

GREEN TRANSITION OF URBAN TRANSPORTATION AND LOW-CARBON TECHNOLOGY INNOVATION: EVIDENCE FROM CHINA

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Abstract. Based on panel data from 265 Chinese prefecture-level cities covering the period from 2008 to 2023, this study utilizes China's Low-Carbon Transportation System (LCTS) pilot policy as a quasi-natural experiment and applies a staggered difference-in-differences (DID) model to empirically examine the impact of urban transportation green transition on low-carbon technology innovation (LCTI). The results indicate that the LCTS pilot policy has a statistically significant and positive effect on promoting urban LCTI. Mechanism analysis indicates that the policy exerts its incentive effect mainly through two channels: government-provided green financial support, which alleviates the funding constraints for low-carbon technology R&D, and the demand-pull effect due to heightened public environmental awareness. Furthermore, heterogeneity analysis shows that the positive impact of the LCTS pilot policy on LCTI is more pronounced in cities with higher marketization levels, lower energy cleanliness (higher coal dependence), and stronger intellectual property protection. This study not only enriches the theoretical understanding of the relationship between transportation green transition and technological innovation but also provides empirical evidence and policy implications for formulating differentiated policies to advance urban low-carbon development and achieve the “dual carbon” goals.

Keywords: *green transportation system, low-carbon technology innovation, green finance, public environmental concern*

Introduction

Global climate change presents a profound challenge to sustainable development, demanding substantial reductions in greenhouse gas emissions across all sectors (Tu et al., 2022; Wang et al., 2021). The transportation industry, a significant contributor to global carbon emissions and energy consumption, is central to this challenge, particularly in rapidly urbanizing economies (Zhang et al., 2025; Zhao et al., 2023). In response, China has established ambitious “dual-carbon” targets—aiming for peak carbon emissions before 2030 and carbon neutrality by 2060—placing the green transformation of urban transportation high on the national strategic agenda (Li et al., 2025). Indeed, China has witnessed a dramatic shift towards greener transportation over the past decade. The stock of New Energy Vehicles (NEVs) surpassed 30 million by the end of 2024, with NEV sales consistently accounting for over 40% of new vehicle sales in recent years. Simultaneously,

urban public transit networks, including metro systems exceeding 10,000 km nationwide, and the world's most extensive high-speed rail network have rapidly expanded, fundamentally altering mobility patterns. Achieving these goals necessitates not only incremental improvements but also fundamental shifts driven by technological innovation, specifically in low-carbon technologies innovation (LCTI). LCTI is crucial for decoupling transportation activity from carbon emissions, fostering industrial upgrading, and optimizing energy structures (Lyu et al., 2024; Ci et al., 2024; Liu et al., 2022).

While the imperative for innovation is clear, the mechanisms through which targeted environmental policies stimulate LCTI, particularly within the transportation sector, require deeper empirical investigation. Existing literature offers valuable insights into the drivers of broader green innovation. Studies evaluating China's comprehensive place-based environmental policies, such as the Low-Carbon City (LCC) pilots and regional Emissions Trading Scheme (ETS) pilots, consistently find positive effects on green patenting activity (Chen et al., 2022a; Pan et al., 2022; Li et al., 2022; Zhang et al., 2024a). These effects are often attributed to fiscal incentives, reduced financing constraints, enhanced capital allocation, and regulatory pressures that drive firms towards greener production methods (Pei and Wang, 2022; Ma et al., 2021; Zhu et al., 2022). However, this body of work typically aggregates various environmentally friendly technologies under the umbrella of "green innovation," often failing to isolate the specific impact on LCTI relevant to distinct sectors like transportation. Furthermore, while general environmental regulations are examined (Wang et al., 2022; Shi et al., 2024; Pan and Zhao, 2024; Shen et al., 2022; Peng et al., 2021), the unique effects of sector-specific policies targeting the green transformation of transportation remain less understood.

Recognizing the strategic importance of the transport sector, China initiated the Low-Carbon Transportation System (LCTS) pilot policy in 2011 and 2012 across 26 cities. This policy aimed to promote a systemic shift towards sustainability through measures including the adoption of new energy vehicles (NEVs), development of intelligent transportation networks, optimization of freight logistics, and enhancement of green infrastructure (Zhao, 2024; Zhang et al., 2023a). Recent evaluations of the LCTS policy have begun to emerge, yet they predominantly focus on its direct environmental or economic outcomes, rather than its specific impact on innovation. For instance, several studies employing difference-in-differences (DID) methodologies have confirmed that the LCTS policy significantly reduces urban carbon emissions (Zhao, 2024; Sun, 2025; Sun and Zhao, 2024), lowers carbon intensity (Sun, 2025), and improves carbon performance or efficiency (Zhao, 2024; Zhang et al., 2023a). Others have found positive effects on broader green development, measured by Green Total Factor Productivity (GTFP) (Yu et al., 2025). While these studies often acknowledge technological innovation or development as a mediating channel through which the LCTS policy achieves emission reductions or productivity gains (Zhao, 2024; Sun, 2025; Yu et al., 2025; Sun and Zhao, 2024), they do not treat LCTI as the primary outcome of interest. Consequently, a critical gap persists: there is insufficient empirical evidence on whether and how China's targeted LCTS policy directly stimulates urban Low-Carbon Technological Innovation specifically within the transportation domain and related fields. The specific pathways through which such a sector-focused policy might uniquely drive LCTI, distinct from broader environmental mandates, remain underexplored.

This study aims to fill this gap by investigating the direct causal impact of China's LCTS pilot policy on urban LCTI. Leveraging the policy's staggered implementation across cities as a quasi-natural experiment, we utilize a staggered DID model with panel data for 265 Chinese prefecture-level cities from 2008 to 2023. Our primary measure for LCTI focuses

on patent applications within the Y02 classification (“technologies for mitigating or adapting to climate change”), providing a targeted indicator relevant to low-carbon advancements.

The main contributions of this paper are threefold. First, it provides one of the first systematic evaluations of the direct effect of a specialized, transport-oriented policy (LCTS) on domain-specific LCTI as the primary dependent variable, moving beyond the aggregated “green innovation” metrics and mediator analyses prevalent in the literature. Second, it empirically tests and confirms two specific micro-level mechanisms—government-provided green financial support (supply-side incentive) and heightened public environmental awareness (demand-pull effect)—through which the LCTS policy stimulates LCTI, offering nuanced insights into the policy transmission process. Third, by examining heterogeneous policy effects based on city-level marketization, energy structure (cleanliness), and intellectual property protection, this study provides an empirical basis for designing more targeted and effective policies to foster LCTI in diverse urban contexts, thereby supporting China’s “dual-carbon” objectives and contributing insights relevant to global sustainable transport initiatives.

The remainder of this paper proceeds as follows: *Hypothetical development* develops the research hypotheses. *Materials and methods* describes the data, variables, and empirical methodology. *Results* presents the main empirical results, including baseline findings, robustness checks, and mechanism tests. *Heterogeneity analysis* discusses the heterogeneity analysis. *Conclusions* summarizes the core findings of this study, condenses the key conclusions regarding the impact of urban transportation green transition on low-carbon technology innovation, and further reiterates the practical policy insights derived from the research. *Discussion* provides a detailed discussion encompassing the theoretical and practical implications of our findings, along with limitations and future research directions.

Hypothetical development

LCTS and LCTI

In neoclassical economic theory, technological innovation is recognized as the primary driver of long-term economic growth and the restructuring of industrial systems. For energy-intensive sectors such as transportation, LCTI represents not only a crucial pathway to achieving industry sustainability but also an essential strategy for mitigating carbon emissions and enhancing resource allocation efficiency. Since 2011, China has progressively launched the pilot policy of the Low-Carbon Transportation System (LCTS), aiming to facilitate a green and low-carbon transformation of the transportation sector through coordinated policy interventions. This policy framework spans multiple domains, including the promotion of new energy vehicles, the development of charging infrastructure, and the modernization of intelligent transportation systems (Zhao, 2024).

Theoretically, the implementation of the LCTS policy, with its multi-faceted approach involving regulatory pressure, infrastructure investment, and market guidance, is expected to create a conducive environment for innovation within the transportation sector and related technological fields. The policy’s systemic nature suggests a potential overall positive influence on the propensity and capacity of urban actors (firms, research institutions) to engage in developing and adopting low-carbon technologies. Therefore, our primary hypothesis focuses on assessing the net aggregate impact of the LCTS policy intervention on urban LCTI.

Building on this, this paper formulates Research Hypothesis *H1*: The implementation of the Low-Carbon Transportation System (LCTS) pilot policy leads to a significant net increase in urban Low-Carbon Technology Innovation (LCTI).

