendings).

4.3.4. Mechanism Variables

To shed light on the underlying pathways through which the LCCPP influences carbon productivity, this paper constructs mechanism variables in the following two aspects:

- (1) Green Technological Innovation (*app*). Following the index construction method of [75], we proxy green technological innovation using the count of green invention patents granted in each city.
- (2) Economic Agglomeration (*eag*). Following the index construction method of [76], we proxy economic agglomeration using the ratio of secondary- and tertiary-sector employment to urban built-up area.

4.3.5. Moderating Variables

This is an important indicator of local governments' efforts in environmental governance. We measure city-level environmental regulation stringency using industrial Sulfur Dioxide (SO₂) removal per unit of GDP [77]. The rationale for using this indicator is twofold. On one hand, it reflects both firms' actual investment in pollution abatement and the effectiveness of those measures. It is primarily an outcome-based indicator of pollution reduction rather than a measure of procedural regulatory efforts. What matters is the actual tonnage of SO₂ removed from industrial sources by firms operating their own desulfurization facilities or investing in pollution control equipment. Thus, this figure captures the observable responses of regulated entities to regulatory pressure [78]. On the other hand, the indicator also reflects firms' economic responses to regulatory pressure. SO₂ is a conventional industrial air pollutant in China. Firms need to purchase desulfurization equipment and cover operation and maintenance costs for pollution control facilities. Such investment represents another form of economic response to regulatory pressure. They will internalize these costs only when facing substantive emission reduction obligations. Consequently, a higher SO₂ removal rate per unit of output implies that firms in that locality face relatively stringent emission limits. By construction, higher values of this proxy reflect more stringent environmental regulation at the city level [79]. The calculation formula is as follows:

$$er_{it} = \frac{SO2remove_{it}}{GDP_{it}} \quad (4)$$

Here, $SO2remove_{it}$ is the volume of industrial SO₂ removed (in tons) in city i in year t , and GDP_{it} is the GDP (in hundred million yuan) of region i in year t . Thus, higher values of this ratio reflect more spending on pollution abatement per unit of output, implying tighter environmental regulation.

Table 1 reports the descriptive statistics of the core variables.

Table 1. Descriptive statistics for the main variables.

Variable Name	Variable	Observations (N)	Mean	Median	Min	Max
Urban Carbon Productivity	carbonprod	4692	0.713	0.519	0.048	9.265
LCCPP	did	4692	0.311	0	0	1
Population Size	ln pop	4692	5.883	5.936	2.898	8.136
Level of Economic Development	ln pgdp	4692	10.633	10.669	8.131	12.486
Level of Financial Development	finance	4692	1.022	0.838	0.075	12.817
Industrial Structure	industry	4692	0.458	0.461	0.107	0.910
Level of Urbanization	urban	4692	0.403	0.337	0	3.266
Scientific and Technological Innovation Capacity	tech	4692	0.003	0.002	0	0.063
Green Technology Innovation	app	4692	0.092	0.008	0	12.010
Economic Agglomeration	eag	4692	0.429	0.370	0.022	2.419
Intensity of Environmental Regulation	er	4692	0.163	0.003	0.000	239.729

5. Analysis of Estimation Results

5.1. Baseline Regression Results

Table 2 presents the estimation output from Model (1). With city and year FE included, column (1) shows the impact of the LCCPP on urban carbon productivity in the absence of any controls, yielding a *did* coefficient of 0.108, significant at the 1% level. Column (3) reports the estimates with controls included; the *did* coefficient is 0.074 and is statistically significant at the 5% level. Economically, this coefficient implies that, due to the LCCPP, pilot cities experienced an average increase of 0.074 metric tons of CO₂ reduction per 10,000 yuan of GDP growth over the sample period, accounting for nearly 10.4% of the mean carbon productivity level across all cities during that period. Thus, relative to non-pilot cities, the LCCPP significantly promotes the rise of carbon productivity among pilot cities. Accordingly, hypothesis H1 is supported.

Table 2. Baseline regression results.

Variable	Carbonprod			
	(1) Without Controlling for Variables	(2) Without Controlling for Variables	(3) Include Control Variables	(4) Include Control Variables
did	0.108 *** (0.040)	0.319 *** (0.085)	0.074 ** (0.034)	0.127 *** (0.058)
ln pop			1.546 *** (0.575)	0.133 *** (0.042)
ln pgdp			0.426 *** (0.051)	0.229 *** (0.040)
finance			0.013 (0.021)	0.004 (0.054)
industry			0.272 (0.183)	−0.780 *** (0.222)
urban			0.003 (0.092)	0.030 (0.132)
Tech			5.517 (4.930)	55.313 * (28.125)
Constant	0.472 *** (0.021)	0.614 *** (0.032)	−12.868 *** (3.279)	−2.352 *** (0.539)
City FE	Yes	No	Yes	No
Year FE	Yes	No	Yes	No
N	4692	4692	4692	4692
R ²	0.232	0.045	0.420	0.206

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; figures in parentheses are robust standard errors at the city level.

5.2. Robustness Tests

5.2.1. Parallel Trends Test

One of the fundamental prerequisites for valid estimation under a multi-period DID framework is that the treated and non-treated groups satisfy the common trends condition. This implies that, prior to any policy intervention, the two groups displayed similar movement patterns, whereas afterward, they followed distinctly different paths. The following model is estimated to test this assumption.

$$carbonprod_{it} = \alpha + \sum_{k=-10}^{13} \beta_k \cdot treat_i \times year_{it}^k + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (5)$$

Here, $carbonprod_{it}$ denotes the carbon productivity of city i in year t ; $treat_i$ is a group dummy equal to 1 if city i is among the low-carbon pilot cities and 0 otherwise; $year_{it}^k$ is a relative-year dummy where k indicates the k -th year after city i launched its low-carbon pilot program ($k < 0$ represents the years before the policy, $k = 0$ is the year the policy took

effect, and $k > 0$ represents the years after the policy). Accordingly, β_k is the policy effect coefficient for year k , measuring the disparity in carbon productivity between the treated and control cities. X_{it} refers to the control variables, μ_i and λ_t stand for city and year FE, respectively, and ε_{it} is the stochastic error. Using the period just before the policy ($k = -1$) as the reference, the parallel trends condition is met if the β_k coefficients are not statistically significant for all pre-treatment years.

