HAS GREEN UPGRADING OF TRANSPORTATION SYSTEMS REDUCED CARBON EMISSIONS? EVIDENCE FROM CHINA

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Abstract. The promotion of new energy vehicles (NEVs) is a key strategy for advancing low-carbon cities and building an ecological civilization. This study empirically examines the impact of NEV promotion and its mechanisms on urban carbon emissions using panel data from 75 prefecture-level cities in China (2006-2020). The findings show that: (1) NEV promotion reduces local carbon emissions and has spillover effects on neighboring areas. This result remains consistent after various robustness checks. (2) The impact of different NEV models and application sectors on emissions varies. Pure electric vehicles have a significantly greater carbon reduction effect than hybrid vehicles. Regions with higher electrification in the public sector amplify the environmental benefits of NEVs. Specifically, new energy buses, taxis, and logistics vehicles contribute more significantly to reducing emissions. (3) NEV promotion reduces emissions mainly by optimizing the gasoline and diesel consumption ratio and boosting innovation in enterprises. (4) Policy evaluation shows that the "Ten Cities, Thousand Vehicles" pilot program significantly reduces urban carbon emissions, achieving the goal of low-carbon development through NEVs. The results provide new theoretical insights for decarbonizing transportation and cities and offer empirical evidence for more effective policy measures.
Keywords: *new energy vehicles, carbon reduction, energy structure optimization, technological innovation, spatial spillover, DID model*

Introduction

Achieving 'carbon peaking' and 'carbon neutrality' is a solemn commitment made by China in response to climate change. It represents a significant strategy for global climate governance and drives broad and profound economic and social transformation. Energy consumption is a key determinant of carbon emissions, and the transportation sector, as the second-largest energy consumer, is an important source of carbon emissions. In 2021, energy consumption in China's transportation sector accounted for 10% of the total national energy consumption. Road transportation was the primary contributor to carbon emissions in this sector, accounting for over 70% of total transportation-related emissions (Xu et al., 2019; Zhang et al., 2022). Since the end of the last century, with the increase in urban residents' income levels, the number of motor vehicles in cities has been growing at a high rate, which is reflected in the structure of urban energy consumption as an increase in energy consumption due to motor vehicles (Xie and Wang, 2022). At the same time, the energy types used by most urban transportation systems remain relatively simple, with fuel-powered vehicles being the "main force" in urban transportation systems (Hu et al., 2021). Moreover, the current fuel standards and vehicle exhaust emission standards in China lag those of developed countries, and some vehicles' exhaust purification devices have not been functioning effectively, resulting in a continual rise in carbon dioxide emissions from motor vehicles. Under the practical requirements of the "dual carbon" goals, reducing carbon emissions in urban transportation has become a formidable task. At this stage, guiding microeconomic entities to choose low-carbon consumption behaviors is a key approach to solving this problem. Green behavioral choices in the transportation sector mainly involve promoting public transportation and

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clean transportation systems. In response, cities in developed regions have begun gradually constructing low-carbon transportation systems. Since 2009, national and local governments have used policy support measures to promote the development of new energy vehicles and the adoption of low-carbon transportation systems. They have also increased the proportion of electricity consumption in the urban energy structure through various means, which helps reduce urban dependence on fossil fuels. Meanwhile, exploring the green upgrading of transportation systems and whether the use of new low-carbon transportation systems can bring about carbon reduction effects has become an important topic in academic research.

With new energy vehicles (NEVs) as the backbone, China has been promoting the green upgrade of the transportation sector for over a decade. However, whether the long-standing promotion and use of new energy vehicles have effectively reduced carbon emissions across society and achieved the intended goals remains a question. This paper will use panel data from 115 Chinese cities from 2006 to 2020 to examine the impact, characteristics, and pathways of new energy vehicle promotion and use on regional carbon emissions. It is worth noting that in the international market, the primary types of new energy vehicles sold are battery electric vehicles (BEVs) and hybrid electric vehicles (HEVs). The EV Outlook report published by the International Energy Agency (IEA) includes only these two vehicle types in its sales statistics, reinforcing the legitimacy and broad recognition of this classification in the global market. Similarly, statistical data from the China Passenger Car Association and the Yearbook of Energy-Saving and New Energy Vehicles also focus primarily on BEVs and HEVs, further demonstrating their dominant position in the market. Therefore, this study considers only battery electric vehicles and hybrid electric vehicles.