While *H1* posits an overall positive relationship, understanding how this effect materializes requires examining the specific pathways through which the LCTS policy might operate. Building upon innovation theory and policy analysis, we propose two potential mediating mechanisms: the role of government-supported green finance in alleviating supply-side constraints, and the influence of heightened public environmental awareness in stimulating demand-pull innovation. The following sections elaborate on these potential transmission channels.

LCTS, green finance support and LCTI

Low-carbon technology innovation (LCTI) is characterized by high investment, long cycles, and significant risks. Its research and development processes often encounter severe financing constraints (Jiang et al., 2023). Under the market mechanism, financial institutions typically adopt a cautious stance toward funding low-carbon technology R&D due to challenges in accurately assessing technical prospects and managing associated risks. This behavior leads to an insufficient supply of innovation capital and results in “market failure” (Jia et al., 2023). In this context, government-led green financial support emerges as a critical means to alleviate such constraints. The LCTS policy precisely creates an institutional opportunity for the targeted allocation of green financial resources.

The LCTS policy centers on promoting the green transformation of the transportation system. Its design features clearly defined directions for financial support. According to the policy, pilot cities are required to ensure financial backing for key areas such as new energy vehicle R&D, intelligent transportation infrastructure, and low-carbon fuel applications, using instruments like green loans, green bonds, and dedicated funding programs. For instance, certain pilot cities provide loan subsidies for new energy vehicle enterprises or establish innovation funds focused on low-carbon transportation technologies, thereby directly lowering corporate financing costs. Meanwhile, the policy encourages financial institutions to allocate green loan quotas to low-carbon transportation projects and addresses their lending concerns through risk compensation mechanisms. This dual approach of “policy implementation combined with incentive guidance” has significantly strengthened governmental support for green finance in low-carbon transportation technologies.

In terms of the operational mechanism, green financial support promotes LCTI through three channels: First, it alleviates financial constraints by providing funding guarantees for enterprises to purchase R&D equipment, hire professional talents, and conduct pilot-scale experiments (Yang et al., 2022). Second, it mitigates innovation risks; through policy-based guarantees or risk-sharing mechanisms, it reduces losses incurred by enterprises due to R&D failures (Yu et al., 2021). Third, it guides resource aggregation; the targeted allocation of green financial instruments sends clear signals to the market, attracting social capital to follow up investments in low-carbon technology fields and forming a synergistic effect of capital. Therefore, the LCTS policy, by strengthening government-supported green finance, injects critical resources into LCTI, constituting a significant transmission pathway through which the policy influences innovation (Huang et al., 2022).

Based on this, this paper proposes research hypothesis *H2a*: Urban traffic green transformation (LCTS policy) can promote LCTI by enhancing government-supported green financial support.

LCTS, public environmental awareness and LCTI

As a key manifestation of social preferences, public environmental awareness exerts a significant guiding influence on the structure of market demand and the direction of corporate innovation (Zhao and Li, 2025). The implementation of the LCTS policy is not merely a technical measure for transportation transformation; rather, it reshapes the public's perception of low-carbon development through policy advocacy, infrastructure upgrading, and behavioral guidance, thereby generating demand-driven momentum for technological innovation.

In terms of the policy's impact on public environmental awareness, the LCTS pilot program has enhanced public environmental attention through multi-dimensional interactions. On one hand, during the policy implementation, the large-scale deployment of low-carbon transportation facilities—such as new energy buses, shared bicycles, and charging piles—has allowed the public to intuitively perceive the tangible progress of green transformation. This “visible” policy effect has strengthened public recognition of low-carbon concepts. On the other hand, the government has popularized low-carbon knowledge through media campaigns, community education, and other initiatives, linking transportation emission reduction to improvements in air quality, healthy lifestyles, and other livelihood issues, which has stimulated active public concern about environmental quality. For instance, activities such as “Car-Free Days” and “Green Travel Promotion Months” carried out in pilot cities have directly deepened the public's understanding of concepts like “carbon emissions” and “new energy,” thereby elevating residents' environmental awareness (Li et al., 2023).

The elevation of public environmental awareness further drives LCTI through a “demand-pull” mechanism (Chen et al., 2022b). According to the demand-pull theory of innovation, market demand serves as the core driver of technological advancement. As public environmental awareness strengthens, consumer preferences tilt toward low-carbon products (Zhao et al., 2025)—for example, a greater inclination toward new energy vehicles over conventional fuel-powered cars, and stronger support for public transportation services adopting low-carbon technologies. This shift in demand structure sends clear signals to enterprises: only through technological innovation can they meet market needs and gain competitive advantages. Concurrently, public attention to environmental quality creates social pressure, prompting governments to strengthen regulations on the application of low-carbon technologies (e.g., stricter emission standards), which further compels enterprises to increase R&D investment (Hu et al., 2025).

Based on this, this paper proposes research hypothesis *H2b*: Urban traffic green transformation (LCTS policy) can promote LCTI by enhancing public environmental awareness.

Materials and methods

Empirical strategy

Given the phased implementation characteristics of the Low-Carbon Transportation System Pilot Policy (where different cities were included in the pilot program at different times), this paper treats it as a quasi-natural experiment. To evaluate the actual effect of the policy on urban LCTI, we employ a difference-in-differences (DID) model. The DID approach is a widely used econometric technique for estimating the causal effect of a specific intervention (like a policy) by comparing the change in outcomes over time between a group exposed to the intervention (the treatment group) and a group that is not (the control group).

The basic structure of the DID model relies on comparing outcomes before and after the intervention for both groups. It calculates the difference in the average outcome for the treatment group before and after the treatment, and subtracts the difference in the average outcome for the control group over the same period. This “difference of differences” isolates the average treatment effect on the treated (ATT), assuming that, in the absence of the treatment, both groups would have followed parallel trends in the outcome variable.

In this study, the LCTS pilot cities constitute the treatment group, while non-pilot cities serve as the control group. Because the LCTS policy was implemented in different cities at different times (staggered adoption in 2011 and 2012), we utilize a generalized or staggered DID framework. This framework accommodates variation in treatment timing by comparing each treated unit to the control units (or units not yet treated) in the periods before and after its specific treatment initiation. The model specification includes unit (city) fixed effects and time (year) fixed effects. City fixed effects control for unobserved time-invariant heterogeneity across cities, while time fixed effects capture common shocks or trends affecting all cities in a given year. By incorporating these fixed effects, the model effectively controls for confounding factors and isolates the causal impact of the LCTS policy. The specific staggered DID model used in this paper is formulated as follows:

$$LCTI_{it} = \beta_0 + \beta_1 GTS_{it} + \beta_c Controls_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (Eq.1)$$

In Equation 1, $LCTI_{it}$ denotes the level of low-carbon technology innovation in city i during year t . GTS_{it} is a policy dummy variable: it takes the value of 1 if city i designated as a LCTS pilot city in or after year t , and 0 otherwise. $Controls_{it}$ represents a set of control variables that may affect LCTI. μ_i and λ_t account for city fixed effects and time fixed effects, respectively. ε_{it} is the random error term. To mitigate issues of heteroskedasticity and serial correlation, standard errors are clustered at the city level in this study.

Variables

Explained variable (LCTI)

In this paper, the per capita green patent applications in each city are used to measure the level of urban low-carbon technology innovation (LCTI). Low-carbon technology innovation has a clear technical boundary. In the Cooperative Patent Classification (CPC) jointly released by the United States Patent and Trademark Office and the European Patent Office in 2013, technologies under class Y02 are specifically defined as “technologies for mitigating or adapting to climate change”, covering fields directly related to low-carbon transformation such as new energy utilization, energy-saving technologies, and carbon capture. Based on data availability and international comparability, this paper calculates the annual number of Y02 patent applications in each city divided by the year-end total population to obtain the per capita low-carbon patent applications, which serves as the core indicator for measuring the level of urban low-carbon technology innovation (LCTI) (Liu and Sun, 2021; Chen et al., 2022c).

Core explanatory variable (GTS)

The core explanatory variable is the green transportation system, measured by a dummy variable. Specifically, if a city is included in the list of LCTS pilot cities in year t , the value of GTS for that city in year t and subsequent years is 1; otherwise, it is 0.

Mediating variables

(1) Green Finance (*GFIN*). Drawing on the methodologies of He et al. (2020) and Dong et al. (2024), this paper constructs a composite index using the entropy weight method to measure the intensity of green financial support at the city level, covering seven dimensions: green credit, green investment, green insurance, green bonds, green subsidies, green funds, and green equity.

(2) Public Environmental Concern (*PEC*). Following the measurement approaches for public environmental awareness in existing studies (Wang et al., 2024; Ren and Ren, 2024), this paper uses the annual search frequency of keywords such as “carbon dioxide,” “carbon emissions,” and “low carbon” by urban residents on Baidu Search Engine. This frequency is divided by the city’s year-end total population to obtain the per capita search frequency, which serves as a proxy variable reflecting the level of public attention to environmental issues.

