LOW-CARBON TRANSPORT TRANSITION AND URBAN GREEN DEVELOPMENT IN CHINA: A QUASI-NATURAL EXPERIMENT

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Abstract. This study investigates how low-carbon transportation policies influence urban green development in China by leveraging the Low-Carbon Transportation System (LCTS) pilot program as a quasi-natural experiment. Adopting city-level panel data from 2006 to 2015 and a staggered Difference-in-Differences (DID) approach, the policy's impact on Green Total Factor Productivity (GTFP) is quantitatively assessed. Results indicate that LCTS significantly enhances green development efficiency in pilot cities, driven by reduced carbon emissions, optimized energy consumption patterns, and the adoption of green technologies such as intelligent transportation systems and electric vehicles. Mechanism analysis confirms that the policy curbs transportation-related energy use and emissions while fostering technological innovation. Spatial heterogeneity reveals negative spillover effects on neighboring cities' green technology progress, underscoring the need for regional coordination. The findings provide empirical support for scaling low-carbon transportation reforms and integrating fiscal, technological, and industrial incentives to achieve China's dual-carbon goals. This research offers actionable insights for global policymakers seeking to balance economic growth with environmental sustainability.
Keywords: *urban transportation, policy green total factor productivity, staggered difference-in-differences, spatial spillovers, technological innovation, dual-carbon goals*

Introduction

The issue of climate change has become a major challenge for human survival and development in this century. Actively addressing climate change and promoting green and low-carbon development has become a global consensus. As the world's largest carbon emitter, China faces even more arduous responsibilities and challenges. An analysis of carbon emissions across various industries in China reveals that the transportation sector consistently ranks among the highest emitters (Lin and Benjamin, 2017). The transportation sector is widely recognized as one of the top three sources of carbon emissions and a major energy consumer (Bai et al., 2020, 2023). Rapid urbanization intensifies the dual challenge for Chinese cities, cutting emissions and boosting energy efficiency. Given the considerable carbon mitigation potential within the transportation sector, advancing urban green transformation is of paramount significance. For instance, the number of petrol vehicles has increased annually by more than 400,000 in Beijing (Wu et al., 2023), leading to a rapid growth in carbon emissions. This growth contributes to traffic congestion and exacerbates environmental issues, including vehicle emissions and air pollution, posing a negative impact on urban green development. Thus, promoting the low-carbon transformation of the transportation sector is not only a

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necessary measure to address climate change but also a core initiative to promote urban green development.

Governments are increasingly implementing low-carbon transportation policies, such as the European Green Deal (Boix-Fayos and de Vente, 2023), the UK's Net Zero Emissions (Dixon and Brush, 2022), and Canada's 2030 Emissions Reduction Plan (Chen et al., 2022). China has also promoted pilot projects including the Low-carbon Transportation System Construction, Green Transportation Provinces, and Green Freight Delivery system (Zhao et al., 2022; Wu et al., 2022). The transportation system is a key area for reducing carbon emissions, controlling pollution, and promoting sustainable economic development. Related policies are commonly regarded as generating substantial green value. However, research indicates that low-carbon transportation policies often fall short of expectations (Li et al., 2022; Zhao et al., 2022a). While they are theoretically beneficial for urban green development, empirical evidence on their actual effectiveness remains limited, highlighting a critical gap with both theoretical and practical significance (Chang et al., 2023). This study aims to rigorously evaluate the causal effect of China's low-carbon transportation pilot policy on urban green development efficiency, while uncovering the underlying mechanisms through which such policies drive sustainable transformation. By employing a staggered Difference-in-Differences (DID) approach and analyzing energy consumption, emissions, and green technology adoption, we provide new empirical insights into the policy's effectiveness and broader implications for sustainable urban governance.

Adopting China's low-carbon transportation system construction as a quasi-experiment, this quantitatively assesses the impact of this transformation on urban green development efficiency. The analysis leverages a unique dataset containing city-level carbon emission data in China and applies a staggered DID model for estimation. The results indicate that low-carbon transportation transformation has significantly improved the green development efficiency of pilot cities. This study also correct potential biases in two-way fixed effects estimators under multiple time points, confirming that such biases do not significantly affect the baseline results. Mechanism analysis reveals that low-carbon transportation transformation optimizes transport modes and energy allocation, reducing energy consumption in pilot cities and effectively curbing greenhouse gas and pollutant emissions. Moreover, pilot cities have introduced more green technologies, such as new energy vehicles and intelligent transportation systems, facilitating a transition toward a greener and more sustainable urban development.

The main contributions of this study are as follows. First, unlike previous studies that assess the effectiveness of transportation governance from either the supply or demand side (Wang et al., 2022; Liu et al., 2023), this study quantitatively evaluates the impact of low-carbon transportation policies on overall urban green development. It fully accounts for the synergies between supply- and demand-side factors in the low-carbon transition and examines the effectiveness of policy design and implementation through the lens of carbon reduction. Second, by analyzing energy consumption, carbon emissions, and green technology levels, this study explores the driving mechanisms of urban green development under different low-carbon transportation policy models. Finally, rather than focusing solely on the environmental impact of the transportation system (Duranton and Turner, 2011), this study situates transportation reform within the broader global discourse on carbon reduction and sustainable economic development. By examining this relationship in depth, it provides valuable insights for policymakers seeking to balance economic growth with environmental protection.