The possible marginal contributions of this paper are as follows: (1) It integrates the market promotion of new energy vehicles and regional carbon emissions into the same analytical framework, studying the carbon reduction effects of China's new energy vehicles from the perspective of green upgrading of transportation systems. This provides empirical evidence for the formulation of green consumption policies. (2) Based on the effects of energy structure optimization and technological innovation, this paper verifies the mechanism through which the green upgrade in the transportation sector reduces urban carbon emissions, offering feasible solutions for governments to accelerate the promotion of new energy vehicles and decarbonize the transportation sector. (3) From the perspectives of heterogeneity and spatial spillover, this paper examines the heterogeneous impacts of different new energy vehicle models, varying vehicle energy consumption characteristics, and different application fields of new energy vehicles on urban decarbonization. It also analyzes the environmental externality spillover effects of new energy vehicles on surrounding areas, based on the spatial interactivity characteristics of transportation. (4) Using a multi-period DID model, this paper evaluates the effectiveness of China's first new energy vehicle promotion policy.

The innovations of this paper are as follows: (1) Methodological innovation: This paper identifies and constructs an effective instrumental variable—charging pile quantity—to mitigate possible reverse causality and other endogeneity issues between new energy vehicles and regional carbon emissions. (2) Data innovation: Using panel data on the sales of new energy vehicles from 115 Chinese cities between 2006 and 2020, the paper examines the specific impact of the green transformation and upgrade of transportation systems on regional carbon emission levels at a macro level. (3) Theoretical innovation: Based on the theories of externalities and spatial interaction, this paper constructs a general analytical framework for the impact of new energy vehicles on regional carbon emissions by analyzing the degree, transmission mechanisms, and specific characteristics of new energy vehicle adoption in the transportation sector.

The structure of the remaining chapters is as follows: Section 2 provides a literature review and theoretical analysis; Section 3 introduces the model and variable settings used in this study; Section 4 presents the analysis of baseline regression results, heterogeneity discussion, exploration of impact mechanisms, and spatial spillover effects; Section 5 offers further discussion on the policies for promoting the application of new energy vehicles; and Section 6 concludes the paper with policy recommendations.

Literature review and theoretical analysis

Literature review

Since the 1990s, scholars have started to explore the relationship between new energy vehicles (NEVs) and carbon emissions. Most scholars agree that the substitution of traditional fuel-powered vehicles by NEVs can effectively reduce carbon emissions from transportation (DeLuehi et al., 1989). Teixeira and Sodre (2016) evaluated the replacement of traditional fuel vehicles by NEVs in Brazil and found that the carbon emissions of NEVs are 10 times lower than those of traditional fuel-powered vehicles. Elshurafa and Peerbocus (2020) showed that in Saudi Arabia, each 1% increase in the deployment of NEVs leads to a 0.5% reduction in carbon emissions. Similar conclusions were drawn in studies conducted in the United States, China, and South Korea (Li et al., 2016; Jenn, 2020). Zhao and Sun (2022) discovered that China's NEV promotion policy has a dynamic spatial spillover effect on carbon emissions in the transportation sector. Zhao et al. (2021) found that there is a dual-threshold effect between capital allocation efficiency and vehicle carbon emissions. When the intensity of research and development (R&D) investment, the intensity of R&D personnel involvement, or the ratio of patents to R&D personnel is at a low level, improvements in capital allocation efficiency significantly increase vehicle carbon emissions. Xie et al. (2021) validated that NEV subsidy policies improve urban air quality, and the study found that for every 1% increase in subsidy size, air pollution is reduced by approximately 0.15%.

However, some scholars are more pessimistic about the carbon reduction effect of NEVs. For example, Holland et al. (2016) established a general equilibrium model based on discrete choice, and the authors argued that driving electric vehicles generates significant externalities because, in most cases, local electricity is supplied by power grids from other regions. As a result, most (91%) of the pollution caused by driving electric vehicles is "transferred" to other areas, while the pollution transfer ratio for fuel-powered vehicles is only 19%. A similar conclusion was reached by Li and An (2023), who found that in China, where the power structure has not yet decoupled from carbon emissions, the use of NEVs merely shifts carbon emissions from the vehicle operation process to the electricity production process. In practice, electric vehicles are still "driven by coal."