The test results are displayed in Figure 1. In the period preceding the LCCPP, the regression coefficients were statistically insignificant at all time points, suggesting that the groups *did* not differ substantially before the policy. This points to broad satisfaction of the parallel trends assumption. In the aftermath of the policy, however, the estimated coefficient on the main explanatory variable became positive and statistically significant. Thus, it can be inferred that following the introduction of the LCCPP, the trajectories of the treated and control groups started to move apart gradually yet consistently, with the policy impact growing stronger over time. This implies that the policy contributed to improving carbon efficiency in pilot cities to some extent. Moreover, this policy effect was sustained rather than transitory, indicating that the positive gains generated by the policy were long-lasting.

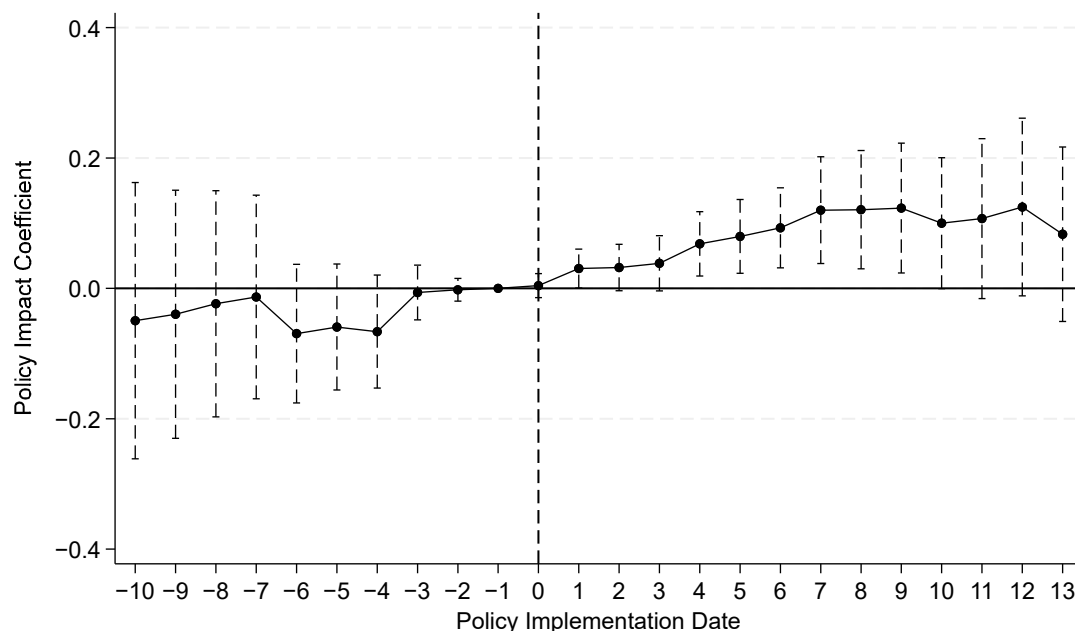


Figure 1. Parallel trends test. The vertical dashed line indicates the policy implementation year (year 0).

5.2.2. Urban Placebo Test

To further test the robustness of our results to omitted variables, we conduct a placebo test using random simulation. The procedure involves three steps. First, while holding the policy timing fixed, we randomly draw from the full sample several cities matching the actual treatment group size, assign them as pseudo-treatment cities, and treat the rest as controls. Second, we construct a fictitious policy dummy by assigning a value of one to these pseudo-treated cities in the actual policy years. Third, we re-estimate the baseline model with all other controls unchanged. We repeat this procedure 500 times, yielding 500 pseudo-DID coefficient estimates and their associated p -values. The results are shown in Figure 2. Of the 500 estimated coefficients, the vast majority cluster around zero, with p -values largely above 0.1. Moreover, the true *did* estimate of 0.074 lies well in

the right-hand tail of the coefficient distribution. This indicates that our results are unlikely to be driven by unobserved random factors, confirming that our conclusion is quite robust.

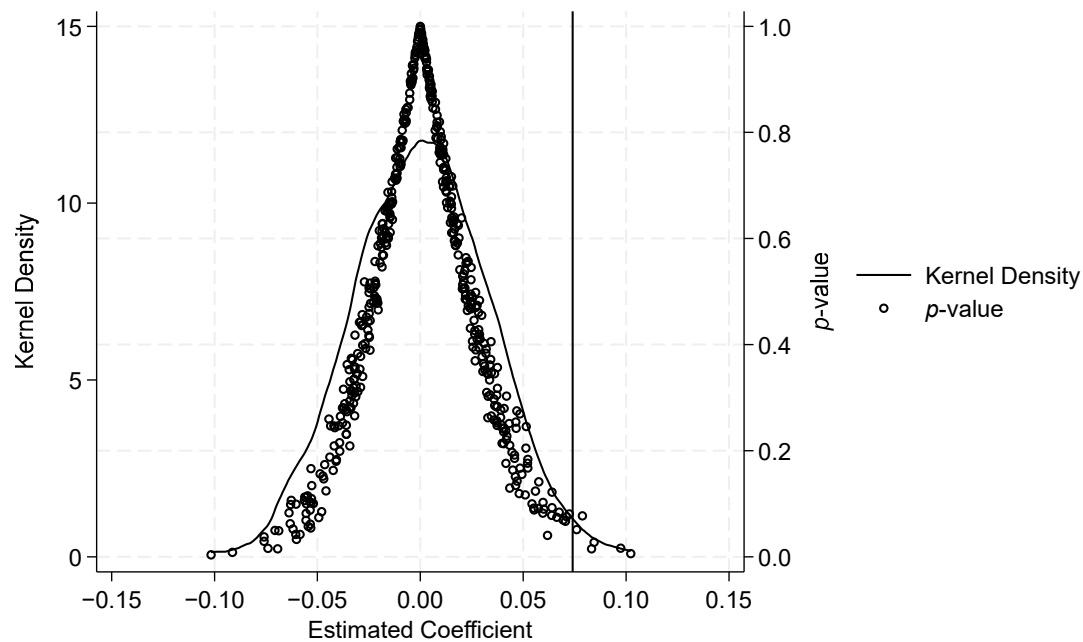


Figure 2. Urban placebo test.