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From a practical standpoint, assessing the effectiveness of China's urban low-carbon transportation transformation within the framework of green development holds significant implications. First, evaluating the impact of different low-carbon transportation policies enables the formulation of targeted strategies to curb future carbon emissions, thereby supporting China's commitment to achieving its dual-carbon goals (carbon peaking and carbon neutrality) while enhancing its competitiveness in the global green economic transition. Also, China's experience in urban low-carbon transportation reform can serve as a valuable reference for other developing countries, offering both theoretical insights and practical guidance to advance global low-carbon development.

The subsequent sections are structured as follows: Following section provides a literature review and introduces the policy background, pilot project objectives, and policy details. Materials and Methodology outline our research design, including data reliability, sources, variable definitions, and model specifications. Result part presents the empirical results and robustness tests. Then, the mechanisms and driving factors through which low-carbon transportation transformation influences urban green development are further analyzed in Discussion part. Finally, we summarize the findings and offer policy recommendations.

Literature review and policy background

Research on the effectiveness of transportation policies

Existing research and policy practices on transportation governance primarily focus on environmental management, with insufficient attention to low-carbon transportation policies and their impact on green development. Studies on the environmental effects of transportation governance often adopt a single-factor analysis from either the supply or demand side, which may undermine confidence in the effectiveness of low-carbon governance policies or raise doubts about their actual impact (Viard and Fu, 2015; Rahman et al., 2021). An example of this is that, driving restriction policies are intended to reduce emissions by suppressing the travel demand, yet their actual effectiveness remains debated (Chen et al., 2021; Sun et al., 2022). Similarly, while roadmap expansion is considered a key supply-side measure aimed at alleviating congestion and reducing emissions, research suggests it may instead increase overall traffic volume, ultimately counteracting emission reduction efforts (Chen and Klaiber, 2020; Bansal and Graham, 2023). Some studies further suggest that the promotion of electric vehicles does not necessarily lead to a significant reduction in traffic-related emissions (Wang et al., 2021, 2022). Moreover, in the short term, when travel demand remains largely unchanged, the effectiveness of supply- and demand-side policies is closely linked to their integration with different transportation modes (Hoehne and Chester, 2017). However, many current policy designs and implementations tend to overlook this critical factor. For example, research on vehicle restriction measures indicates that after implementation, travel demand has not effectively shifted to low-emission public transportation modes such as subways or buses (Davis, 2017), which may explain why these policies often fail to achieve their intended outcomes.

Current research on low-carbon transportation governance policies predominantly focuses on individual factors, lacking a systematic assessment of their overall effectiveness (Banister et al., 2011). As a result, policy recommendations remain fragmented and fail to contribute to a comprehensive governance framework. Therefore, the evaluation of low-carbon transportation policies urgently requires a holistic

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perspective, incorporating key dimensions such as urban green development, to reassess policy design and implementation pathways, thereby enhancing their scientific rigor and practical effectiveness.

Research on low-carbon transportation and green development

The theory of Green Development originated from the concept of the green economy proposed by David Pierce in 1989. Initially centered on ecological environmental protection, regarded as a single factor. Then it has progressively evolved into a synergistic framework aimed at maximizing the coordinated benefits of "society-economy-ecology". Existing literature demonstrates that low-carbon transformation in transportation can improve green development in three synergistic pathways: (1) carbon emission reduction, (2) energy consumption pattern restructuring, and (3) new green technology adoption. These interconnected mechanisms collectively form the core for low-carbon urban mobility transformation, targeting emission mitigation, enhanced energy efficiency, and sustainable urban development.

Reducing carbon emissions

The core goal of reducing carbon emissions is to improve air quality and mitigate climate change by reducing the direct emissions of greenhouse gases. Specifically, carbon emissions can be reduced through two main means in transportation: reducing the frequency of private car use (Bieker et al., 2021; Bleviss, 2021) and optimizing the transportation system (Kazancoglu et al.,2021; Di Lullo et al., 2022). First, reducing the private car use frequency is a direct means of reducing carbon emissions. Cities can reduce congestion and improve public transportation efficiency through regulatory means, such as implementing restrictions for urban vehicles (Chang et al., 2021) and low or zero emission zones (Zhai and Wolff, 2021), to encourage citizens to choose low-carbon travel modes. An efficient public transportation network (such as subways, light rails, and bus systems) can replace short-distance private car trips, effectively reducing traffic emissions (Jonidi Jafari et al., 2021). Second, the construction of an intelligent transportation system (ITS) can significantly improve traffic fluidity and reduce traffic congestion. Through real-time data analysis and traffic signal optimization, intelligent transportation systems can adjust traffic flow, reduce unnecessary stops and waiting times, thereby reducing carbon emissions caused by traffic congestion (Zhao et al., 2022a). Therefore, through comprehensive measures of optimizing public transportation and intelligent transportation management, cities can greatly reduce greenhouse gas emissions in the transportation sector.