Based on the above analysis, the environmental benefits of NEVs have long been a focus of academic attention. However, existing studies have yet to reach a consensus. Most of the current literature examines the environmental impact of NEVs from a single perspective--such as life cycle analysis, policy promotion, or spatial spillover effects. Moreover, these studies often rely on a single indicator, such as carbon emissions or carbon intensity, and typically adopt policy dummy variables as the core explanatory variable. There remains a lack of empirical research assessing the actual effects of NEV

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promotion on urban carbon emissions. Overall, the absence of a systematic investigation into the relationship between NEVs and carbon emissions has indirectly contributed to the divergence of research conclusions.

Theoretical analysis

Energy structure optimization effect

Under the policy context of restricting the use and purchase of internal combustion engine vehicles, the green upgrading of the transportation sector--namely, the promotion and application of NEVs as the primary substitute for traditional fuel vehicles--can reduce the market share of internal combustion engine vehicles, thereby decreasing gasoline consumption and lowering urban carbon emissions. Prior to the emergence of NEVs, consumers could only choose internal combustion engine vehicles when purchasing cars. The introduction of NEVs has provided consumers with more diversified choices. On one hand, the Chinese government has vigorously promoted the adoption of NEVs through a series of policies including subsidies, tax reductions, purchase incentives, and priority road access. These measures have reduced consumers' purchase costs, increased the market attractiveness of NEVs, weakened the competitiveness of internal combustion engine vehicles, and compressed their market space. Moreover, according to the "2021 Bloomberg New Energy Finance's (BNEF) reports", the power battery--accounting for the largest share of NEV production costs (generally 39.8%)--significantly influences the pricing of NEVs. With advancements in battery technology, fluctuations in raw material prices, and economies of scale, global battery costs have declined steadily, from 684 USD/kWh in 2013 to 140 USD/kWh in 2020, further reducing the purchase cost of NEVs and enhancing their price competitiveness in the market. In addition, the operating costs of NEVs are generally lower than those of traditional internal combustion engine vehicles, including lower energy and maintenance costs (Liu et al., 2021). According to the 2019 BNEF's reports, with the continued decline in battery costs, NEVs have already gained a competitive advantage over internal combustion engine vehicles in terms of total cost of ownership. This economic attractiveness has encouraged more consumers to purchase and use NEVs, thereby reducing the market share of internal combustion engine vehicles and helping to lower fossil fuel consumption among urban vehicle fleets and improve their carbon emission performance. This mechanism is hereinafter referred to as the "energy structure optimization effect." Based on this, the study proposes the following hypothesis:

Hypothesis 1: The promotion and use of new energy vehicles can reduce urban carbon emissions by decreasing the consumption of gasoline and other fossil fuels, thereby exerting an energy structure optimization effect.

Technological innovation effect

Enterprises in the growth stage of an industry exhibit high sensitivity to market scale with respect to innovation activity, and foreseeable future demand can significantly stimulate both R&D investment and innovation output (Lv and Huang, 2021). According to the theory of demand-induced innovation, shifts in market demand serve as a key driver of technological advancement. When consumer and market preferences increasingly favor environmentally friendly and high-efficiency transportation tools, firms are incentivized to allocate resources toward technological R&D to meet these evolving needs. For low-carbon strategic emerging industries, such as the NEV sector, consumer

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demand is characterized by strong dynamism and has become an indispensable factor in analyzing the impact of demand on low-carbon innovation. In 2010, China formally designated its NEV industry as one of the seven strategic emerging industries. Generally, during the initial development stage of such low-carbon industries, market demand is relatively limited, necessitating government-led demonstration and promotion efforts to cultivate a foundational level of public-sector demand. This, in turn, helps local enterprises achieve technological diffusion and maturation. As industry transitions from nurturing to the growth phase, market demand becomes both large in scale and highly diversified, resulting in a surge in private consumption. This expansion in both the volume and quality of demand jointly accelerates low-carbon innovation. On one hand, the vast domestic demand environment fosters the development of advanced factor endowments among domestic firms and becomes a sustained driving force for technological innovation. The large demand scale encourages firms to increase R&D inputs, enabling internal economies of scale; meanwhile, it promotes specialized division of labor and concentrated innovation in niche technological areas, contributing to external economies of scale. The relaxation of restrictions on foreign capital entry further accelerates innovation through competitive pressure, and the clustering of global high-quality resources enhances the micro-level environment for innovation. On the other hand, sophisticated and demanding consumer expectations generate both pressure and direction for corporate technological upgrades and iterative development. In the short term, the domestic market size is generally an exogenous factor that firms cannot alter (Lin and Fu, 2022). Consequently, enterprises must adopt market-oriented competitive strategies tailored to the specific domestic demand context. Accompanying the trend of consumption upgrading, diversified and high-quality consumer demand inherently contains strong incentives for technological advancement.