5.2.3. Year Placebo Test

To further test whether the LCCPP generates an anticipatory effect, we conduct a year-specific placebo test. Specifically, we construct fictitious policy dummies for two, three, four, and five years before the policy start date— did^{-2} , did^{-3} , did^{-4} , and did^{-5} —and substitute them for the actual policy variable in the baseline regression. If the coefficients on these fictitious policy variables are insignificant, then they are unlikely to produce results comparable to those from the baseline model; in other words, the baseline findings cannot be simply attributed to policy-induced expectations. As shown in Table 3, none of the coefficients on did^{-2} , did^{-3} , did^{-4} , or did^{-5} is statistically significant. Thus, we find no evidence of anticipatory effects of the LCCPP, which supports the robustness of our baseline conclusions. Furthermore, this finding helps alleviate concerns about sample selection arising from non-random policy assignment. Had pilot cities systematically differed from non-pilot cities prior to the policy for reasons unrelated to the policy itself, at least some of these fictitious policy variables would have shown positive and significant effects. Our results do not support that scenario.

Table 3. Year placebo test.

Variable	Carbonprod			
	(1) Two Years Ahead	(2) Three Years Ahead	(3) Four Years Ahead	(4) Five Years Ahead
did^{-2}	0.067 (0.047)			
did^{-3}		0.064 (0.063)		
did^{-4}			0.049 (0.065)	
did^{-5}				0.034 (0.070)

Table 3. Cont.

Variable	Carbonprod			
	(1) Two Years Ahead	(2) Three Years Ahead	(3) Four Years Ahead	(4) Five Years Ahead
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes
N	4692	4692	4692	4692
R ²	0.418	0.417	0.417	0.416

5.2.4. Additional Robustness Checks

(1) Controlling for Concurrent Policy Interference

Over the course of the LCCPP rollout, China also implemented various other environmental and economic policies. To eliminate the potential interference of these simultaneous policies on urban carbon productivity, we add two dummy variables to the baseline model corresponding to the Innovative City Pilot Policy and the Carbon Emission Trading Pilot Policy—both of which were implemented alongside the LCCPP. Specifically, *innovate* is a dummy variable indicating the Innovative City Pilot Policy, taking the value 1 for cities that are classified as Innovative City Pilots and are also subject to the LCCPP in that year, and 0 otherwise; *carbontrade* is a dummy indicator for the Carbon Emission Trading Pilot Policy, taking the value 1 if a city is selected as a pilot and also covered by the LCCPP in that year, and 0 otherwise. Columns (1), (2), and (3) of Table 4 report that, when we control for the Innovative City Pilot Policy, the Carbon Emission Trading Pilot Policy, and both policies jointly, the *did* coefficient on the main explanatory variable remains positive and statistically meaningful. Moreover, this coefficient does not change substantially from the baseline estimate (0.074). Thus, the LCCPP's positive impact on carbon productivity cannot be attributed to other policies implemented during the same period. In other words, omitted variable bias does not appear to be a concern here, lending support to our main findings.

Table 4. Robustness results I.

Variable	Control for Other Policy Disturbances During the Same Period		
	(1) Exclude the Interference of Innovative Pilot Policy	(2) Exclude the Impact of Carbon Emissions Trading Pilot Policy	(3) Exclude the Interference of Both Policies at the Same Time
did	0.066 * (0.034)	0.070 ** (0.035)	0.062 * (0.035)
innovate	0.096 *** (0.034)		0.096 *** (0.033)
Carbontrade		0.027 (0.065)	0.029 (0.064)
Constant	−12.690 *** (3.321)	−12.806 *** (3.216)	−12.622 *** (3.255)
City FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Control variables	Yes	Yes	Yes
N	4692	4692	4692
R ²	0.425	0.420	0.425

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; figures in parentheses are robust standard errors at the city level.

(2) Alternative PSM-DID Specifications

In the baseline regression, sample selection bias may still cause some endogeneity, as treatment and control group assignment is not purely random. We therefore employ propensity score matching (PSM) to balance the two groups and reduce observable differences. Specifically, we use the control variables from the baseline regression as matching covariates and estimate the propensity score for each sample using a Logit model. Given the limited sample size, we adopt 1:2 nearest neighbor matching instead of 1:1 to avoid excessive sample loss, and also perform kernel matching as a robustness check.

Figure 3 plots the kernel density of propensity scores for the treatment and comparison groups, both pre- and post-matching. The kernel densities of the two groups diverge noticeably before matching, but converge markedly afterward—evidence that the matching effectively balances the covariates and satisfies the common support requirement.

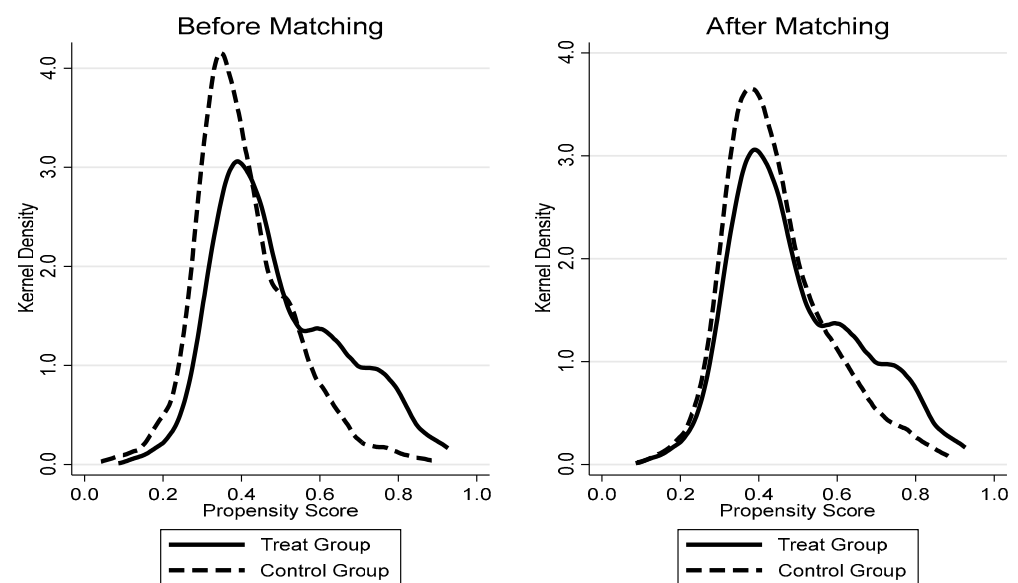


Figure 3. Kernel density plots of propensity scores pre- and post-PSM.