Changing the energy consumption pattern

Changing the energy consumption pattern is widely regarded as an other effective means to promote urban green development. Its core is to shift from traditional fossil fuels to clean and renewable energy sources, reducing dependence on fossil energy and the associated carbon emissions and environmental pollution. First, promoting electric vehicles is a major measure to change the energy consumption pattern (Breuer et al., 2021). Since 2001, China has launched the "Major Science and Technology Project for Electric Vehicles (863 Plan)", and in 2013, it began to fully promote the popularization of electric vehicles (EVs) and electric buses nationwide, significantly reducing the energy consumption of traditional internal combustion engine vehicles and lowering carbon

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dioxide emissions (Li et al., 2021). In this process the government has further promoted the market acceptance and popularity of electric vehicles through policy support such as providing purchase subsidies, exempting registration fees, and building charging facilities (Yan and Sun, 2021). In addition, the introduction of green fuels, such as hydrogen energy, electricity, and other low-carbon fuels, is gradually replacing traditional diesel and gasoline (Li and Taghizadeh-Hesary, 2022), promoting the optimization of the energy structure of transportation tools and thus reducing the carbon emissions of the transportation system.

Introducing new technologies supporting decision-making

The integrated application of new technologies,such as big data, artificial intelligence and Internet of Things (IoT), has demonstrated significant improvements in the carbon efficiency of urban transportation systems, providing critical technical support for sustainable urban development. Empirical studies illustrate that smart transportation system (Zhao et al., 2022a), autonomous driving technologies (Massar et al., 2021), and IoT based shared mobility platforms (Zhou et al., 2023) can significantly improve systemic operational efficiency while reducing carbon emissions caused by transportation inefficiencies. Also, AI-based driving assistance systems contribute to reducing traffic delays and energy waste attributable to human factors (Bhatti et al., 2023; Qin et al., 2025). Shared mobility solutions, including bike-sharing and e-scooter programs, enhance vehicle utilization rates while decreasing empty-run ratios, thereby facilitating low-carbon urban mobility transitions.

Background of China's low-carbon transportation plan

To address climate change, China has identified transportation as one of three key industries targeted for low-carbon transformation. In 2011, the Ministry of Transport issued two foundational policy documents: Guidelines for Establishing a Low-Carbon Transportation System (LCTS) and Pilot Implementation Plan for Low-Carbon Transportation System Development (Zhang et al., 2023; Liu et al., 2023), marking the launch of a nationwide pilot initiative. The first-phase pilots (2011) covered 10 cities—including Tianjin, Chongqing, Shenzhen, Xiamen, Hangzhou, Nanchang, Guiyang, Baoding, Wuhan and Wuxi, focusing on road, waterway, and urban passenger transport. In 2012, the second phase expanded to 16 additional cities including Beijing, Kunming, Xi'an, Ningbo, Guangzhou, Shenyang, Harbin, Huai'an, Yantai, Haikou, Chengdu, Qingdao, Zhuzhou, Bengbu, Shiyan and Jilin, with projects spanning low-carbon urban transport, ports, waterways, and highways.

The pilot program of LCTS emphasized six core dimensions: (1) from infrastructural innovation point, developing low-carbon construction methodologies to reduce emissions in transport infrastructure projects; (2) At the aspect of energy transition, accelerating alternative fuel adoption in operational vehicles/vessels to optimize energy mix; (3) in the view of system efficiency, advancing low-carbon transport organization models to enhance network-wide efficiency; (4) regarding behavioral change, to promote public awareness and adoption of low-carbon travel modes; (5) for digital transformation, deploying intelligent transport systems to improve management capabilities; and (6) in terms of governance capacity, establishing monitoring and evaluation frameworks for transport-sector emissions.

This paper employs the LCTS pilot program as a quasi-natural experiment based on three key methodological considerations. First, the selected pilot cities are a strategically

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representative sample that includes both economically developed coastal cities and strategically significant central/western urban centers. By explicitly selecting metropolises with large transportation sectors (e.g., Beijing, Shanghai) along with developing industrial cities (e.g., Zhuzhou, Shiyan) these findings can be condensed to ensure cross-sequel validity between elastic net in heterogeneous urban settings for implementation. Second, the multifaceted nature of the intervention across urban passenger transport, freight logistics, and infrastructure modernization yields a concentrated policy environment conducive to measuring integrated decarbonization outcomes. This spatial boundedness enables precise attribution of observed effects to specific policy mechanisms while controlling for extra-jurisdictional spillovers. Third, the experimental design capitalizes on substantial inter-city variation in policy implementation. Such variation stems not merely from differential economic development and infrastructure endowments, but more fundamentally from: (1) path dependencies in urban form, (2) modal split characteristics, and (3) deeply embedded travel behavior patterns. The program's dual focus on supply-side technological deployment and demand-side mobility management provides a unique opportunity to examine the contextual mediation of policy effectiveness.

This research design advances beyond conventional policy evaluation by treating cities not as uniform administrative units, but as complex socio-technical systems where decarbonization trajectories emerge from dynamic institutional-technological-behavioral co-evolution. The quasi-experimental framework permits both cross-sectional comparison and longitudinal analysis of policy maturation processes.

Materials and methodology

Materials

This study employs panel data from 281 prefecture-level and above cities in China (2006–2015), mainly sourced from the China City Statistical Yearbook, China Regional Statistical Yearbook, China Energy Statistical Yearbook, China Environmental Statistical Yearbook, China Statistical Yearbook, Provincial Statistical Yearbooks, China Industrial Statistical Yearbook, China Urban Construction Statistical Yearbook, China Science and Technology Statistical Yearbook, China Environmental Statistical Yearbook, and China Stock Market & Accounting Research (CSMAR) Database. Missing values were addressed via interpolation, and cities with significant data gaps were excluded. In our model design key variables include, Green Total Factor Productivity (GTFP) as the Dependent Variable, Low-Carbon Transportation Pilot Policy (Pilot) as the Core Explanatory Variable, Economic development, education level, environmental regulation and financial development as the Control Variables.