Control variables

To minimize omitted variable bias, this paper incorporates the following control variables, drawing on existing literature on the determinants of green technological innovation:

1. Economic Development Level (*EDEP*), measured by the natural logarithm of per capita GDP.
2. Road Density (*ROAD*), proxied by per capita road area.
3. Degree of Opening-Up (*OPEN*), represented by the ratio of total trade volume to GDP in each city.
4. Human Capital Level (*HC*), measured by the average years of education per capita in the city.
5. Urbanization (*URB*), calculated as the ratio of non-agricultural population to the total population of the city.
6. Industrial Structure (*IS*), expressed as the ratio of output value of the tertiary industry to that of the secondary industry.

The sources, definitions and units of all variables are summarized in *Table 1*.

Data

This study uses a sample of 265 Chinese cities spanning the period 2008–2023, with data sourced from multiple channels and subjected to rigorous screening and processing. Data on Y02-class patents, which measure urban LCTI, are obtained from the Incopat patent retrieval platform, filtered in accordance with the Cooperative Patent Classification (CPC) standards jointly issued by the United States Patent and Trademark Office and the European Patent Office in 2013. City-level socioeconomic data, such as per capita GDP, population size, and industrial structure indicators, are primarily extracted from the China Urban Statistical Yearbook. Data related to transportation infrastructure, including per capita road area, are sourced from the China Urban Construction Statistical Yearbook. Data for other variables are retrieved from the EPS Database. Data on Baidu search indices, used to measure public environmental concern, are collected and collated from the Baidu Index platform, focusing on search frequencies for relevant keywords. For minor missing values in some variables, linear interpolation is applied to impute the missing data, resulting in a balanced panel dataset with 4240 observations. *Table 2* summarizes the descriptive statistics for all variables.

Table 1. *The sources, definitions and units of all variables*

Variable	Definition	Unit	Data source	Year span
Dependent variable				
<i>LCTI</i>	Per capita Y02 patent applications (Low-Carbon Technology Innovation)	Patents per 10,000 people	Incopat patent database (filtered by Y02 classification); Population data from China City Statistical Yearbook	2008-2023
<i>A_LCTI</i>	Per capita Y02 authorized patents (Alternative measure for robustness test)	Patents per 10,000 people	Incopat patent database (filtered by Y02 classification); Population data from China City Statistical Yearbook	2008-2023
Core Explanatory Variable				
<i>GTS</i>	Dummy variable for LCTS pilot policy (1 if pilot city in year t or after, 0 otherwise)	Binary (0 or 1)	Official government documents (Ministry of Transport announcements)	2008-2023
Mediating variables				
<i>GFIN</i>	Green Finance composite index (based on entropy weight method)	Index value	Calculated based on data from China City Statistical Yearbook, EPS Database, local government reports	2008-2023
<i>PEC</i>	Public Environmental Concern (Per capita Baidu search index for relevant keywords)	Searches per 10,000 people	Baidu Index platform; Population data from China City Statistical Yearbook	2011-2023
Control variables				
<i>EDEP</i>	Economic Development Level (Logarithm of per capita GDP)	Log of Yuan per person	China City Statistical Yearbook	2008-2023
<i>ROAD</i>	Road Density (Per capita road area)	Square meters per person	China Urban Construction Statistical Yearbook	2008-2023
<i>OPEN</i>	Degree of Opening-Up (Ratio of total trade volume to GDP)	Ratio	China City Statistical Yearbook	2008-2023
<i>HC</i>	Human Capital Level (Average years of education per capita)	Years	Calculated based on census data and educational statistics from China City Statistical Yearbook and provincial yearbooks	2008-2023
<i>URB</i>	Urbanization (Ratio of non-agricultural population to total population)	Percentage (%)	China City Statistical Yearbook	2008-2023
<i>IS</i>	Industrial Structure (Ratio of tertiary to secondary industry output value)	Ratio	China City Statistical Yearbook	2008-2023

Table 2. *Descriptive statistical results*

Variables	N	Mean	SD	Min	Max
LCTI	4240	0.315	0.476	0	3.628
GTS	4240	0.067	0.244	0	1
EDEP	4240	10.498	0.709	8.762	12.001
ROAD	4240	15.713	7.107	0.390	36.038
HC	4240	2.011	0.026	0.001	12.168
OPEN	4240	0.293	0.712	0.019	24.877
IS	4240	1.283	0.604	0.315	3.861
URB	4240	54.156	15.806	22.563	94.870

LCTI = Low-Carbon Technology Innovation; GTS = Green Transportation System (dummy variable for LCTS pilot policy); EDEP = Economic Development Level; ROAD = Road Density; HC = Human Capital Level; OPEN = Degree of Opening-Up; IS = Industrial Structure; URB = Urbanization; N = Number of observations; Mean = Arithmetic mean; SD = Standard Deviation; Min = Minimum value; Max = Maximum value

Results

Benchmark regression analysis

In the baseline regression analysis, we empirically examine the impact of urban green transportation transformation on LCTI by constructing a staggered difference-in-differences model. The regression results in *Table 3* show that in Model (1), the regression coefficient of *GTS* on *LCTI* is 0.802, which is significant at the 1% level, initially indicating that the low-carbon transportation pilot policy has a significant promoting effect on LCTI. Model (2) adds city fixed effects and year fixed effects to Model (1), and the coefficient of *GTS* is 0.447, still significant at the 1% level. Model (3) further incorporates control variables into Model (1), and the coefficient of *GTS* remains significant at the 1% level. Finally, Model (4) comprehensively considers control variables, city fixed effects, and year fixed effects, with the coefficient of *GTS* being 0.402 and significant at the 1% level. These findings demonstrate that the low-carbon transportation pilot policy significantly enhances the level of urban LCTI, thereby validating Hypothesis *H1*.

Table 3. Benchmark regression results

Variables	(1) LCTI	(2) LCTI	(3) LCTI	(4) LCTI
GTS	0.802*** (0.115)	0.447*** (0.061)	0.348*** (0.086)	0.402*** (0.056)
EDEP			0.257*** (0.030)	0.191*** (0.050)
ROAD			0.004* (0.002)	-0.003 (0.002)
HC			2.249*** (0.831)	1.479*** (0.566)
OPEN			0.050** (0.020)	-0.083 (0.062)
IS			-0.104*** (0.015)	0.076*** (0.024)
URB			0.005*** (0.002)	-0.002 (0.002)
_cons	0.264*** (0.018)	0.286*** (0.004)	-2.679*** (0.267)	2.358*** (0.518)
City FE	NO	YES	NO	YES
Year FE	NO	YES	NO	YES
N	4240	4240	4240	4240
R-squared	0.169	0.812	0.560	0.827

LCTI = Low-Carbon Technology Innovation (dependent variable, measured by per capita Y02 patent applications); GTS = Green Transportation System (core explanatory variable, dummy for LCTS pilot policy); EDEP = Economic Development Level; ROAD = Road Density; HC = Human Capital Level; OPEN = Degree of Opening-Up; IS = Industrial Structure; URB = Urbanization; FE = Fixed Effects (City FE = City Fixed Effects; Year FE = Year Fixed Effects); ***p < 0.01, **p < 0.05, *p < 0.1 (statistical significance at the 1%, 5%, and 10% levels, respectively). Robust standard errors clustered at the city level are in parentheses

Parallel trend test

In the baseline regression analysis, we employed a difference-in-differences (DID) model to examine the impact of the Low-Carbon Transportation Pilot Policy (GTS) on urban low-carbon technology innovation (LCTI). A critical prerequisite for the validity of DID estimates is the parallel trends assumption, which requires that the trends of the treatment group and the control group would have remained consistent in the absence of policy intervention. If this assumption is violated, DID estimates may erroneously attribute inherent differences to policy effects. To verify the parallel trends assumption, this study conducts a test using the event study methodology.

The results of the parallel trends test are presented in *Figure 1*: In the pre-policy period ($t=-5$ to $t=-2$), the coefficients fluctuate around 0 and are statistically insignificant, indicating that the LCTI trends of the treatment and control groups were essentially consistent before the policy implementation, thus satisfying the parallel trends assumption. In the post-policy period ($t = 1$ to $t = 8+$), most coefficients are positive and gradually become significant, reflecting a significant increase in the level of LCTI after the policy was implemented. These findings provide strong support for the reliability of the baseline regression results.