We re-estimate the *did* model with the matched sample. Table 5, Column (1) reports 1:2 nearest-neighbor matching results, and Column (2) reports kernel matching results. The key coefficient remains positive and significant (10% in Column 1, 5% in Column 2), matching the baseline. Thus, the LCCPP's positive effect on carbon productivity is robust to sample selection bias.

(3) Heterogeneity in Treatment Effects

When estimating two-way FE models with multiple periods of data, the homogeneity of treatment effects assumption is often difficult to satisfy, as treatment effects may vary over time or across units. This can lead to the problem of “using treated units as controls,” commonly referred to as “bad comparisons.” If treated units appear in both groups, estimation results may be biased. To assess whether these issues affect our conclusions, we conduct two robustness checks: one relying on the Goodman-Bacon decomposition [80], and the other employing the Callaway–Sant’Anna DID estimator [81] (hereinafter Callaway and Sant’Anna Difference-in-Differences, CSDID).

We first apply the Goodman-Bacon decomposition. The results show that the estimated average treatment effect on urban carbon productivity under the two-way FE framework is 0.074. Among the various weights in the decomposition, “bad comparisons” account for only about 0.9%, a very small share. Furthermore, 19.7% of the control group had not yet received the treatment by the end of the observation period, and 79.4% never received it at

all. This suggests that substantial bias due to heterogeneous treatment effects is unlikely, and the baseline DID estimate can be considered reliable. Second, employing Callaway and Sant’Anna, we re-run the policy effect using units that had not yet received the treatment before policy implementation as controls. The estimated average treatment effect remains positive, at about 0.087, and is statistically significant at the 5% level. The dynamic effects show that the pre-policy coefficients are all insignificant, confirming the parallel trends assumption, while most post-policy coefficients are positive and significant, with a clear upward trend over time. The CSDID estimate (0.087) is close to the baseline estimate (0.074) in both magnitude and significance, further reinforcing the reliability of our core results.

Table 5. Robustness results II.

Variable	PSM-DID Estimation		Other Robustness Tests	
	(1) Nearest Match	(2) Nuclear Match	(3) Adjust the Sample Period	(4) The Control Variable is Lagged by one Period
did	0.061 * (0.033)	0.073 ** (0.034)	0.056 ** (0.027)	0.080 ** (0.035)
Constant	−10.762 *** (2.289)	−12.885 *** (3.273)	−10.266 *** (3.106)	−12.113 *** (3.132)
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	No
One period behind	No	No	No	Yes
N	3405	4687	3588	4416
R ²	0.404	0.419	0.394	0.395

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; figures in parentheses are robust standard errors at the city level.

(4) Adjustment of the Sample Period

Since the onset of the COVID-19 pandemic in early 2020 may have disrupted urban economic activities and carbon emissions, complicating the identification of policy effects, we confine the sample to 2007–2019 to account for pandemic effects and re-estimate the model. The estimate for *did* in Table 5, Column (3), is 0.059 and is statistically significant at the 5% level, which is broadly consistent with our main findings. This indicates that our results are not driven by the choice of a specific sample period. That is, the LCCPP’s beneficial impact on carbon productivity is not an artifact of particular sample periods, and the internal validity of our baseline conclusions appears to be well supported.

(5) Lagging of Control Variables by One Period

To address potential endogeneity due to reverse causality, we follow [82] and replace all control variables with their one-period lags and re-run the regression. Column (4) of Table 5 presents the estimates. The *did* coefficient is 0.080, significant at 5% and similar to the baseline, confirming that the LCCPP’s positive effect is robust to reverse causality.

(6) Re-Estimating DML Models

To verify that the baseline findings are not driven by model specification, this paper conducts robustness checks from two aspects: algorithm improvement and parameter tuning. Given the considerable collinearity between some control variables and their quadratic terms, the standard Least Absolute Shrinkage and Selection Operator (LASSO) may yield poor variable selection results. We therefore use elastic-net and ridge regressions as diagnostics to examine whether changing the type of machine-learning approach affects the estimated treatment effects. We also alter the cross-validation split ratios from the

default 1:4 to 1:2 and 1:6 to examine how the results respond to alternative data partitions. As shown in Table 6, neither the changes to the model structure nor the variations in sample splitting affect the conclusion: the estimated coefficient on *did* persists as positive and statistically significant across both the 1% and 5% significance levels. Thus, the LCCPP's positive impact on urban carbon productivity remains robust and does not change with alternative algorithms or data partitioning schemes.

Table 6. Robustness results III.

Variable	Reset the Dual Machine Learning Model				
	(1) Lasso Regression	(2) Ridge Regression	(3) Elastic Net Regression	(4) Change the Sample Split Ratio (1:2)	(5) Change the Sample Split Ratio (1:6)
<i>did</i>	0.103 *** (0.039)	0.086 ** (0.037)	0.101 *** (0.039)	0.103 *** (0.039)	0.103 *** (0.039)
The term of the control variable	Yes	Yes	Yes	Yes	Yes
the quadratic term of the control variable	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
N	4692	4692	4692	4692	4692
R ²	0.020	0.027	0.020	0.021	0.020

Note: ** $p < 0.05$, *** $p < 0.01$; figures in parentheses are robust standard errors at the city level.

6. Extended Analysis

6.1. Heterogeneity Analysis

In theory, the effectiveness of the LCCPP varies across cities with different resource endowments, development stages, and urban characteristics. To further reveal the heterogeneity of policy effects, this study performs subgroup regressions across four dimensions: level of economic development, designation as an innovative pilot city, urban carbon emissions, and designation as a key city for environmental protection.