Model setup

The policy requires local governments in pilot cities to implement low-carbon transformations in local transportation systems. This study adopts this policy pilot as a quasi-experiment and utilizes the DID model, designating pilot cities as the treatment group and other cities as the control group. The DID approach effectively addresses endogeneity concerns (Jiang et al., 2023) arising from non-random administrative selection of pilot cities by accounting for cross-group differences (between pilot and non-pilot cities) and temporal trends (before and after policy implementation). Leveraging the

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exogenous policy shock, the method isolates the net treatment effect by comparing outcome changes between the treatment group (pilot cities) and the control group (non-pilot cities), while controlling for confounding factors such as macroeconomic fluctuations. Unless otherwise specified, the following analysis clusters standard errors at the city level.

Moreover, due to the varying implementation years of the policy across different regions, this study employs a staggered DID model to investigate the changes in the green total factor productivity (TFP) differences between pilot and non-pilot cities before and after the low-carbon transportation transformation.

$$GTFP_{ct} = \alpha + \beta Pilot_{ct} + \gamma X_{ct} + \mu_c + \lambda_t + \varepsilon_{ct} \quad \text{(Eq.1)}$$

The variable definitions in *Equation (1)* are denoted as follows:

- GTFP_{ct} represents the GTFP level of city c in year t.
- Pilot_{ct} is a dummy variable indicating the low-carbon transportation policy.
- X_{ct} denotes a set of control variables.
- μ_c and λ_t represent city fixed effects and year fixed effects, respectively.
- ε_{ct} denotes the random error term.
- the coefficient β,which is the focus to estimate of this study and captures the impact of low-carbon transportation transformation on urban green total factor productivity. Unless otherwise specified, the following analysis clusters standard errors at the city level.

Variable selection

Dependent variable: green total factor productivity (GTFP)

It is important to note that in the existing literature, GTFP is often used to measure the overall level of urban green development and to represent the efficiency of green economic growth (Cui et al., 2019; Zhao et al., 2022). Also, conventional methodologies such as Data Envelopment Analysis (DEA), Stochastic Frontier Analysis (SFA), and the Malmquist index for productivity measurement are predominantly employed. However, these approaches—whether DEA, SFA, or Malmquist index—exhibit limitations in handling scenarios where input and output variables simultaneously demonstrate radial and non-radial characteristics. To address this issue, our study adopts the hybrid Super-SBM model (Tone and Tsutsui, 2010; Zhang et al., 2017; Chen et al., 2024), as illustrated in *Equation (1)*, which uniquely integrates radial and non-radial distance functions within a unified analytical framework, thereby resolving the technical constraints inherent in conventional DEA and SFA methods. In real-world systems, the interplay among economic activities, resource utilization, and environmental impacts presents inherent complexity. The Super-SBM model explicitly accounts for desirable outputs (e.g., economic gains) and undesirable outputs (e.g., environmental pollutants) in operational processes. Notably, it accommodates the non-radial relationship between conventional inputs (e.g., labor and capital) and outputs, while capturing the radial inter-dependency between energy inputs and undesirable outputs. This dual capability enables the model to holistically evaluate static production efficiency by quantifying resource utilization and output performance under predefined technological and temporal constraints. Specifically, the model decomposes inefficiency values into three distinct components: input inefficiency, desirable output inefficiency, and undesirable output inefficiency. This

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decomposition facilitates granular identification of performance bottlenecks across production dimensions. The computational framework for GTFP is now formalized as follows:

$$y^* = min\theta \frac{\theta - \varepsilon_x \sum_{i=1}^{m} \frac{\omega_i^- S_i^-}{x_{ic}}}{\varphi + \varepsilon_y \sum_{r=1}^{s} \frac{\omega_r^+ S_r^+}{y_{rc}} + \varepsilon_b \sum_{p=1}^{q} \frac{\omega_p^{b-} S_p^{b-}}{b_{pc}}}$$

$$s.t. \begin{cases} \sum_{j=1}^{n} \lambda_j x_{ij} + S_i^- - \theta x_{ic} = 0, i = 1, \cdots, m \\ \sum_{j=1}^{n} \lambda_j y_{rj} - S_r^+ - \varphi y_{rc} = 0, r = 1, \cdots, s \\ \sum_{j=1}^{n} \lambda_j b_{pj} + S_p^{b-} - \varphi b_{pc} = 0, i = 1, \cdots, q \\ \lambda_j \geq 0, s_i^- \geq 0, s_r^+ \geq 0, s_p^{b-} \geq 0 \end{cases} \quad \text{(Eq.2)}$$