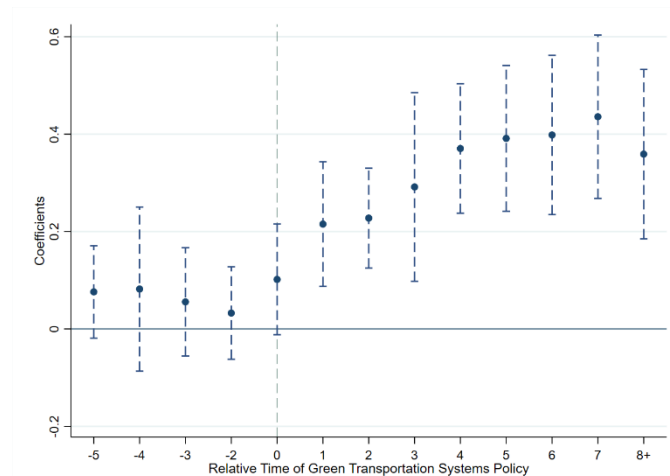


Figure 1. Results of the parallel trends test

Placebo test

To ensure the robustness of our findings, we conducted a placebo test. The testing procedure is as follows: A group of cities was randomly selected from all cities as a “pseudo-treatment group,” and a “policy implementation year” was randomly assigned to simulate a non-existent policy. This process was repeated 1000 times; in each iteration, a set of random policy variables was generated, regression analyses were performed, and the regression coefficients and their significance levels were recorded.

The results of the placebo test, presented in *Figure 2*, show that the coefficient density distribution is primarily concentrated around 0, forming a symmetric bell-shaped curve. This indicates that in the absence of an actual policy, the impact of most randomly generated policy variables on LCTI is close to zero with small fluctuations. Meanwhile, the P-value distribution reveals that the P-values of most regression coefficients are greater than 0.1, suggesting these coefficients are statistically insignificant. These results

imply a low probability of observing a significant policy effect in the absence of a real policy impact, thereby validating the robustness and reliability of our research findings.

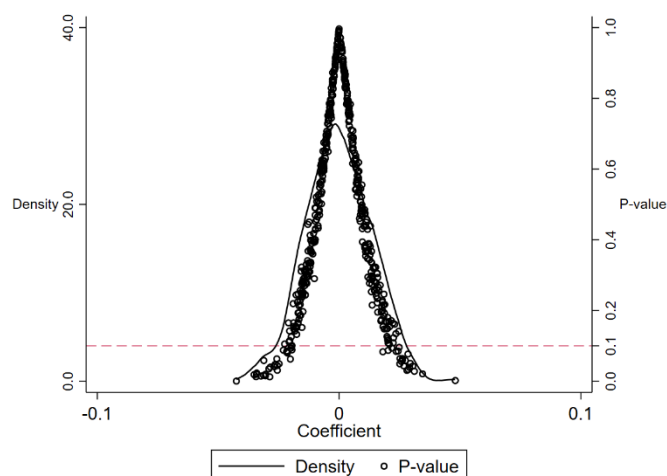


Figure 2. Results of the placebo test

PSM-DID

We further conduct a robustness check using the propensity score matching-difference-in-differences (PSM-DID) approach. This method effectively mitigates sample selection bias by balancing the distribution of covariates between the treatment and control groups. We first excluded policy-affected cities from the original sample, retaining the remaining cities as potential control group candidates. Then, we reselected control group cities for the treatment group through propensity score matching, a method that balances covariate distributions between the two groups, thereby reducing the impact of sample selection bias on estimation results. After matching, we re-estimated the policy effects using the DID model. As shown in *Table 4*, the estimated coefficient of *GTS* remains significantly positive, confirming that the Low-Carbon Transportation Pilot Policy has a robust promoting effect on LCTI.

Table 4. PSM-DID

Variables	(1) LCTI
GTS	0.257*** (0.056)
_cons	1.407*** (0.488)
Controls	YES
City FE	YES
Year FE	YES
N	3708
R-squared	0.857

PSM-DID = Propensity Score Matching-Difference-in-Differences (a robustness check methodology); LCTI = Low-Carbon Technology Innovation (dependent variable); GTS = Green Transportation System (dummy variable for LCTS pilot policy); FE = Fixed Effects (City FE = City Fixed Effects; Year FE = Year Fixed Effects); *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors clustered at the city level are in parentheses

Additionally, we performed a covariate balance test (presented in *Fig. 3*) to validate the effectiveness of propensity score matching. The results indicate that the standardized bias of each covariate is significantly reduced after matching, demonstrating that the matching process successfully balanced the covariate distributions between the treatment and control groups, thus enhancing the reliability of the estimation results.

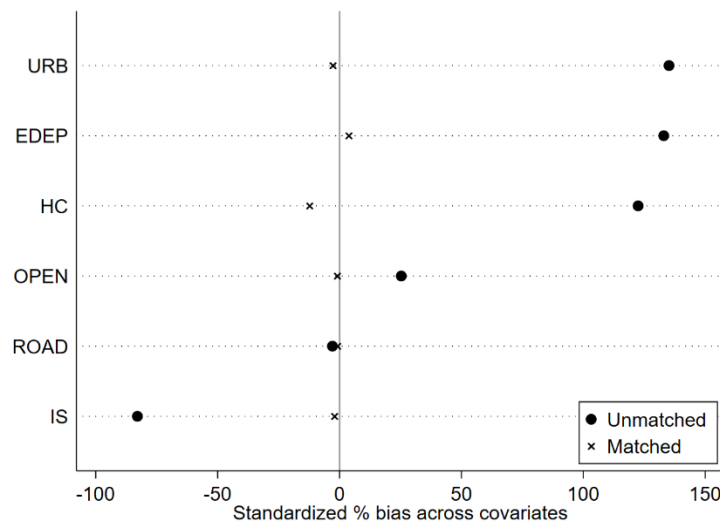


Figure 3. Results of balance test for covariates

Other robustness tests

In the baseline regression analysis, we further conducted a series of robustness tests to ensure the stability and reliability of the identified policy effects.

(1) Replacing the explained variable (with authorized patents)

In the baseline regression, we used the number of low-carbon patent applications as the explained variable. Considering that patent applications may include low-quality innovations that fail to pass examination, authorized patents are more reflective of substantive achievements in technological innovation. To verify that the policy effect is not merely driven by application behavior, this paper replaces the explained variable with the per capita number of authorized low-carbon patents (*A_LCTI*) and re-estimates the model.

The regression results, presented in Column (1) of *Table 5*, show that the estimated coefficient of *GTS* is 0.142, which is significant at the 5% level. This indicates that even when the explained variable is replaced with authorized patents, the promoting effect of *GTS* on *LCTI* remains significant. This validates the robustness of the baseline regression results, suggesting that the green transportation transformation policy not only increases the number of patent applications but also boosts the number of authorized patents, reflecting the policy's positive impact on the quality of technological innovation.

(2) Excluding the impact of the COVID-19 pandemic

The outbreak of the COVID-19 pandemic in 2020 had a significant impact on global economic activities, technological R&D, and the operation of transportation systems,

which may have interfered with the measurement of LCTI and the identification of policy effects. To eliminate the influence of this exogenous shock, this paper shortens the sample period to 2008–2019 (pre-pandemic) and re-estimates the model to test the robustness of the policy effect.

Column (2) of *Table 5* reports the regression results: the estimated coefficient of *GTS* is 0.298, which is significantly positive at the 1% statistical level. This result is consistent in direction with the coefficient of *GTS* in the baseline regression (0.402) and maintains statistical significance. It indicates that after excluding the pandemic’s interference with economic activities, R&D investment, and transportation systems, the promoting effect of urban green transportation transformation on LCTI remains robust.

(3) Eliminating interference from other policies

While advancing low-carbon transformation in the transportation sector, China has also implemented a series of comprehensive low-carbon development policies such as the “Low-Carbon City Pilot Policy” (Yin et al., 2023; Liu et al., 2025a). Such policies overlap with the “Low-Carbon Transportation Pilot Policy” in objectives (e.g., both take reducing carbon emissions as the core) and may affect urban LCTI through similar mechanisms (e.g., promotion of green technologies, environmental incentives), thereby posing potential interference to the identification of policy effects in this study. To clarify the independent role of the transportation-specific policy, this paper excludes cities included in the “Low-Carbon City Pilot Policy” from the sample and retains only those not covered by this policy for regression testing.

The regression results in Column (3) of *Table 5* show that the estimated coefficient of the core explanatory variable *GTS* is 0.417, which is significantly positive at the 1% statistical level. This result indicates that even after excluding the potential overlapping effects of the “Low-Carbon City Pilot Policy,” the promoting effect of the “Low-Carbon Transportation Pilot Policy” on urban LCTI remains robust, and its independent effect is not overshadowed by other low-carbon policies.