Therefore, the growth in NEV sales continuously expands the market, improving the performance of businesses along the entire new energy vehicle industry chain. Using sales revenue, these companies can further invest in technological R&D, improve innovation levels, and strengthen consumer loyalty to NEVs. Moreover, as the green and low-carbon concept spreads and market orientation shifts, the increasing penetration of NEVs has attracted traditional car manufacturers to also transition towards NEVs. Facing market competition, traditional car companies are investing more in NEV technology research (Lu et al., 2021). For instance, taking the core technology of NEVs-“three electrics” (battery, motor, and electronic control) as an example (Li et al., 2022), the electronic control technology is key to the management of NEV power systems, which includes battery management systems, motor controllers, and vehicle controllers. This technology optimizes battery charging and discharging strategies, enhances battery life, improves energy utilization efficiency, and reduces energy loss. Advanced electronic control technologies also optimize NEV operational efficiency and energy usage, reducing unnecessary energy waste (Chan, 2007). Additionally, the increased sales of intelligent connected NEVs encourage car manufacturers to invest in R&D for intelligent driving and autonomous driving technologies. These innovations help vehicles intelligently analyze traffic conditions, reduce urban traffic congestion, and lower exhaust emissions (Zhao et al., 2022; Liu and Sun, 2023). Moreover, they enable vehicles to operate more efficiently, reducing energy consumption. Overall, the promotion of NEVs facilitates transportation technology innovation. The increase in NEV sales also improves manufacturers' performance, which further drives R&D investment, enhancing transportation technology. As transportation technology advances, urban traffic

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congestion will decrease, and exhaust emissions will be reduced. Based on this, the following hypothesis is proposed:

Hypothesis 2: An increase in NEV sales will improve transportation technology, thereby reducing urban carbon emissions.

The logical framework of this paper is shown in *Figure 1*.