The variable definitions in *Equation (2)* are illustrated as follows,

- y^*represents the optimal efficiency value of GTFP measured via the Super-SBM model.
- i,$r$and p denote input factors, desirable output factors, and undesirable output factors, respectively.
- m, s and q correspond to the number of input factors, desirable outputs, and undesirable outputs.
- The parameter θ is the radial efficiency value.
- ε_x (where $0 \leq \varepsilon_x \leq 1$) is a composite parameter that integrates both radial adjustment ratios and non-radial slack vectors.
- The weight of the input factors is denoted by ω_i^-, subject to the constraints $\sum_{i=1}^{m} \omega_i^- = 1, \omega_i^- \geq 0$.
- The slack variable s_i^- represents the non-radial slack of the i-th input.
- The input vector of the c-th city is x_{ic}, and φ signifies the non-radial efficiency value.
- The parameterε_y (with $0 \leq \varepsilon_y \leq 1$) similarly combines radial and non-radial slack adjustments.
- The weight of the r-th desirable output is ω_r^+, and ω_p^{b-}denotes the weight of the p-th undesirable output. The slack pair (S_r^+, S_p^{b-}) quantifies the gaps between the r-th desirable output and the p-th undesirable output; if both values exceed zero, this implies that actual inputs and outputs fall short of the production frontier, signifying inefficiencies in static GTFP and highlighting potential for optimization.
- ε_b integrates both radial adjustment ratios and non-radial slack vectors, subject to condition $0 \leq \varepsilon_b \leq 1$.
- b_{pc} denotes the p-th undesirable output of the c-th city.
- The relative weight of the j-th input factor is denoted by λ_j, while (x_{ij}, y_{rj}) defines the input-output vector of the j-th decision-making unit (DMU).

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Correlation coefficients are calculated via the entropy weight method to objectively reflect disparities in GTFP across DMUs. If condition $y^{*} = 1$ holds, the DMU is deemed efficient. Based on existing methodologies (Zhang et al., 2014; Lin and Du, 2015), the input-output indicators selected in this study are summarized in *Table 1*. Furthermore, total factor GTFP is decomposed into the Green Efficiency Technology (GET) index and the Green Technology Change (GTC) index.

Table 1. *Input and output indicators for measuring green total factor productivity (GTFP)*

Indicator Type	Indicator Name	Indicator Selection	Unit	Sources
Input Indicators	Labor Input	Year-end Number of Employed Person in Urban Units	10,000 persons	China Statistical Yearbook
		Number of Industrial Enterprises Above Designated Size	Number of enterprises	China Industrial Statistical Yearbook
	Capital Input	Urban Construction Land Surface	km²	China Urban Construction Statistical Yearbook
		Urban Fixed Asset Investment	100 million yuan	China Statistical Yearbook, Provincial Statistical Yearbooks
		Urban R&D Expenditure	100 million yuan	China Science and Technology Statistical Yearbook
	Energy Input	Total Electricity Consumption in Urban Area	10,000 kWh	China Energy Statistical Yearbook, Provincial Statistical Yearbooks
		Total Urban Gas Supply	10,000 m³	China Urban Construction Statistical Yearbook
		Total Urban Water Supply	10,000 tons	China Urban Construction Statistical Yearbook
Output Indicators	Desirable Outputs	Urban real GDP	100 million yuan	China Statistical Yearbook, Provincial Statistical Yearbooks
		Total Per Capita Social Consumption	yuan	China Statistical Yearbook, Provincial Statistical Yearbooks
		Urban Green Area	km²	China Urban Construction Statistical Yearbook
	Undesirable Outputs	Wastewater Discharge	10,000 tons	China Environmental Statistical Yearbook, Provincial Environmental Reports
		Sulfur Dioxide Emissions	tons	China Environmental Statistical Yearbook, MEE (Ministry of Ecology and Environment) Reports
		Dust Emissions	tons	China Environmental Statistical Yearbook, MEE Reports

Fig. 1 presents a comparative visualization of GTFP levels before and after policy implementation. Statistical analysis reveals a significant divergence in GTFP measurements, with post-policy values demonstrating a marked increase relative to baseline measurements. Notably, spatial heterogeneity is observed across pilot cities, with

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regions characterized by stronger environmental regulations and advanced technological infrastructure exhibiting more pronounced GTFP improvements. Furthermore, the policy appears to generate positive spatial spillover effects, as neighboring non-pilot cities and regions also experience a statistically significant rise in GTFP, specifically areas around Chengdu, Nanchang, Wuxi and Haikou, suggesting knowledge diffusion, industrial linkage effects, or policy emulation. This spatial dependence indicates that the policy's impact extends beyond the treated areas, contributing to broader regional green development. These findings underscore the importance of considering both direct treatment effects and indirect spillover mechanisms when evaluating environmental policy efficacy.

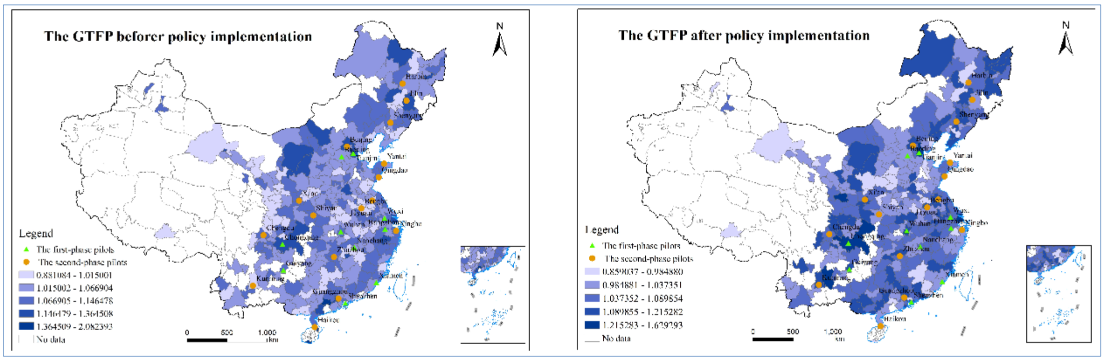

Figure 1. *Spatial distribution of GFTP before and after policy implementation*

Core explanatory variable: $Pilot_{ct}$

This variable $Pilot_{ct}$ captures the policy effect of Low-carbon Transportation System (LCTS) on GTFP. A binary indicator is constructed such that $Pilot_{ct} = 1$if city c is designated as a low-carbon transportation pilot city in year t, and $Pilot_{ct} = 0$ otherwise.