Table 5. Results of robustness test

Variables	(1) A_LCTI	(2) LCTI	(3) LCTI
GTS	0.142** (0.070)	0.298*** (0.047)	0.417*** (0.070)
_cons	0.583 (0.961)	1.501*** (0.456)	1.475*** (0.501)
Controls	YES	YES	YES
City FE	YES	YES	YES
Year FE	YES	YES	YES
N	4240	3180	3276
R-squared	0.937	0.829	0.769

A_LCTI = Alternative Low-Carbon Technology Innovation (alternative dependent variable, measured by per capita authorized Y02 patents); LCTI = Low-Carbon Technology Innovation (original dependent variable); GTS = Green Transportation System (dummy variable for LCTS pilot policy); FE = Fixed Effects (City FE = City Fixed Effects; Year FE = Year Fixed Effects); ***p < 0.01, **p < 0.05, *p < 0.1. Robust standard errors clustered at the city level are in parentheses. Column (1) replaces LCTI with A_LCTI; Column (2) restricts the sample to 2008–2019 (excluding COVID-19 impacts); Column (3) excludes cities covered by the Low-Carbon City (LCC) pilot policy

Mechanism test

While the baseline regression has confirmed that the Low-Carbon Transportation Pilot Policy significantly promotes urban low-carbon technology innovation (LCTI), the specific pathways through which the policy influences innovative activities require further verification. Drawing on a dual “supply-demand” perspective, this paper proposes two potential transmission mechanisms: first, government-led green financial support alleviates innovation funding constraints (supply side); second, increased public environmental concern induces changes in market demand (demand side). In this section, we further examine the specific mechanisms through which green transportation transformation drives low-carbon innovation.

Green financial support

LCTI is characterized by high investment, high risk, and long cycles, with funding constraints often serving as a critical bottleneck restricting corporate R&D activities (Zhang et al., 2024b; Yu et al., 2021). As a policy instrument, green finance can specifically reduce the financing costs of low-carbon projects through dedicated loans, green bonds, subsidies, and other means, providing financial security for technological R&D (Tang et al., 2023). Column (1) of *Table 6* reports the regression results of *GTS* on green financial support (*GFIN*): the estimated coefficient of *GTS* is 0.012, which is significantly positive at the 1% level. This indicates that the implementation of the Low-Carbon Transportation Pilot Policy has significantly enhanced urban green financial support—pilot cities, in response to policy objectives, are more inclined to use financial tools to guide social capital toward low-carbon transportation technologies, such as offering credit preferential terms or financing guarantees for projects like new energy vehicle R&D and intelligent transportation system construction.

By strengthening government guidance on green finance, the pilot policy alleviates the funding constraints of LCTI, thereby providing necessary resource support for corporate R&D activities and ultimately promoting the improvement of urban LCTI levels (Liu et al., 2025b). Hypothesis *H2a* is thus validated.

Public environmental concern

As the primary driver of market demand, the public’s heightened environmental awareness can stimulate corporate innovation by influencing shifts in consumer preferences (Wang et al., 2025). When a city implements the Low-Carbon Transportation Pilot Policy, initiatives such as policy dissemination and infrastructure upgrades contribute to increased public awareness of climate change. This, in turn, encourages individuals to favor low-carbon products and support the adoption of environmentally friendly technologies. Through this “demand-led innovation” mechanism, enterprises are incentivized to increase R&D investments to meet the growing market demand for low-carbon solutions.

Column (2) of *Table 6* reports the regression results of *GTS* on public environmental concern (*PEC*): the estimated coefficient of *GTS* is 0.147, which is significantly positive at the 1% level. Hypothesis *H2b* is thus validated. This indicates that the pilot policy has significantly raised the public’s attention to environmental issues. In this context, the rising public demand for low-carbon products and services sends market signals that incentivize innovation, prompting enterprises to allocate R&D resources toward low-carbon technologies, ultimately driving urban LCTI.

Table 6. Mechanism test results

Variables	(1) GFIN	(2) PEC
GTS	0.012*** (0.003)	0.147*** (0.018)
_cons	0.421*** (0.023)	-0.180** (0.081)
Controls	YES	YES
City FE	YES	YES
Year FE	YES	YES
N	4240	3445
R-squared	0.852	0.839

GFIN = Green Finance (first mediating variable, composite index); PEC = Public Environmental Concern (second mediating variable, per capita Baidu search frequency); GTS = Green Transportation System (core explanatory variable, dummy for LCTS pilot policy); LCTI = Low-Carbon Technology Innovation (the core dependent variable in the baseline model, referenced here to clarify the mechanism's target); FE = Fixed Effects (City FE = City Fixed Effects; Year FE = Year Fixed Effects); *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors clustered at the city level are in parentheses

Heterogeneity analysis

The baseline regression and robustness tests confirm that the Low-Carbon Transportation Pilot Policy significantly enhances urban LCTI, with its effect channeled through two key pathways: green financial support and public environmental concern. However, given the substantial differences among Chinese cities in terms of resource endowments, institutional environments, and stages of development, the policy's impact may vary across cities with different characteristics. Building on this insight, this paper further examines the heterogeneous effects of green transportation transformation on urban LCTI from three perspectives: the level of marketization, energy structure (specifically energy cleanliness), and intellectual property protection.

Marketization

The level of marketization reflects the degree to which market mechanisms influence resource allocation, and variations in this level may affect both the efficiency of policy signal transmission and the dynamism of innovation factor flows (Zeng et al., 2021). To investigate whether the impact of the Low-Carbon Transportation Pilot Policy on LCTI differs across cities with varying marketization environments, this paper employs the regional marketization index—categorized based on the median value—to classify the sample into two groups: “high marketization level” and “low marketization level,” and performs subgroup regressions accordingly (Chen et al., 2023). The results are reported in Columns (1) and (2) of Table 7.

The regression results indicate that in cities with higher marketization levels, the estimated coefficient of *GTS* is 0.324 and statistically significant at the 1% level. In contrast, in cities with lower marketization levels, the *GTS* coefficient is 0.214. A test for coefficient differences ($p < 0.01$) confirms that this discrepancy is highly significant. This suggests that the Low-Carbon Transportation Pilot Policy exerts a stronger promoting effect on LCTI in cities with higher marketization levels.

Table 7. Results of heterogeneity analysis

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	High marketization	Low marketization	High energy cleanliness	Low energy cleanliness	High IPP	Low IPP
	LCTI	LCTI	LCTI	LCTI	LCTI	LCTI
GTS	0.324*** (0.057)	0.214*** (0.069)	0.366*** (0.078)	0.285** (0.126)	0.456*** (0.077)	0.248* (0.143)
_cons	2.525*** (0.761)	0.767 (0.537)	3.245*** (0.961)	0.025 (0.475)	1.966*** (0.532)	2.095*** (0.487)
Test for group differences	0.110***		0.152***		0.208***	
Controls	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
N	2114	2119	2117	2112	2116	2115
R-squared	0.835	0.868	0.867	0.878	0.880	0.862

LCTI = Low-Carbon Technology Innovation (dependent variable); GTS = Green Transportation System (dummy variable for LCTS pilot policy); IPP = Intellectual Property Protection (proxied by provincial-level patent infringement case closure rate); FE = Fixed Effects (City FE = City Fixed Effects; Year FE = Year Fixed Effects); *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors clustered at the city level are in parentheses. Grouping criteria: (1) “High Marketization”/“Low Marketization”: split by the median of the regional marketization index; (2) “High Energy Cleanliness”/“Low Energy Cleanliness”: split by the median of the ratio of coal consumption to total energy consumption; (3) “High IPP”/“Low IPP”: split by the median of the provincial patent infringement case closure rate. “Test for group differences” reports the significance of coefficient disparities between subgroups

The underlying logic can be explained as follows: In cities characterized by a more developed market environment, price and competition mechanisms are more effective, making enterprises more responsive to policy guidance and enabling them to adjust R&D strategies promptly in response to low-carbon transformation signals. Meanwhile, efficient factor flows—such as those involving capital and talent—facilitate the precise alignment of policy instruments like green finance with innovation demands, thereby alleviating funding constraints for R&D. Furthermore, clear delineation between government and market functions minimizes distortions caused by administrative interventions in innovation processes, fostering stable innovation expectations and encouraging long-term R&D investment (Zhang et al., 2023b). Consequently, a well-functioning market mechanism significantly enhances the policy incentives associated with green transportation reforms by strengthening the transmission of policy signals, improving the efficiency of resource allocation, and reinforcing innovation expectations.