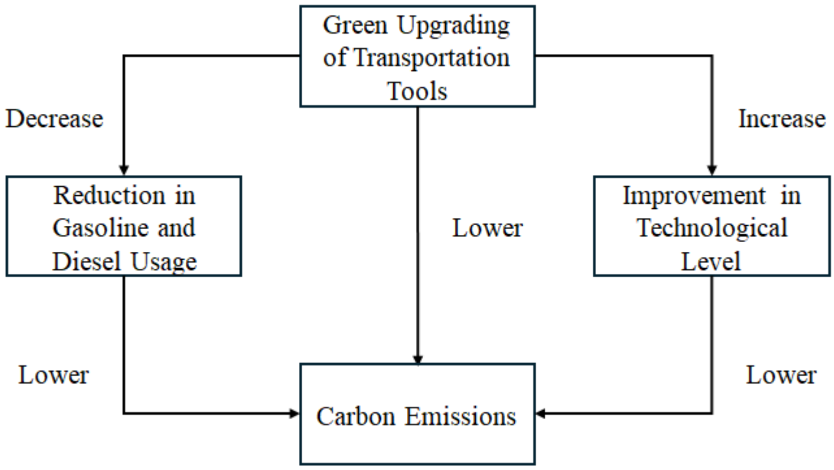

Figure 1. *Logical framework*

Empirical facts analysis

Electricity plays an indispensable role throughout the life cycle of BEVs, HEVs, and internal combustion engine vehicles (ICEVs). All three vehicle types require electricity during the manufacturing phase, and for NEVs in particular, electricity serves as the core energy source during operation. Consequently, electricity consumption significantly influences the life-cycle carbon emissions of NEVs. However, the environmental externalities of NEVs are highly dependent on the structure of electricity generation. For instance, if electricity is generated entirely from fossil fuels such as coal, the adoption of NEVs merely alters the pathway of carbon emissions, shifting them upstream to the electricity generation process rather than eliminating them. To systematically compare the life-cycle carbon emissions of NEVs and ICEVs under different electricity generation scenarios, this study adopts the methodology of Yang (2023), establishing three types of electricity structure scenarios: a baseline electricity mix scenario, a marginal electricity mix scenario, and a high-clean-energy scenario. Given the robust analytical foundation of the GREET model in evaluating life-cycle vehicle and fuel technologies, and its relatively comprehensive framework covering both vehicle and fuel cycles, this study utilizes GREET2021 (Wang et al., 2021) to simulate the life-cycle carbon emissions of the three vehicle types under these different scenarios. The selection of representative vehicle types and the parameter settings for life-cycle variables draw upon existing studies by Qiao et al. (2017), Wang et al. (2013), Sullivan et al. (2013), and Yang et al. (2021). To maintain consistency in temporal and spatial boundaries throughout the study, the baseline scenario adopts China's overall power generation mix in 2020, the marginal electricity scenario uses China’s newly added generation capacity in 2020, and the high-clean-energy scenario refers to estimates from the CHINA 2050 High Renewable Energy Penetration Scenario and Roadmap Study, which projects that clean energy will account for 85.7% of China’s electricity consumption under this scenario (as shown in *Table 1*).

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Table 1. *Electricity generation structure under three scenarios*

Electricity Source	Emission Factor (kg CO_2e/kWh)	Baseline Scenario (%)	Marginal Scenario (%)	High Clean Energy Scenario (%)
Coal-fired power	0.971	66.8	36.2	10.0
Hydropower	0.035	17.4	17.2	14.5
Nuclear power	0.014	4.7	6.0	4.3
Wind power	0.006	6.0	20.7	35.4
Solar power	0.048	3.4	12.6	28.5
Biomass power	0.230	1.7	7.3	7.3

Figure 2 illustrates the life-cycle carbon emissions of ICEVs, BEVs, and HEVs under different electricity generation structure scenarios. The arrows in the figure represent the direction of change in vehicle life-cycle carbon emission intensity as the electricity mix shifts. From the baseline electricity mix to the marginal mix and then to the high-clean-energy scenario, the carbon intensity of electricity production decreases from 0.636 kg CO_2e/kWh to 0.382 kg CO_2e/kWh and further to 0.135 kg CO_2e/kWh. As shown in the *Figure 2*, the changes in the electricity structure have a significantly greater impact on BEVs and HEVs than on ICEVs. This is primarily because BEVs and HEVs experience a substantial reduction in carbon emissions during the fuel cycle of the use phase, whereas ICEVs only witness marginal reductions in indirect emissions stemming from electricity consumption during the manufacturing and maintenance phases (Yang et al., 2023).

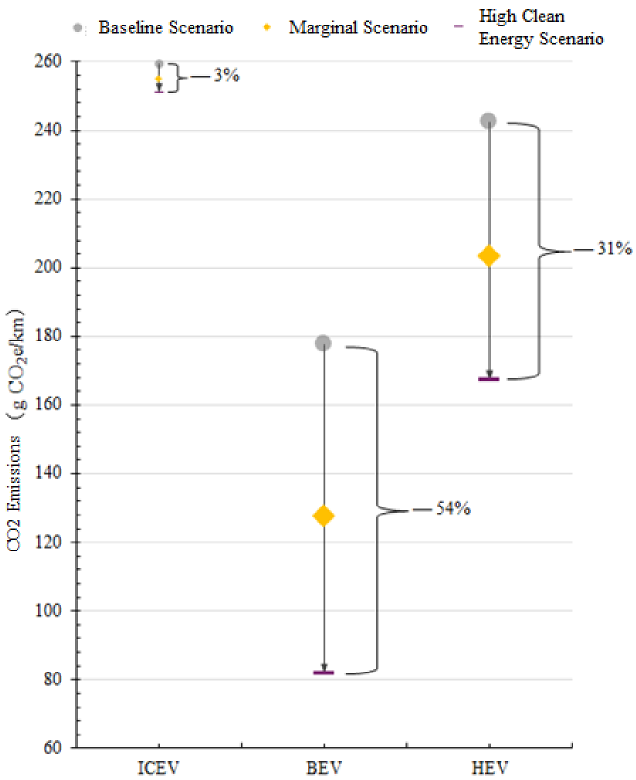

Figure 2. *Lifecycle carbon emissions of ICEV, BEV, and HEV under different electricity generation structures*

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For BEVs and HEVs, transitioning from the baseline to the high-clean-energy scenario leads to a 54% and 31% decrease in life-cycle carbon intensity, respectively. Their corresponding carbon footprints drop from 178 g/km to 81.5 g/km for BEVs, and from 242 g/km to 167 g/km for HEVs. In contrast, ICEVs exhibit only a modest reduction in carbon emissions from 260 g/km to 251 g/km--a mere 3% decrease. Under the marginal electricity scenario, BEVs and HEVs emit 50% and 20% less carbon, respectively, compared to ICEVs. In the high-clean-energy scenario, the emissions reduction potential becomes even more pronounced, with BEVs and HEVs achieving 68% and 33% reductions relative to ICEVs.