6.1.1. Heterogeneity Analysis by Economic Development Level

Economic development level influences a city's technology level, factor endowments, and policy implementation capacity, which may cause the LCCPP to have varying effects across cities. To investigate this possibility, we split the sample cities by their location relative to the Hu-Huan-Yong Line into two groups: developed regions (east of the line) and underdeveloped regions (west of the line), and perform separate regressions for each group. Columns (1) and (2) of Table 7 report the findings. For the developed group, the estimated *did* coefficient is 0.079, significant at the 5% level, implying that the policy increases carbon productivity by about 0.079 tons per 10,000 yuan of GDP, accounting for approximately 11.1% of the sample average. For the underdeveloped region group, the *did* coefficient is 0.031 but is not statistically significant. A test for group differences in the *did* coefficients indicates that they differ significantly at the 5% level. Thus, the policy effect in developed regions is more than twice as large as that in underdeveloped regions. In other words, the LCCPP's favorable impact on carbon productivity is concentrated in economically developed areas and is insignificant in underdeveloped ones. One possible explanation is that developed regions have a stronger economic foundation and a more diversified industrial structure, which can provide sufficient financial support and market space for low-carbon technology R&D and application. Thus, this enhances policy effectiveness. In contrast, underdeveloped regions face constraints such as a weaker economic base, greater

difficulty in industrial upgrading, and a weaker capacity to respond to policy incentives, which may help explain why the policy effects are not yet significant in these areas.

Table 7. Heterogeneity analysis I.

Variable	Level of Economic Development		Innovative Pilot Cities	
	(1) Developed Regions	(2) Underdeveloped Regions	(3) Yes	(4) No
did	0.079 ** (0.038)	0.031 (0.036)	0.123 ** (0.060)	−0.012 (0.040)
Constant	−13.624 *** (3.546)	−3.365 (2.013)	−17.909 *** (6.296)	−6.389 *** (1.040)
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes
N	4250	442	1683	3009
R ²	0.435	0.244	0.522	0.377
p-value	0.014		0.000	

Note: This *p*-value, derived from Fisher's exact test (1000 bootstrap replications), tests the significance of between-group differences in the adjustment coefficients. These notes also pertain to Table 8 and are not reiterated. ** *p* < 0.05, *** *p* < 0.01; figures in parentheses are robust standard errors at the city level.

Table 8. Heterogeneity analysis II.

Variable	Urban Carbon Emissions		Key Cities for Environmental Protection	
	(1) High Carbon Emissions	(2) Low Carbon Emissions	(3) Yes	(4) No
did	0.095 ** (0.036)	0.028 (0.060)	0.111 ** (0.054)	−0.038 (0.037)
Constant	−7.756 *** (1.728)	−18.727 *** (4.352)	−19.740 *** (5.156)	−6.407 *** (0.947)
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes
N	2346	2346	1887	2805
R ²	0.486	0.483	0.554	0.418
p-value	0.020		0.000	

Note: ** *p* < 0.05, *** *p* < 0.01; figures in parentheses are robust standard errors at the city level.

6.1.2. Heterogeneity Analysis: Innovative vs. Non-Innovative Cities

The National Innovative City Pilot Program was implemented in batches from 2008 onward by the Ministry of Science and Technology and the NDRC, aiming to strengthen urban innovation capacity through better allocation of innovation resources. It can be argued that the LCCPP is effective only if a city has sufficient innovation capacity. To test this, we split the sample into innovative and non-innovative groups according to the national innovative pilot city designation, and perform group-wise estimation; the results are reported in Table 7, columns (3) and (4). For the innovative city group, the *did* coefficient is 0.123 and significantly positive at the 5% level, implying that the policy raises carbon productivity by 0.123 tons per 10,000 yuan of GDP, equivalent to approximately 17.3% of the sample mean. For the non-innovative city group, the estimated *did* coefficient is −0.012 and is not statistically significant. A test for group differences in the *did* coefficients indicates that they differ significantly at the 1% level. Thus, the estimated policy impact in innovative

cities (0.123) substantially exceeds that in their non-innovative counterparts, indicating that the effect of the LCCPP is concentrated in innovative cities and is not observed in non-innovative ones. A plausible explanation is that innovative cities are more adept at assimilating external technologies and have better green innovation endowments, enabling policy incentives to translate more effectively into carbon productivity improvements; in contrast, non-innovative cities, due to their limited innovation capacity, fail to generate such effects. This result offers supplementary evidence for the green technology innovation mechanism discussed earlier.

6.1.3. Heterogeneity Analysis by Carbon Emission Level

Following [22], we split the sample into high- and low-emission city groups according to the median level of carbon emissions, and perform separate estimations for the two subsamples, with the results presented in Table 8, columns (1) and (2). For the high-emission group, the *did* coefficient is 0.095, which is significantly positive at the 5% level, implying that the policy increased carbon productivity by 0.095 tons per 10,000 yuan of GDP, equivalent to 13.3% of the sample mean. For the low-emission group, the *did* coefficient is 0.028 and is not statistically significant. A test for group differences in the *did* coefficients indicates that they are significantly different at the 5% level. Thus, the program's effect in high-emission cities is more than triple that in low-emission cities, revealing that the policy's positive influence is largely restricted to high-emission areas, while low-emission cities show no meaningful response. One possible explanation is that high-emission regions tend to have a concentrated industrial structure heavily reliant on energy-intensive, high-pollution industries, and are mostly industrialized areas with high energy intensity. Consequently, they face substantial pressure to reduce carbon emissions, making policy incentives more effective. In contrast, low-emission cities tend to have lower baseline emissions, with a number of them being service-oriented or centered on high-technology sectors, leaving limited room for further emission reductions. Thus, the marginal effect of policy measures is diminished, which explains the insignificant result in this group. These findings suggest that the LCCPP has a "targeted" emission reduction effect, playing a more pronounced role in high-emission regions.