Control variables: X_{ct}

Other factors influencing the urban GTFP are included as control variables Based on existing research, the control variables selected in this study mainly include: Economic Development Level ($Pgdp$) measured by the natural logarithm of per capita GDP to proxy urban economic development; Education Level ($Cult$) represented by the natural logarithm of annual urban education expenditure; Environmental Regulation ($Envir$) captured via the natural logarithm of annual bus passenger volume, serving as a proxy for environmental governance intensity; Financial Development Level (Fin) quantified as the ratio of total deposits in urban financial institutions to GDP. To investigate the potential existence of a Kuznets curve for GTFP, the squared term of economic development level ($Pgdp2$) is incorporated into the model.

Data details and descriptive statistics

Given data availability and to ensure a degree of policy environment continuity, this study employs panel data spanning 2006–2015 for 281 prefecture-level and above cities in China, covering both the 11th Five-Year Plan (2006–2010) and 12th Five-Year Plan (2011–2015) periods. The data are sourced from the China City Statistical Yearbook, China Regional Statistical Yearbook, China Energy Statistical Yearbook, China

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Environmental Statistical Yearbook, the CSMAR Database. Cities with significant data gaps were excluded, and remaining missing values were addressed using interpolation methods. Descriptive statistics for key variables are summarized in *Table 2*.

***Table 2.** Summary statistics of all key variables (2006–2015)*

Variables	Obs.	Mean	Std.Dev	Min.	Max.
$GTFP$	2800	1.056	0.213	0.113	5.536
GET	2800	1.029	0.205	0.204	4.143
GTC	2800	1.044	0.223	0.242	6.697
$Pgdp$	2798	10.227	0.716	4.595	13.055
$Cult$	2798	12.447	0.854	7.134	15.011
$Envir$	2798	8.578	.958	0.000	12.565
Fin	2798	14.156	0.841	10.961	17.377
$Pgdp2$	2798	105.124	14.616	21.115	170.451

Empirical results

Baseline regression results

Table 3 illustrates the baseline regression results of the impact of low-carbon transportation policies on urban GTFP. Column (1) controls for city and time fixed effects only, without including control variables. Columns (2)–(4) incorporate both city and time fixed effects alongside additional control variables. As shown in *Table 3*, the policy coefficients for the primary dependent variable, GTFP, and its decomposed component, the Green Efficiency Technology (GET) Index, are positive and statistically significant. This indicates that low-carbon transportation system policies significantly enhance urban green development and green technological efficiency. Potential explanations for these findings may include the successful implementation of low-carbon transportation policies, which could drive green development and technological efficiency improvements by promoting technological innovation and adoption, increasing capital investment, providing clear market signals, and integrating synergistically with other environmental policies.

***Table 3.** Impact of low-carbon transportation pilot policy on urban green development: baseline DID estimates*

Variables	(1)	(2)	(3)	(4)
	GTFP	GTFP	GET	GTC
$Pilot$	0.045**	0.049**	0.033*	0.032
	(0.023)	(0.023)	(0.018)	(0.027)
Control Variables	No	Yes	Yes	Yes
City Fe	Yes	Yes	Yes	Yes
Year Fe	Yes	Yes	Yes	Yes
R^2	0.159	0.165	0.102	0.226
N	2800	2798	2798	2798

Notes: All regressions use robust standard errors clustered to the city level in parentheses. N denotes the number of observations, and ***, **, and * indicate that the results are significant at the 1%, 5%, and 10% levels, respectively. Same below

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Parallel trend test

The parallel trend test addresses a critical concern in DID design. This study employs an event study approach to conduct the parallel trend test (Beck et al., 2010), while also examining the dynamic effects of low-carbon transportation policies on urban green total factor productivity (GTFP) post-implementation. The model is specified as follows:

$$GTFP_{ct} = \alpha + \sum_{n=-2}^{4} \beta_n D_{ct}^{n} + \gamma X_{ct} + \mu_c + \lambda_t + \varepsilon_{ct} \qquad \text{(Eq.3)}$$

In *Equation (3)*, D represents a set of dummy variables, where D_{ct}^{n} denotes the n-th year after the sample city's approval as a pilot (negative τ values indicate the τ-th year prior to approval). The estimated coefficients from the regression reflect the dynamic effects of the low-carbon transportation pilot policy on urban GTFP. *Fig. 2* presents the estimated coefficientsβ_n with 95% confidence intervals. Here,$d_1 \sim d_2$corresponds to 1–2 years before policy implementation, $d0$ to the implementation year, and $d1 \sim d4$ to 1–4 years post-implementation. As shown in *Fig. 1*, the coefficients for the pre-policy periods are statistically insignificant at the 5% level, whereas those for the post-policy periods are statistically significant and positive at the 5% level. These results confirm the validity of the parallel trend assumption. Furthermore, they suggest that the low-carbon transportation pilot policy exerts a gradually strengthening and dynamically persistent positive effect on urban GTFP.