In summary, the impact of electricity generation structure on life-cycle emissions varies substantially across vehicle types. While transitioning to a cleaner electricity mix is a gradual process, BEVs consistently demonstrate a clear carbon reduction advantage across all scenarios--especially under high renewable penetration. As China continues to decouple its power sector from fossil fuels, the carbon mitigation potential of NEVs, particularly BEVs, is expected to become increasingly significant.

Materials and methods

Model selection

This study draws on the STIRPAT model proposed by Dietz and Rosa (1997). The STIRPAT model allows the coefficients to be estimated as parameters and also permits the appropriate decomposition of influencing factors (Dietz and Rosa, 1994). It has been widely used in environmental benefit assessments, particularly in analyzing factors affecting air pollution and carbon emissions (Shao et al., 2010). Based on the logarithmic approach of the STIRPAT model, the baseline econometric regression model is set as shown in *Equation (1)*.

$$lnC_{it} = a_0 + a_1 lnEV_{it} + \sum_{j=2}^{11} a_j X_{it} + \mu_i + \gamma_t + \varepsilon_{it} \quad \text{(Eq.1)}$$

In this model, a_j(j=0,1,…,11) are the parameters to be estimated, with μ_i representing the city-fixed effects and γ_t representing the time-fixed effects. The random disturbance term is represented by ε_{it}, where i refers to cities and t refers to years. This equation serves as the baseline econometric model, and robust standard errors are adjusted in all regression analyses.

Variable selection and data sources

Dependent variables

Following Zhang and Zhong (2022), the total carbon dioxide emissions of each city are used to represent regional carbon emissions. In line with Li and Qi's (2011) research design, both carbon emissions levels (denoted as *C*) and carbon emission intensity (denoted as *CI*) are considered as dependent variables in the baseline regression, aiming to provide a more comprehensive analysis (later regressions will use carbon emissions levels as the dependent variable).

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Independent variable

The key independent variable is the scale of the promotion and use of new energy vehicles, represented by the annual sales of new energy vehicles in each city in China (denoted as *EV*).

Control variables

To control for the impact of other factors on regional carbon emissions, this study introduces several key variables that may affect urban carbon emissions, based on a review of the literature and real-world conditions (Yuan and Zhu, 2018; Li et al., 2020). These variables are: (1) Economic Level (*pGDP*); (2) Education Level (*Education*); (3) Green Innovation (*Greentec*); (4) Population Density (*Density*); (5) Industrial Upgrading (*Upind*); (6) Government Intervention (Finance); (7) Level of Openness (*Open*); (8) Fixed Asset Investment (*Invest*); (9) Vehicle Restrictions (*Road*).

Mechanism variables

(1) Energy Structure Optimization Effect (*lnGas_Share*): Measured by the share of gasoline and diesel consumption in the total energy consumption of the city.

(2) Technological Innovation Effect (*lnPatent*): Measured by the number of patent applications related to new energy vehicles in each sample city annually.

Sample data and descriptive statistics

Based on data availability, the sample data for this study includes panel data from 75 cities in China from 2006 to 2020. Missing data is supplemented using linear fitting or interpolation methods. In addition, following the logarithmic transformation approach of the STIRPAT model, and in order to eliminate the effects of heteroscedasticity and differences in measurement scales among different variables, all explanatory variables, explained variables, and control variables are logarithmically transformed. *Table 2* presents the names, symbols, definitions, and data sources of each variable.