Energy structure

Energy structure is a critical factor influencing urban carbon emission intensity and low-carbon transformation pathways. A high-carbon energy consumption pattern dominated by coal exacerbates transformation pressures, which may in turn strengthen the policy’s incentive effect on LCTI (Sun and Chen, 2023). In this paper, urban energy cleanliness is measured by the ratio of coal consumption to total energy consumption (a lower ratio indicates higher energy cleanliness) (Hou et al., 2024). Using the median of

this indicator as the cutoff, the sample is divided into two groups: “higher energy cleanliness” and “lower energy cleanliness,” and subgroup regressions are conducted. The results are presented in Columns (3) and (4) of *Table 7*.

The results show that in cities with lower energy cleanliness, the estimated coefficient of *GTS* is 0.366, significant at the 1% level; in contrast, in cities with higher energy cleanliness, the coefficient of *GTS* is 0.285 (significant only at the 5% level). The inter-group coefficient difference test ($p < 0.01$) indicates that this difference is statistically significant, meaning the promoting effect of the Low-Carbon Transportation Pilot Policy on LCTI is more pronounced in cities with lower energy cleanliness.

Cities with low energy cleanliness (high coal dependence) often face more severe carbon emission constraints and transformation pressures, resulting in a more urgent practical demand for low-carbon technologies (Li and Yang, 2025). On one hand, to achieve low-carbon transformation goals in the transportation sector, such cities need to break through traditional energy dependence through technological innovation (e.g., developing new energy vehicles and clean fuel technologies), leading to a stronger “reverse coercive effect” from policy implementation (Lee et al., 2023). On the other hand, a high-carbon energy structure may prompt local governments to introduce more robust incentive measures (such as R&D subsidies and preferential policies for technology introduction) when implementing the pilot policy, accelerating the agglomeration of innovation factors in low-carbon fields. Conversely, cities with higher energy cleanliness face less pressure from carbon emissions, resulting in weaker urgency in demand for low-carbon technologies, and the marginal incentive effect of the policy on innovation is relatively limited.

Intellectual property protection

Intellectual property protection serves as a fundamental institutional mechanism for stimulating technological innovation, with its strength directly influencing the R&D incentives of innovators and their propensity to commercialize innovations (Yuan and Li, 2025). In the context of low-carbon technology development—which entails substantial investment and high risk—strong intellectual property protection mitigates the risk of infringement, safeguards the monopoly rents of R&D entities, and thereby enhances the effectiveness of policy-induced innovation incentives. Following Chen and Wu (2022), this study employs the provincial-level patent infringement case closure rate as a proxy for the intensity of intellectual property protection. Based on the median value of this indicator, the sample is categorized into two groups: “high intellectual property protection level” and “low intellectual property protection level,” with subgroup regression analyses conducted accordingly. The corresponding results are reported in Columns (5) and (6) of *Table 7*.

The regression results indicate that in cities with stronger intellectual property protection, the estimated coefficient of *GTS* is 0.456 and statistically significant at the 1% level. In contrast, in cities with weaker intellectual property protection, the *GTS* coefficient is 0.248, which is only significant at the 10% level. The inter-group coefficient difference test ($p < 0.01$) confirms that this discrepancy is statistically significant. These findings suggest that the promoting effect of the Low-Carbon Transportation Pilot Policy on LCTI is more pronounced in cities with robust intellectual property protection.

This result can be attributed to the fact that LCTI is characterized by long R&D cycles, high input costs, and susceptibility to imitation. Cities with robust intellectual property protection systems can mitigate the risks of unauthorized use of innovations through

stricter enforcement mechanisms (Chen and Chen, 2024). On one hand, research and development entities, confident that their innovation outcomes will be adequately protected, are more inclined to allocate resources toward developing low-carbon transportation technologies—such as new energy vehicle powertrains and intelligent transportation energy-saving algorithms. On the other hand, a strong intellectual property environment curtails “free-riding” behavior, preserving the R&D motivation of innovators and reinforcing the policy’s effectiveness in promoting innovation. Conversely, in cities with weak intellectual property protection, uncertainty regarding returns on innovation discourages enterprises from investing in R&D, thereby weakening the policy’s capacity to drive low-carbon technological advancement (Luo et al., 2025).

Conclusions

Using panel data from 265 Chinese cities spanning 2008–2023, this study treats the Low-Carbon Transportation System (LCTS) pilot policy as a quasi-natural experiment and employs a staggered difference-in-differences (DID) model to empirically examine the impact of urban green transportation transformation on LCTI. The findings indicate that urban green transportation transformation exerts a significant promoting effect on LCTI. Specifically, the implementation of the LCTS policy has significantly enhanced the level of urban LCTI, and this conclusion remains robust after a series of robustness tests.

In terms of mechanism analysis, the study reveals that the LCTS policy promotes LCTI primarily through two pathways. First, green financial support provided by the government significantly alleviates enterprises’ financing constraints, offering essential financial guarantees for low-carbon technology R&D. Second, the improvement of public environmental awareness, through a demand-pull mechanism, incentivizes enterprises to increase R&D investment in low-carbon technologies, thereby driving technological innovation.

The results of heterogeneity analysis show that the promoting effect of the LCTS policy on LCTI varies significantly across cities with different characteristics. The policy effect is more pronounced in cities with a higher level of marketization, indicating that a well-developed market mechanism can effectively enhance the policy’s implementation effect. Additionally, the policy’s promoting effect is more prominent in cities with lower energy cleanliness, reflecting the urgent demand for low-carbon technologies in these cities. Meanwhile, the policy’s promotion of LCTI is more evident in cities with a higher level of intellectual property protection, highlighting the importance of a strong intellectual property protection environment for innovation incentives.

Discussion

Theoretical implications

Our research contributes to several strands of literature at the intersection of environmental economics, innovation studies, and urban policy.

First, we enrich the understanding of how environmental policies influence technological innovation. While a substantial body of work confirms that broad environmental regulations or place-based policies like Low-Carbon City (LCC) pilots and Emissions Trading Schemes (ETS) can stimulate general “green innovation” (Chen et al., 2022a; Pan et al., 2022; Li et al., 2022; Zhang et al., 2024a), our study provides crucial

nuance by focusing on a sector-specific policy (LCTS) and its direct impact on domain-specific LCTI (Y02 patents) as the primary outcome. Unlike studies that treat innovation as an intermediate mechanism for achieving emission reductions or productivity gains within the LCTS framework (Sun and Zhao, 2024; Zhao, 2024; Sun, 2025; Yu et al., 2025), our findings demonstrate that targeted transport policies can act as a direct catalyst specifically for low-carbon technological advancement relevant to that sector. This aligns with the Porter Hypothesis, suggesting that well-designed, sector-focused environmental regulations can trigger innovation effects, but extends it by specifying the type of innovation (LCTI) and the policy context (transportation green transition).

Second, our mechanism analysis provides granular insights into the channels driving policy-induced LCTI in the transport sector. By identifying government-supported green finance and public environmental awareness as significant mediators, we empirically validate a dual supply-demand driver model within this specific context. The finding regarding green finance complements studies showing that financial constraints impede green R&D (Jiang et al., 2023; Jia et al., 2023) and that green finance initiatives can unlock innovation (Yang et al., 2022; Huang et al., 2022; Yu et al., 2021). Our contribution lies in linking these financial mechanisms directly to a transport-specific policy intervention. Similarly, while the role of public awareness in shaping environmental behavior and consumption is acknowledged (Zhao and Li, 2025; Li et al., 2023; Wang et al., 2025), our study explicitly connects heightened awareness, spurred by the LCTS policy's visibility and promotion efforts, to the stimulation of LCTI via a demand-pull pathway (Chen et al., 2022b), providing empirical support for theories of demand-led innovation in the context of environmental policy.

Third, the heterogeneity analysis underscores the importance of the institutional and economic context in mediating policy effectiveness, contributing to theories of institutional economics and innovation systems. The finding that higher marketization enhances the policy's impact aligns with literature suggesting that market mechanisms improve resource allocation efficiency and firm responsiveness to policy signals (Zeng et al., 2021; Zhang et al., 2023b). The stronger effect in cities with lower energy cleanliness (higher coal dependence) suggests that greater environmental pressure or a larger "technological gap" can amplify the innovation stimulus from targeted policies, potentially reflecting a "catching-up" effect or stronger regulatory push in more polluted areas (Sun and Chen, 2023; Li and Yang, 2025; Lee et al., 2023). Finally, the pronounced effect in cities with stronger IPP reinforces the critical role of intellectual property rights in incentivizing R&D, particularly for high-risk, long-cycle innovations like LCTI, by securing returns and mitigating infringement risks (Yuan and Li, 2025; Chen and Wu, 2022; Luo et al., 2025; Chen and Chen, 2024). These contextual factors collectively highlight that the success of sector-specific environmental innovation policies is contingent upon the broader institutional and economic landscape.

Practical implications

Our findings offer several actionable insights for policymakers aiming to foster low-carbon transitions through technological innovation, particularly in the transportation sector.