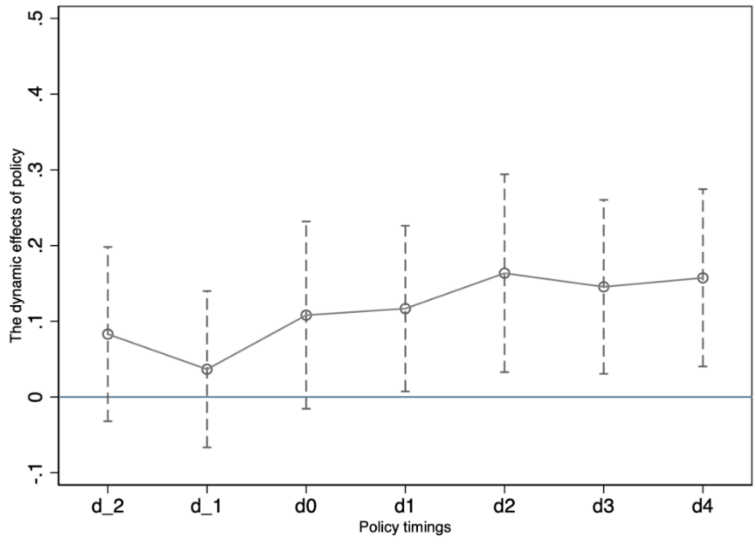

Figure 2. *Parallel trend test*

Robustness checks

Building on the parallel trend test, this study further conducts robustness checks through alternative measurements of the dependent variable, sample truncation, and exclusion of concurrent policy interference to ensure the reliability of the baseline regression results.

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Alternative measurement of the dependent variable

First, we recalculate urban GTFP using the Epsilon-Based Measure (EBM) model proposed by Tone and Tsutsui (2010) and re-estimate the regression. Results are reported in *Table 4*, column ①.

Table 4. *Robustness tests for the impact of low-carbon transportation policy: Alternative models and samples*

Variables	① Alternative Measurement of the Dependent Variable	② Winsorization	③ Low-carbon City Pilot Policy	④ Smart City Pilot Policy	⑤ Environmental Vertical Governance Reform Policy
$Pilot$	0.033*	0.037**	0.047**	0.050**	0.049**
	(0.018)	(0.017)	(0.024)	(0.024)	(0.024)
Control variables	Yes	Yes	Yes	Yes	Yes
City Fe	Yes	Yes	Yes	Yes	Yes
Year Fe	Yes	Yes	Yes	Yes	Yes
R^2	0.102	0.329	0.165	0.165	0.165
N	2798	2593	2798	2798	2798

Sample truncation

To mitigate the influence of extreme values in the dependent variable, we truncate the data at the 1st and 99th percentiles. Regression results are presented in *Table 4*, column ②. The coefficient for the low-carbon transportation pilot policy remains statistically significant and positive, indicating that the baseline findings are robust to extreme values.

Exclusion of concurrent policy interference

To address potential confounding effects from other pilot policies implemented concurrently with the low-carbon transportation policy (e.g., low-carbon city pilot, smart city pilot, and environmental vertical reform pilot policies), we introduce dummy variables for these policies into the baseline model. Regression results are shown in *Table 4*, columns ③–⑤. The coefficient for the low-carbon transportation pilot policy remains significantly positive, while other pilot policies exhibit no statistically significant impact. This confirms that the promoting effect of the low-carbon transportation policy on urban GTFP is robust to interference from concurrent policies.

Discussion and analysis

Mechanism analysis

Reduction in carbon dioxide emissions

LCTS policies effectively reduce CO2 emissions in the transportation sector by enhancing fuel efficiency, promoting new energy vehicles, optimizing traffic management, improving public transit accessibility, implementing demand management, and incentivizing shared mobility. These measures lower fuel consumption and tailpipe emissions, reduce redundant travel, and improve transportation efficiency, collectively

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contributing to a reduced carbon footprint and advancing environmental sustainability goals. Regression results in *Table 5*, column ①, confirm a statistically significant negative coefficient for the Pilot policy.

Table 5. *Mechanisms of low-carbon transportation policy on urban green development: emission reduction, energy savings, and technology adoption*

	①	②	③
	CO2 emissions	**Energy Consumption**	**Green Technology Level**
$Pilot$	-0.083**	-0.102***	0.087***
	(0.042)	(0.029)	(0.029)
Control Variables	Yes	Yes	Yes
City Fe	Yes	Yes	Yes
Year Fe	Yes	Yes	Yes
adj. R^2	0.951	0.812	0.100
N	2794	2765	2798

Reduction in energy consumption

Due to the lack of official city-level statistics on detailed energy consumption by type, this study adopts the method of Wang et al. (2022) to estimate city-level transportation-related energy consumption by disaggregating provincial energy consumption into cities based on their historical within-province shares of carbon emissions. The specific procedure is as follows: first provincial energy consumption data are obtained (including eight primary energy types: raw coal, coke, crude oil, gasoline, kerosene, diesel, fuel oil, and natural gas) from the China Energy Statistical Yearbook. Among these, four energy types closely linked to transportation emissions—crude oil, gasoline, diesel, and fuel oil—are selected. Second, these energy types are converted into kilogram of standard coal equivalent (kgce) using their calorific values to ensure comparability and then aggregated to measure total provincial energy consumption. This study employs China's official energy conversion coefficients from the China Energy Statistical Yearbook, with standard values assigned as follows: gasoline = 1.4714 kgce/kg, diesel = 1.4571 kgce/kg, fuel oil = 1.4286 kgce/kg, and crude oil = 1.4286 kgce/kg (Han et al., 2021). Third, city-level carbon emissions are estimated using nighttime light data to derive their historical within-province shares. These shares are applied to provincial transportation energy consumption to allocate city-level transportation energy consumption. Fourth, we replace carbon emissions in the baseline regression with city-level transportation energy consumption to estimate the impact of low-carbon transportation policies on energy use. Results in *Table 5*, column ②, show a statistically significant negative coefficient for the Pilot policy.