Results

Baseline regression

Table 3 presents the results based on the regression of formula (1). Hausman and F-tests show that fixed effects significantly outperform random effects, and fixed effects are also clearly superior to the mixed regression model. Panel A corresponds to the dependent variable of urban carbon emission levels, while Panel B corresponds to the dependent variable of urban carbon emission intensity. The regression results are reported step-by-step by adding control variables sequentially. In column (1) and column (3) of *Table 3*, the results of the separate regressions for the core independent variable and the two dependent variables are shown. Columns (2) and (4) of *Table 3* report the regression results after the inclusion of control variables. According to the results in columns (2) and (4) of *Table 3*, the coefficients of the variable *lnEV* at the 1% significance level are -0.0514 and -0.0592, respectively, indicating that for every 1% increase in the scale of NEV promotion, the region's carbon emission level, and carbon emissions per unit of GDP decreased by 0.0514% and 0.0592%, respectively. In other words, the increase in the number of new energy vehicles reduces the carbon emission levels in the region. The

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theoretical hypothesis H1 is preliminarily confirmed. The regression coefficients of other control variables are consistent with existing studies (Saldivia et al., 2020; Zhong and Wang, 2022).

Table 2. *Variable names, symbols, meanings, and data sources*

Variable Type	Variable Name	Variable Symbol	Variable Meaning	Data Source
Dependent Variables	Carbon Emissions Level	*C*	Annual carbon dioxide emissions of the city. Unit: tons	Shan et al. (2022) China City Statistics Yearbook
	Carbon Emission Intensity	*CI*	The ratio of annual carbon dioxide emissions to the city's GDP. Unit: tons per ten thousand yuan	
Independent Variable	New Energy Vehicle Promotion and Usage	*EV*	Annual sales of new energy vehicles in the city. Unit: vehicles	Energy Conservation and New Energy Vehicle Yearbook
Control Variables	Economic Level	*pGDP*	Annual per capita GDP level of the city. Unit: %	China City Statistics Yearbook National Intellectual Property Database City Statistical Bureaus Provincial, Autonomous Region, and Municipality Statistical Yearbooks City Government and Public Security Bureau Official Websites
	Education Level	*Education*	The ratio of the number of undergraduate students to the total population in the city. Unit: %	
	Green Technology Innovation	*Greentec*	Total number of green patent applications in the city's WIPO international patent classification green list for the year. Unit: items	
	Population Density	*Density*	Population density per unit area in the city. Unit: ten thousand people per square kilometer	
	Industrial Upgrading	*Upind*	The ratio of tertiary industry output value to secondary industry output value in the city. Unit: %	
	Government Intervention	*Finance*	The ratio of the general public budget to the city's GDP for the year. Unit: %	
	Level of Openness	*Open*	The ratio of foreign investment amount to the city's GDP for the year. Unit: %	
	Fixed Asset Investment	*Invest*	Annual fixed asset investment amount in the city. Unit: ten thousand yuan	
	Vehicle Restrictions	*Road*	Whether the city implemented fuel vehicle restriction policies for the year (dummy variable): Yes = 1; No = 0	
Mechanism Variables	Energy Structure Optimization Effect	*Gas_Share*	The ratio of gasoline and diesel consumption to total energy consumption in the city. Unit: %	China Energy Statistical Yearbook
	Technological Innovation Effect	*Patent*	Number of new energy vehicle patent applications in the city for the year. Unit: items	Qichacha Patent Database

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Table 3. *Baseline regression results*

Variable Name	Panel A:lnC		Panel B:lnCI	
	(1)	(2)	(3)	(4)
lnEV	-0.0581*** (0.0161)	-0.0514*** (0.0160)	-0.0611*** (0.0192)	-0.0592*** (0.0158)
lnpGDP		0.0262 (0.0497)		-0.1871*** (0.0491)
lnEducation		-0.1152*** (0.0345)		-0.1115*** (0.0340)
lnGreentec		-0.0295 (0.0220)		-0.0157 (0.0218)
lnDensity		0.3383*** (0.1057)		-0.0591 (0.1043)
lnUpind		-0.1549** (0.0618)		-0.1705*** (0.0610)
lnFinance		-0.1296* (0.0713)		-0.2843*** (0.0704)
lnOpen		-0.0061 (0.0122)		-0.0014 (0.0121)
lnInvest		0.1433** (0.0637)		-0.2868*** (0.0629)
Road		-0.0408* (0.0247)		-0.0456* (0.0244)
Constant	8.7180*** (0.1084)	6.3388*** (0.9496)	1.0976*** (0.0723)	6.8527*** (0.9375)
City Fixed Effect	YES	YES	YES	YES
Time Fixed Effect	YES	YES	YES	YES
Observations	1125	1125	1125	1125
F-Statistic	224.06	110.96	124.04	112.92
Adj-R^2	0.9441	0.9483	0.9322	0.9401

Note: (1) ***, **, * represent statistical significance at the 1%, 5%, and 10% levels, respectively. The values in parentheses are robust standard errors

Robustness test

(1) Change the data source of the dependent variable. The carbon emission data from the EU Emissions Database for Global Atmospheric Research (EDGAR) is used to replace the city's carbon emission levels in the baseline model. As shown in column (1) of *Table 4*, the carbon reduction effect of new energy vehicles remains robust.