6.1.4. Heterogeneous Effects: Key Environmental Protection Cities vs. Others

This grouping follows the official roster of key environmental protection cities released in 2003 by the former State Environmental Protection Administration. The list covers 113 cities, including provincial capitals, centrally administered municipalities, separately planned cities, and other major industrial urban areas. These cities are subject to stringent environmental regulations and possess relatively strong environmental governance capacity and sound institutional systems. The sample is thus split into key and non-key environmental protection cities, with separate regressions reported in Table 8, columns (3) and (4). For the key environmental protection city group, the *did* coefficient is 0.111 and significant at the 5% level, implying that the policy raised carbon productivity by about 0.111 tons per 10,000 yuan of GDP, equivalent to approximately 15.6% of the full-sample average. For the non-key group, the *did* coefficient is -0.038 and is not statistically significant. The coefficient difference between the two groups is statistically meaningful at the 1% level, as confirmed by a group-difference test. Thus, the policy effect is substantially stronger in key environmental protection cities than in their non-key counterparts, implying that the LCCPP works in the former but not in the latter. One potential reason is that key environmental protection cities possess greater environmental enforcement capability and more mature institutional frameworks, allowing them to react swiftly and efficiently to policy signals and advance low-carbon development. By contrast,

non-key cities have weaker environmental governance capacity and a lower capacity to translate policy initiatives into effective action, which may help explain why the expected policy outcomes are not yet observable in these areas.

6.2. Mechanism Test

According to theoretical analysis, the LCCPP is expected to influence urban carbon productivity via two pathways: green technological innovation and economic agglomeration. Based on this, Hypothesis H2 is tested using a mechanism effects model.

6.2.1. Mediating Role of Green Technology Innovation

Green technological innovation is the first theoretical pathway through which the LCCPP influences carbon productivity. For hypothesis H2 proposed above, this effect operates through two levels: regulation and resources. Regulation involves establishing carbon emission reduction targets and distributing abatement obligations across key carbon-intensive sectors, prompting firms to integrate emission considerations into their R&D investment choices [83]. Resources refer to supportive measures introduced alongside the policy, including R&D subsidies, industrial parks, talent recruitment programs, and others. These measures provide financial support, build platforms, and cultivate talent, thereby reducing the start-up and opportunity costs of green R&D [45].

Therefore, drawing on the theoretical framework above and the measurement approach for green innovation in the literature, this paper employs the count of green invention patents granted within a city to proxy for green technological innovation [84]. Since granted patents have undergone substantive examination by patent offices, they better reflect the novelty and practicality of the technology and thus represent “substantive innovation.” The estimate for the core explanatory variable in Column (1) of Table 9 is 0.155, positive and significant at the 1% level. Economically, the policy corresponds to an average rise of roughly one additional granted green invention patent per city, equivalent to a rise of about 168.5% relative to the sample mean of 0.092. This suggests that the LCCPP is positively correlated with urban green technology development. Drawing on the theoretical analysis, green technological progress enhances carbon productivity through two channels: first, via the direct reduction of carbon emissions achieved by deploying energy-saving and low-carbon technologies in production, which raises energy efficiency and reduces per-unit emission intensity; second, by indirectly facilitating industrial upgrading and improving factor allocation efficiency—guiding capital and labor from energy-intensive, low-efficiency sectors toward high-productivity, low-emission sectors—thereby reducing total carbon emissions while maintaining output growth [52,53]. Overall, these findings provide suggestive evidence consistent with theoretical expectations that green technological innovation may serve as a potential pathway through which the policy exerts its effects.

Table 9. Mechanism test results.

Variable	(1) Green Technology Innovation	(2) Economic Agglomeration
did	0.155 *** (0.054)	0.034 ** (0.016)
Constant	−6.093 *** (2.279)	0.409 (0.470)
City FE	Yes	Yes
Year FE	Yes	Yes
Control variables	Yes	Yes
N	4692	4692
R ²	0.172	0.200

Note: ** $p < 0.05$, *** $p < 0.01$; figures in parentheses are robust standard errors at the city level.

6.2.2. Mediating Role of Economic Agglomeration

The other influence channel is economic agglomeration. According to hypothesis H3, the LCCPP affects the level of economic agglomeration through two pathways: first, enhancing the attractiveness of productive factors; second, improving the internal industrial environment. Regarding the former, the supportive policies available to pilot cities reduce firms' production and operation costs to some extent, creating a "policy haven" effect that attracts factors such as capital, talent, and technology to these regions [56,57]. Regarding the latter, policy measures steer local industrial planning toward low-carbon directions, helping to establish the foundational framework for low-carbon industrial parks and facilitating the co-location and spatial clustering of upstream and downstream firms [59]. Overall, these measures are expected to be positively associated with higher levels of economic agglomeration.

Adopting the measurement strategy of prior work [73], this study employs the share of secondary- and tertiary-industry employment relative to urban built-up area to measure economic agglomeration. The estimate for *did* in Column (2) of Table 9 is 0.034 and is statistically significant at the 5% level. Economically, the policy increased the degree of economic agglomeration by 0.034, accounting for 7.9% of the sample mean. This suggests a significant positive link between the LCCPP and urban economic agglomeration. As theorized earlier, economic agglomeration raises carbon productivity via three main routes: scale economies, which enable firms to share infrastructure and public services, thereby lowering per-unit energy consumption and carbon emissions [61]; knowledge spillovers, which accelerate the spread of low-carbon technologies via intensified technological interaction and knowledge exchange among firms in clustered areas [56]; and specialized division of labor, which drives specialization in pollution control and emission reduction, giving rise to professional environmental service providers that deliver pollution control at lower cost and higher efficiency, curbing carbon emissions while promoting economic growth [67]. Overall, these findings provide suggestive evidence consistent with theoretical expectations that economic agglomeration may serve as a potential pathway through which the policy exerts its effects.