First, the demonstrated success of the LCTS policy in directly driving LCTI suggests that sector-specific environmental policies can be potent tools for stimulating innovation in targeted domains. Policymakers should consider designing and implementing similar focused initiatives in other high-emission sectors, complementing broader environmental

mandates. Continued support and potential expansion of LCTS-like programs are warranted based on their innovation-inducing effects.

Second, given that government-backed green financial support significantly mediates the policy's positive impact, policymakers should enhance and refine these mechanisms. This includes expanding the availability of green loans, bonds, and dedicated funds specifically for transport-related LCTI, streamlining application processes, and potentially incorporating risk-sharing arrangements to encourage private sector investment in novel low-carbon transport technologies. Improving the capacity of financial institutions to assess the value and risk of LCTI projects is also crucial.

Third, the demand-pull effect driven by public awareness highlights the importance of integrating public engagement and education into low-carbon transport strategies. Governments should invest in sustained public campaigns promoting green travel, disseminating information about the benefits of low-carbon technologies (like NEVs), and making green infrastructure (charging stations, bike lanes) more visible. Initiatives like "Car-Free Days" can be effective tools. Linking transport choices to public health and quality of life can further motivate behavioral shifts and strengthen market demand for LCTI.

Fourth, the significant heterogeneity in policy effects underscores the need for context-specific implementation strategies. In regions with lower marketization, policy implementation should be coupled with broader market-oriented reforms to improve resource allocation and reduce administrative friction. In areas heavily reliant on fossil fuels (lower energy cleanliness), the LCTS policy can be a particularly strong lever for innovation, suggesting that intensified policy efforts in these regions could yield substantial LCTI gains. Furthermore, enhancing intellectual property protection and enforcement is critical across all regions, but particularly important for maximizing the innovation returns from LCTS investments. Stronger IPP environments provide greater security for R&D investments.

Fifth, policymakers should promote policy synergy by integrating LCTS policies with broader initiatives related to low-carbon cities, smart city development, green finance reform, and IPP enhancement. A coordinated policy ecosystem can amplify positive effects and avoid conflicting signals, creating a more conducive environment for sustained LCTI.

Limitations and future research

Although this study offers an in-depth analysis of the impact of urban transportation green transformation on LCTI and verifies the robustness of the findings through multiple methods, several limitations remain that should be addressed in future research. First, the current analysis primarily relies on macro-level city data and lacks a deeper examination of micro-level enterprise data. Future studies could seek detailed enterprise-level information—such as R&D investment, patent applications, and economic performance—to more accurately capture the mechanisms through which transportation green transformation policies influence corporate behavior in low-carbon innovation. Second, this study focuses exclusively on Chinese cities. Future research could expand the scope to include other countries, particularly developing nations, to assess the universality and adaptability of such policies across different economic and institutional contexts. Cross-national comparative studies would enhance understanding of the global applicability and challenges of transportation green transformation policies and provide broader policy insights for international climate governance.

REFERENCES

- [1] Chen, C., Lin, Y., Lv, N., Zhang, W., Sun, Y. (2022a): Can government low-carbon regulation stimulate urban green innovation? Quasi-experimental evidence from China's low-carbon city pilot policy. – *Applied Economics* 54(57): 6559-6579.
- [2] Chen, D., Chen, S. (2024): Patent protection policy and firms' green technology innovation: mediating roles of open innovation and human capital. – *Sustainability* 16(5): 2217.
- [3] Chen, L., Bai, X., Chen, B., Wang, J. (2022b): Incentives for green and low-carbon technological innovation of enterprises under environmental regulation: from the perspective of evolutionary game. – *Frontiers in Energy Research* 9. <https://doi.org/10.3389/fenrg.2021.793667>.
- [4] Chen, L., Guo, F., Huang, L. (2023): Impact of foreign direct investment on green innovation: evidence from China's provincial panel data. – *Sustainability* 15(4): 3318.
- [5] Chen, W., Wu, Y. (2022): Does intellectual property protection stimulate digital economy development? – *Journal of Applied Economics* 25(1): 723-730.
- [6] Chen, Z., Zhang, Y., Wang, H., Ouyang, X., Xie, Y. (2022c): Can green credit policy promote low-carbon technology innovation? – *Journal of Cleaner Production* 359: 132061. <https://doi.org/10.1016/j.jclepro.2022.132061>.
- [7] Ci, F., Wang, Z., Hu, Q. (2024): Spatial pattern characteristics and optimization policies of low-carbon innovation levels in the urban agglomerations in the Yellow River Basin. – *Journal of Cleaner Production* 439: 140856. <https://doi.org/10.1016/j.jclepro.2024.140856>.
- [8] Dong, K., Zhao, C., Dong, X., Taghizadeh-Hesary, F. (2024): Can green finance promote inclusive development? Empirical evidence from China. – *Sustainability Science*. <https://doi.org/10.1007/s11625-024-01570-x>.
- [9] He, Z., Liu, Z., Wu, H., Gu, X., Zhao, Y., Yue, X. (2020): Research on the impact of green finance and Fintech in smart city. – *Complexity* 2020(1): 6673386.
- [10] Hou, J., Shi, C., Fan, G., Xu, H. (2024): Research on the impact and intermediary effect of carbon emission trading policy on carbon emission efficiency in China. – *Atmospheric Pollution Research* 15(4): 102045.
- [11] Hu, S., Deng, H., Jiao, H., Qin, S. (2025): Impact of public environmental concern on green technology innovation: a case study of the Yangtze River Delta in China. – *Frontiers in Environmental Science* 12. <https://doi.org/10.3389/fenvs.2024.1465619>
- [12] Huang, Y., Chen, C., Lei, L., Zhang, Y. (2022): Impacts of green finance on green innovation: a spatial and nonlinear perspective. – *Journal of Cleaner Production* 365: 132548. <https://doi.org/10.1016/j.jclepro.2022.132548>.
- [13] Jia, J. S., He, X. Y., Zhu, T. Y., Zhang, E. R. Y. (2023): Does green finance reform promote corporate green innovation? Evidence from China. – *Pacific-Basin Finance Journal* 82: 102165. <https://doi.org/10.1016/j.pacfin.2023.102165>.
- [14] Jiang, Y., Ampaw, E. M., Wu, H., Zhao, L. (2023): The effects of system pressure on low-carbon innovation in firms: a case study from China. – *Sustainability* 15(14): 11066.
- [15] Lee, C.-C., Wang, C.-S., He, Z., Xing, W.-W., Wang, K. (2023): How does green finance affect energy efficiency? The role of green technology innovation and energy structure. – *Renewable Energy* 219: 119417. <https://doi.org/10.1016/j.renene.2023.119417>.
- [16] Li, C., Yang, X. (2025): The impact of financial agglomeration and the transformation of energy consumption structure on the regional green innovation. – *Clean Technologies and Environmental Policy*. <https://doi.org/10.1007/s10098-025-03165-1>.
- [17] Li, C., Li, X., Song, D., Tian, M. (2022): Does a carbon emissions trading scheme spur urban green innovation? Evidence from a quasi-natural experiment in China. – *Energy & Environment* 33(4): 640-662.
- [18] Li, J., Tang, F., Zhang, S., Zhang, C. (2023): The effects of low-carbon city construction on bus trips. – *Journal of Public Transportation* 25: 100057. <https://doi.org/10.1016/j.jpuptr.2023.100057>.