LCTS policies significantly reduce energy consumption in the transportation sector through measures such as improving fuel efficiency, promoting new energy vehicles, optimizing traffic systems, expanding public transit, implementing demand management, and encouraging shared mobility. These initiatives reduce fossil fuel dependency, enhance energy efficiency, minimize unnecessary travel distances, and incentivize non-motorized and public transportation, thereby fostering sustainable development in the transportation sector.

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Enhancement of green technology levels

With the development and application of China's "Internet Plus" strategy, emerging green technologies, such as smart transportation, autonomous driving, shared mobility, carbon-inclusive mechanisms, and electric vehicles—have transformed urban travel patterns. The technological effect on carbon emission efficiency stems from innovations that improve production efficiency, resource utilization, energy conservation, and urban governance. Green technological innovation, digital industry development, industrial structure upgrading, and resource allocation optimization enable real-time traffic information integration (e.g., public transit, road traffic, parking availability) through big data platforms. This integration optimizes travel decisions, alleviates congestion, enhances transportation efficiency, and supports the establishment of a green, low-carbon transportation system. Regression results in *Table 5*, column 3, demonstrate a statistically significant positive coefficient for the Pilot policy.

Policy implications

This work systematically investigates the heterogeneity in low-carbon transportation policy implementation across cities and its effectiveness, aiming to clarify the intrinsic mechanisms linking low-carbon transportation policies to urban green development. Leveraging city-level statistical yearbook data from 2006 to 2015, we treat China's low-carbon transportation pilot cities as a quasi-natural experiment and employ a DID approach to evaluate the impact of low-carbon transportation initiatives on urban GTFP. The analysis focuses on how these policies drive urban green transitions through three pathways: carbon emission reduction, energy conservation, and green technological advancement. Key findings include: (1) Low-Carbon Transportation System development (LCTS) significantly enhances urban green development. (2) Decomposing GTFP reveals that LCTS policies robustly promote green technological progress, reduce energy consumption, and lower carbon emissions. These results withstand rigorous robustness checks, including parallel trend tests, spatial correlation analyses, and alternative geospatial matrix specifications. (3) Heterogeneity across city samples induces negative spatial spillover effects on green development in neighboring cities, primarily manifesting in suppressed green technological progress rather than green technological efficiency. (4) The green development effects are amplified through synergistic improvements in scientific innovation, fiscal support, and industrial restructuring.

Based on empirical findings, this study proposes three targeted strategies to amplify the green transition effects of LCTS policies: (1) Scale and Dynamically Optimize Policy Implementation. Expand pilot-tested interventions to traffic-intensive cities, coupled with AI-enhanced monitoring systems to track emission-energy-technology dynamics and adjust fiscal-technical parameters iteratively. (2) Counteract Spatial Spillovers via Regional Innovation Pacts. Establish cross-city green technology alliances with fiscal compensation mechanisms, channeling advanced low-carbon technologies (e.g., smart traffic systems) from core to neighboring cities while offsetting spillover costs through carbon market interventions. (3) Triangulate Fiscal, Technological, and Industrial Incentives. Deploy tiered subsidies for emission-reducing industries linked to R&D tax rebates, and institutionalize fossil-fuel phaseout timelines in local governance frameworks. As the largest developing economy, China's urban green development demonstrates that spatially calibrated, technology-anchored transportation policies can

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reconcile green growth with equity—a critical blueprint for Global South cities pursuing decarbonization without compromising development imperatives.

Conclusions

This study advances the empirical understanding of low-carbon transportation policies by rigorously evaluating their causal effect on urban green development efficiency through China's pilot initiatives. The staggered DID analysis confirms that these policies not only achieve statistically significant improvements in sustainability metrics but also address methodological biases prevalent in prior assessments. Crucially, the transformation's success hinges on two actionable pathways: structural shifts in energy use (e.g., reduced fossil fuel dependence) and technological leapfrogging (e.g., adoption of intelligent transport systems).

These findings resolve a critical tension in the state-of-the-art literature—between theoretical expectations of policy benefits and observed implementation gaps—by identifying context-specific enablers. For practitioners, the study underscores the need to pair infrastructure investments with innovation incentives, particularly in emerging economies where urban mobility demand is growing rapidly. Future work should explore scalability challenges, including fiscal constraints and behavioral barriers, to inform global decarbonization strategies. Additionally, our work focuses on prefecture-level cities in China, potentially limiting generalizability to rural areas or other countries, and relies on proxy measures for energy consumption due to data constraints. Further studies could incorporate micro-level data (e.g., firm- or household-level) to validate mechanisms, explore long-term policy effects beyond 2015, and compare cross-country low-carbon transportation strategies using standardized metrics.

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