7. Moderating Effect of Environmental Regulation

Drawing on the preceding theoretical discussion, we explore how environmental regulation intensity shapes the LCCPP effect. We adopt the approach of [85] by incorporating a policy–regulation interaction term into our baseline specification, which gives the moderation model shown in Equation (6).

$$carbonprod_{it} = \alpha + \beta_1 did_{it} \times er_{it} + \beta_2 did_{it} + \beta_3 er_{it} + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (6)$$

Here, er_{it} is the environmental regulation intensity of city i at year t , quantified as the ratio of industrial SO₂ removal to GDP. The interaction coefficient β_1 for $did_{it} \times er_{it}$ captures the moderating role of environmental regulations in the LCCPP's policy effects. A significant β_1 indicates that environmental regulations play a positive moderating role.

Table 10, Column (1), shows the estimation results. The estimated *did* coefficient is 0.071, significant at the 5% level, which is in line with the baseline estimates and further confirms the positive impact of the LCCPP on carbon productivity. Economically, the policy improves carbon productivity by about 0.071 tons per 10,000 yuan of GDP, equivalent to approximately 10.0% of the sample average. The interaction term $did \times er$ has a coefficient of 0.028, significant at the 10% level, implying that a one-point rise in environmental regulation intensity translates into about 0.028 tons per 10,000 yuan of additional carbon productivity improvement attributable to the policy. This result verifies hypothesis H4 proposed in

this paper: stricter environmental regulations intensify firms' emission reduction pressure, prompting them to respond more actively to low-carbon policies and thereby amplifying the policy's positive effect on carbon productivity. To address the concern that environmental regulation intensity might vary endogenously with the LCCPP, we re-estimate the model with the interaction term based on the one-year lag of environmental regulation intensity. Column (2) of Table 10 shows a coefficient of 0.031 for $did \times l.er$, which is significant at the 10% level. This is in accordance with the main results and offers further confirmation of the robustness of the positive moderating effect.

Table 10. Adjust test results.

Variable	(1)	(2)
did	0.071 ** (0.035)	0.068 * (0.035)
did $\times$ er	0.028 * (0.016)	
did $\times$ l. er		0.031 * (0.018)
Constant	−12.800 *** (3.277)	−12.969 *** (3.149)
City FE	Yes	Yes
Year FE	Yes	Yes
Control variables	Yes	Yes
N	4692	4416
R ²	0.421	0.422

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; figures in parentheses are robust standard errors at the city level.

8. Conclusions, Implications, and Limitations

8.1. Conclusions

Employing a balanced panel of 276 prefecture-level and above cities across China spanning 2007 to 2023, this paper uses a multi-period DID approach to explore how the LCCPP affects urban carbon productivity, and further investigates the underlying transmission mechanism, heterogeneity effects, and moderating effects. The key findings are summarized below.

First, the LCCPP generates a significantly positive effect on urban carbon productivity. Baseline results show that pilot cities gained about 0.074 tons per 10,000 yuan of GDP in carbon productivity over non-pilot cities, equivalent to 10.4% of the sample mean. This conclusion is robust to parallel trends tests, placebo checks, controlling for concurrent policies, and PSM-DID estimation.

Second, there appears to be some lag in the policy's positive effect. The parallel trends test indicates that although the positive influence emerges soon after the policy takes effect, it takes time to reach its peak. This implies that a low-carbon transition cannot occur overnight, as it involves changes in technology, industry, and institutions alike.

Third, green technological innovation and economic agglomeration are two important potential pathways through which the policy may affect carbon productivity. The mechanism analysis provides evidence consistent with theoretical expectations for these two channels: the policy is significantly positively associated with both green technological innovation and economic agglomeration, and the existing literature has demonstrated theoretically and empirically that these variables can influence carbon productivity. Accordingly, these results ought to be viewed as suggestive evidence that aligns with theoretical expectations.

Fourth, the policy effects differ considerably across city types. Heterogeneity analysis indicates that the LCCPP's promotive effect on carbon productivity is stronger in developed regions (east of the Hu Huanyong Line), innovation-oriented cities, high-emission areas, and key environmental protection cities. In contrast, in less developed regions and non-innovation-driven cities, the policy effects are not statistically significant. This implies that successful policy implementation depends on several preconditions: a city's resource endowment, innovation capacity, emission reduction pressure, and its environmental governance capacity. Thus, the mechanism of the LCCPP is not uniformly applicable across all cities; it can only succeed when a sufficient level of economic development and governance capacity is in place.

Fifth, environmental regulation stringency exerts a positive moderating influence—the more stringent the regulation, the greater the policy's effect on carbon productivity. The moderation analysis reveals that the LCCPP's positive effect on carbon productivity is more pronounced under tighter environmental regulations. This suggests that environmental regulation and low-carbon policy are mutually reinforcing. In regions with stringent environmental regulations, firms face stronger pressure to reduce emissions. They are more motivated to innovate, which helps strengthen the latter's contribution to carbon productivity. In sum, these two policy instruments constitute complementary institutional arrangements rather than substitutes.

8.2. Implications

Based on these empirical results, we offer a set of policy implications.

First, gradually expand the coverage of the LCCPP according to each city's endowments and select pilot cities on a scientific basis. Empirically, although the LCCPP has positive effects overall, substantial regional differences remain in economic development, innovation capacity, and environmental governance. Therefore, when expanding the pilot scheme, priority should be given to areas with stronger performance in these three dimensions to ensure smooth policy implementation. For areas that do not yet meet the entry requirements, a preparatory phase could be established to allow them to gradually build low-carbon infrastructure and institutions before formally joining the program.

Second, strengthen the incentives for green technological innovation through targeted policies. The mechanism analysis provides evidence supporting the theoretical expectation that green technological innovation is a major channel for policy transmission. To ensure this channel functions effectively, governments at all levels need to build a supportive policy system covering the full innovation chain. During R&D, greater fiscal support and tax relief are needed to bring down the marginal cost of green innovation. At the commercialization stage, more green technology trading platforms and mechanisms should be built to support partnerships across industry, academia, and research sectors, thereby shortening the path from lab to market. In terms of diffusion and adoption, effective demand should be stimulated through government green procurement and first-of-a-kind insurance schemes. Throughout the process, stronger intellectual property protection is needed to ensure that firms receive adequate returns on their green innovation investments, thereby encouraging greater efforts in green R&D.