- [19] Li, X. Y., Hu, J., Lyu, X., Bhuiyan, M. A. (2025): Are low-carbon city pilot policies conducive to carbon reduction? An analysis of experiences from China. – *Environment Development and Sustainability*. DOI: 10.1007/s10668-024-05776-y
- [20] Liu, K., Huang, T., Xia, Z., Xia, X., Wu, R. (2025a): The impact assessment of low-carbon city pilot policy on urban green innovation: a batch-time heterogeneity perspective. – *Applied Energy* 377: 124489. <https://doi.org/10.1016/j.apenergy.2024.124489>.
- [21] Liu, S., Qian, J., Wen, H., Wang, Y. (2025b): The impact of green finance pilot cities on enterprises' green innovation performance: an empirical study in China. – *Sustainability* 17(3): 948. <https://doi.org/10.3390/su17030948>.
- [22] Liu, Y., Chen, L., Huang, C. (2022): Study on the carbon emission spillover effects of transportation under technological advancements. – *Sustainability* 14(17): 10608. <https://doi.org/10.3390/su141710608>.
- [23] Liu, Z., Sun, H. (2021): Assessing the impact of emissions trading scheme on low-carbon technological innovation: evidence from China. – *Environmental Impact Assessment Review* 89: 106589. <https://doi.org/10.1016/j.eiar.2021.106589>.
- [24] Luo, Y. S., Xu, L., Xu, J., Wu, C. (2025): Can the construction of intellectual property court promote corporate green innovation? Evidence from Chinese listed firms. – *Asian Journal of Technology Innovation*. <https://doi.org/10.1080/19761597.2025.2471275>.
- [25] Lyu, Y., Bai, Y., Zhang, J. (2024): Digital transformation and enterprise low-carbon innovation: a new perspective from innovation motivation. – *Journal of Environmental Management* 365: 121663. <https://doi.org/10.1016/j.jenvman.2024.121663>.
- [26] Ma, J., Hu, Q., Shen, W., Wei, X. (2021): Does the low-carbon city pilot policy promote green technology innovation? Based on green patent data of Chinese a-share listed companies. – *International Journal of Environmental Research and Public Health* 18(7): 3695. <https://doi.org/10.3390/ijerph18073695>.
- [27] Pan, A., Zhang, W., Shi, X., Dai, L. (2022): Climate policy and low-carbon innovation: evidence from low-carbon city pilots in China. – *Energy Economics* 112: 106129. <https://doi.org/10.1016/j.eneco.2022.106129>.
- [28] Pan, Q., Zhao, S. (2024): The impact of low-carbon city pilot policy on urban green technology innovation: based on government and public perspectives. – *Plos One* 19(7). <https://doi.org/10.1371/journal.pone.0306425>.
- [29] Pei, F., Wang, P. (2022): The impact of the low-carbon city pilot policy on green innovation in firms. – *Frontiers in Environmental Science* Volume 10. <https://doi.org/10.3389/fenvs.2022.987617>.
- [30] Peng, H., Shen, N., Ying, H., Wang, Q. (2021): Can environmental regulation directly promote green innovation behavior?—based on situation of industrial agglomeration. – *Journal of Cleaner Production* 314. <https://doi.org/10.1016/j.jclepro.2021.128044>.
- [31] Ren, X., Ren, Y. (2024): Public environmental concern and corporate ESG performance. – *Finance Research Letters* 61: 104991. <https://doi.org/10.1016/j.frl.2024.104991>.
- [32] Shen, T., Li, D., Jin, Y., Li, J. (2022): Impact of environmental regulation on efficiency of green innovation in China. – *Atmosphere* 13(5): 767. <https://doi.org/10.3390/atmos13050767>.
- [33] Shi, L., Wang, Y., Jing, L. (2024): Low-carbon city pilot, external governance, and green innovation. – *Finance Research Letters* 67: 105768. <https://doi.org/10.1016/j.frl.2024.105768>.
- [34] Sun, J. (2025): Can green transport policy drive urban carbon emission reduction? Evidence from pilot cities of China's low-carbon transportation system. – *Frontiers in Environmental Science* Volume 13. <https://doi.org/10.3389/fenvs.2025.1660200>.
- [35] Sun, J., Chen, J. (2023): Digital economy, energy structure transformation, and regional carbon dioxide emissions. – *Sustainability* 15(11): 8557. <https://doi.org/10.3390/su15118557>.

- [36] Sun, T.-T., Zhao, B. (2024): Steering towards sustainability: how does low-carbon transportation policy impact urban carbon emissions in China? – *Environment, Development and Sustainability*. <https://doi.org/10.1007/s10668-024-05874-x>.
- [37] Tang, D., Chen, W., Zhang, Q., Zhang, J. (2023): Impact of digital finance on green technology innovation: the mediating effect of financial constraints. – *Sustainability* 15(4): 3393. <https://doi.org/10.3390/su15043393>.
- [38] Tu, Z. G., Cao, Y., Kong, J. Y. (2022): The impacts of low-carbon city pilot projects on carbon emissions in China. – *Atmosphere* 13(8). <https://doi.org/10.3390/atmos13081269>.
- [39] Wang, J., Wu, H., Liu, Y., Wang, W. (2025): Corporate green technology innovation under external pressure: a public and media perspective. – *Journal of Environmental Planning and Management* 68(8): 1834-1857. <https://doi.org/10.1080/09640568.2023.2298252>.
- [40] Wang, T., Song, Z., Zhou, J., Sun, H., Liu, F. (2022): Low-carbon transition and green innovation: evidence from pilot cities in China. – *Sustainability* 14(12). <https://doi.org/10.3390/su14127264>.
- [41] Wang, Y., Fang, X., Yin, S., Chen, W. (2021): Low-carbon development quality of cities in China: evaluation and obstacle analysis. – *Sustainable Cities and Society* 64: 102553. <https://doi.org/10.1016/j.scs.2020.102553>.
- [42] Wang, Z., Sun, H., Ding, C., Zhang, X. (2024): Does public environmental concern cause pollution transfer? Evidence from Chinese firms' off-site investments. – *Journal of Cleaner Production* 466: 142825. <https://doi.org/10.1016/j.jclepro.2024.142825>.
- [43] Yang, Y., Su, X., Yao, S. (2022): Can green finance promote green innovation? The moderating effect of environmental regulation. – *Environmental Science and Pollution Research* 29(49): 74540-74553.
- [44] Yin, H., Qian, Y., Zhang, B., Perez, R. (2023): Urban construction and firm green innovation: evidence from China's low-carbon pilot city initiative. – *Pacific-Basin Finance Journal* 80: 102070. <https://doi.org/10.1016/j.pacfin.2023.102070>.
- [45] Yu, C.-H., Wu, X., Zhang, D., Chen, S., Zhao, J. (2021): Demand for green finance: resolving financing constraints on green innovation in China. – *Energy Policy* 153: 112255. <https://doi.org/10.1016/j.enpol.2021.112255>.
- [46] Yu, L., Li, H. X., Jiang, Y. (2025): Low-carbon transport transition and urban green development in China: a quasi-natural experiment. – *Applied Ecology and Environmental Research* 23(4): 8111-8129.
- [47] Yuan, B., Li, W. (2025): Legal infrastructures for firm innovation: effects of intellectual property protection in the era of digital economy. – *Finance Research Letters* 71: 106343. <https://doi.org/10.1016/j.frl.2024.106343>.
- [48] Zeng, W., Li, L., Huang, Y. (2021): Industrial collaborative agglomeration, marketization, and green innovation: evidence from China's provincial panel data. – *Journal of Cleaner Production* 279: 123598. <https://doi.org/10.1016/j.jclepro.2020.123598>.
- [49] Zhang, F., Wang, Q., Li, R. (2025): Industrial robots and urban carbon emissions: exploring mechanisms and implications. – *Sustainable Development*. <https://doi.org/10.1002/sd.3401>.
- [50] Zhang, H., Sun, X., Ahmad, M., Wang, X. (2024a): Heterogeneous impacts of carbon emission trading on green innovation: firm-level in China. – *Energy & Environment* 35(7): 3504-3529.
- [51] Zhang, W., Zhao, Y., Meng, F. (2024b): ESG performance and green innovation of Chinese enterprises: based on the perspective of financing constraints. – *Journal of Environmental Management* 370: 122955. <https://doi.org/10.1016/j.jenvman.2024.122955>.
- [52] Zhang, X., He, P., Liu, X., Lu, T. (2023a): The effect of low-carbon transportation pilot policy on carbon performance: evidence from China. – *Environmental Science and Pollution Research* 30(19): 54694-54722.
- [53] Zhang, Z., Zheng, C., Lan, L. (2023b): Smart city pilots, marketization processes, and substantive green innovation: a quasi-natural experiment from China. – *Plos One* 18(9). <https://doi.org/10.1371/journal.pone.0286572>.

- [54] Zhao, C., Dong, K., Wang, K., Taghizadeh-Hesary, F. (2023): How can Chinese cities escape from carbon lock-in? The role of low-carbon city policy. – *Urban Climate* 51. <https://doi.org/10.1016/j.uclim.2023.101629>.
- [55] Zhao, J., Li, Y., Wu, T., Jiang, W. (2025): Can public environmental concern drive changes in residents' green consumption behavior? – *Sustainability* 17(12): 17125352. <https://doi.org/10.3390/su17125352>.
- [56] Zhao, X. (2024): Can green transportation accelerate carbon neutrality? Evidence from low-carbon transport systems pilot. – *Energy* 313: 134139. <https://doi.org/10.1016/j.energy.2024.134139>.
- [57] Zhao, X., Li, S. (2025): Artificial intelligence and public environmental concern: impacts on green innovation transformation in energy-intensive enterprises. – *Energy Policy* 198: 114469. <https://doi.org/10.1016/j.enpol.2024.114469>.
- [58] Zhu, R., Long, L., Gong, Y. (2022): Emission trading system, carbon market efficiency, and corporate innovations. – *International Journal of Environmental Research and Public Health* 19(15): 9683. <https://doi.org/10.3390/ijerph19159683>.