Third, guide economic agglomeration to contribute to emission reduction and efficiency improvement according to city size and development stage. The mechanism analysis provides suggestive evidence that economic agglomeration may serve as a potential pathway. In large cities and advanced regions, industrial activities should be directed toward low-carbon industrial parks and green technology clusters to realize economies of scale and knowledge spillovers; meanwhile, the intensity of urbanization should be properly regulated, and the use of market-based instruments—including carbon pricing

and environmental taxes—can help mitigate the potential negative side effects of over-agglomeration. In smaller urban centers and less developed localities, the top priority is to improve transport, energy, and digital infrastructure, enhance the business environment, reduce institutional barriers to factor mobility, and increase the attractiveness of these locations to investors and talent, thereby enabling moderate industrial agglomeration.

Fourth, develop differentiated and tailored action plans for city types where policy effects are not yet observable. Heterogeneity tests demonstrate notable disparities in how policies perform among different city categories; therefore, as the central government expands the LCCPP, it should implement differentiated policies according to city characteristics. For less developed regions, more central fiscal transfers should be allocated, and a “Special Fund for Low-Carbon Transition Infrastructure” should be established to finance clean energy replacement, energy-saving retrofits, and low-carbon transport systems, thereby gradually addressing key constraints on low-carbon development. At the same time, a “targeted technical assistance” mechanism should be set up to pair developed regions with underdeveloped ones, facilitating the geographical spread of advanced technological know-how and raising the overall national level. For non-innovative cities, measures should be taken to encourage collaboration with nearby innovative cities, and technology import mechanisms should be established to enable the adaptation and adoption of green technologies, thus compensating for their lack of independent innovation capacity through technology transfer. At the same time, such cities should be encouraged to focus on the diffusion and adoption of medium- and low-tech green technologies, enabling a gradual green transition based on their existing industrial base. For high-carbon cities, strict caps on total carbon emissions should be imposed, and sufficient transition funds should be provided, with financial allocations linked to carbon reduction performance. For non-key environmental protection cities, gaps in governance capacity need to be addressed promptly, pollution monitoring mechanisms need to be strengthened, and environmental law enforcement needs to be toughened to ensure low-carbon policies can function effectively. Through such tailored approaches, cities of various types can identify suitable low-carbon transition pathways according to their own circumstances and gradually close the policy effectiveness gap.

Fifth, environmental regulations should be strengthened in tandem with the LCCPP, as they provide mutually reinforcing support and together constitute an integrated policy package. The moderation analysis clearly shows that stricter environmental regulations enhance the policy’s positive effects. Therefore, alongside efforts to promote the LCCPP, local governments should strengthen their environmental regulatory systems. Through stringent emission limits, comprehensive monitoring systems, and effective enforcement mechanisms, firms will face continuous pressure to comply and to innovate. More specifically, efforts are needed to accelerate the shift from terminal treatment to front-end source prevention, coordinate pollutant discharge permits with carbon emission management systems, and develop sector-specific, phased carbon reduction roadmaps to send clear and predictable policy signals and reduce institutional uncertainty for investment decisions. At the same time, for regions with high abatement potential but weak technological foundations, reasonable transition periods and technology upgrade subsidies should be provided to avoid undermining firm competitiveness through overly stringent regulations. Regulatory pressure should be precisely coordinated with other policy instruments, so that they can both reduce carbon emissions and improve efficiency, enabling a virtuous cycle between environmental governance and low-carbon development.

8.3. Limitations

Of course, this paper has some limitations alongside its contributions.

First, the calculation of several critical metrics faces restrictions due to insufficient city-level accessible data. Consequently, this research evaluates green technological innovation using the number of granted green patents, and environmental regulation intensity using the amount of industrial SO₂ removed per unit of GDP. Although these proxies are widely used in the literature and capture important aspects of the underlying concepts, they have clear limitations. For example, a large number of green patents does not guarantee that high-quality green technology has been developed and will eventually reach the market; similarly, high SO₂ removal per unit of GDP cannot be taken as definitive evidence of stringent regulation, as the observed rate may reflect the region's industrial structure and pollution control capacity rather than regulatory stringency per se. As more granular data become accessible, subsequent studies could usefully revisit the validity of these measures.

Second, this study does not quantify the magnitude of indirect effects through the two potential channels. Owing to the strict exogeneity assumption of conventional mediation analysis and potential measurement error in the mechanism variables, we are unable to quantify the indirect effects along these pathways formally. We have therefore adopted cautious language, characterizing the mechanistic evidence as suggestive and consistent with theoretical expectations, rather than as precise confirmation. Future research could draw on richer micro-level data and employ mediation analysis or structural equation modeling to conduct more rigorous quantitative assessments of these causal chains.

Third, this study does not explicitly consider potential spatial spillovers between cities. An LCCPP implemented in one city may affect the carbon productivity in neighboring areas via channels such as technology diffusion, industrial relocation, or policy demonstration effects. However, accurately identifying such spillovers requires constructing an appropriate spatial weight matrix and employing spatial econometric models. Such a strategy would drastically increase model complexity and add more parameters, which would go beyond the scope of this paper's analysis. The omission of spatial interdependence may bias the treatment effect estimates. We therefore acknowledge this as an important limitation. Future research could explicitly model and estimate spillover effects by incorporating spatial econometric models with more objectively justified spatial weight specifications.

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Abbreviation

Abbreviation	Full Form
CO ₂	Carbon Dioxide
CEADs	Carbon Emission Accounts and Datasets
COVID-19	Coronavirus Disease 2019
CPI	Consumer Price Index
CNIPA	China National Intellectual Property Administration
CSDID	Callaway and Sant’Anna Difference-in-Differences
DID	Difference-in-Differences
EU ETS	European Union Emissions Trading System
FE	Fixed Effects
GDP	Gross Domestic Product
GHG	Greenhouse Gas
IEA	International Energy Agency
IPCC	Intergovernmental Panel on Climate Change
LASSO	Least Absolute Shrinkage and Selection Operator
LCCPP	Low-Carbon City Pilot Policy
NDRC	National Development and Reform Commission
PSM	Propensity Score Matching
R&D	Research and Development
SO ₂	Sulfur Dioxide
WIPO	World Intellectual Property Organization
WMO	World Meteorological Organization

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