(2) Change the proxy for the core independent variable. Following Li et al. (2022), the ratio of annual NEV sales to city population (denoted as *lnperEV*) replaces the core independent variable in equation (1). The results in column (2) of *Table 4* show that the coefficient of *lnperEV* remains significantly negative at the 1% level.

(3) Change the sample period. Using panel data from 2013 to 2020, following China's further promotion of NEVs, the regression results in column (3) of *Table 4* show the baseline results remain robust.

(4) Exclude provincial capital cities. Excluding provincial capitals from the sample, the results in column (1) of *Table 4* show that the coefficient of *lnEV* is significantly negative at the 5% level.

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(5) Difference generalized method of moments (GMM). Introducing the first-order lag of city carbon emissions (denoted as $lnC_{(t-1)}$) in the baseline model to construct a dynamic panel model. The results in column (5) of *Table 4* show that Difference GMM passes the autocorrelation (AR) and Sargan over-identification tests, with the coefficient of *lnEV* significantly negative at the 1% level.

(6) System GMM. Using System GMM to test the impact of NEV promotion on urban carbon emissions, the results in column (6) of *Table 4* show that the coefficient of *lnEV* remains significantly negative, confirming the robustness of the baseline regression results.

Table 4. *Robustness test*

Variable Name	Change the data source of the dependent variable	Change the proxy for the core independent variable	Change the sample period	Exclude provincial capital cities	Difference GMM	System GMM
	(1)	(2)	(3)	(4)	(5)	(6)
$lnC_{(t-1)}$					0.6295***	0.8683***
					(0.0475)	(0.0476)
lnEV	-0.0096**		-0.0692***	-0.0436**		
	(0.0041)		(0.0151)	(0.0189)		
lnperEV		-0.0529***				
		(0.0161)				
Constant	14.5925***	5.9250***	9.3105***	9.8261***		-2.3796***
	(0.2432)	(0.9440)	(1.0940)	(1.5218)		(0.5492)
Control Variable	YES	YES	YES	YES	YES	YES
City Fixed Effect	YES	YES	YES	YES	YES	YES
Time Fixed Effect	YES	YES	YES	YES	YES	YES
$Adj\text{-}R^2$	0.9959	0.9483	0.9617	0.9451		
AR(1)					0.001	0.001
AR(2)					0.736	0.615
Sargan					0.124	0.786
Observations	1125	1125	600	725	975	1050

Note: (1) ***, **, * represent statistical significance at the 1%, 5%, and 10% levels, respectively. The values in parentheses are robust standard errors

Endogeneity

Considering the potential omitted variables or reverse causality between the promotion of new energy vehicles and regional carbon emissions, this section uses the number of charging stations in each city as an instrumental variable to address this endogeneity. On one hand, the level of charging infrastructure coverage determines the scale of NEV promotion (Franke and Krems, 2013), and the improvement of charging infrastructure has significantly increased NEV sales in China (Li and Liu, 2023). Therefore, they are correlated. On the other hand, charging infrastructure, as an important pillar of green transportation energy, does not directly affect urban carbon emissions (Li et al., 2022), ensuring homogeneity.

In the construction of the instrumental variable, the number of charging stations is log-transformed to reduce errors caused by dimensional issues, and a one-period lag (denoted

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as $lnCharger_{t-1}$) is used to alleviate contemporaneous endogeneity. The data on charging stations comes from the "Energy Conservation and New Energy Vehicle Yearbook." The regression results in *Table 5* show that the coefficient of $lnCharger_{t-1}$ is significantly negative at the 1% level, and the variable passes both the exclusion test and the weak instrument test. Furthermore, the coefficient of *lnEV* remains largely unchanged, further confirming that the promotion of new energy vehicles is a key factor in reducing urban carbon emissions.

Table 5. *Instrumental variable 2SLS estimation results*

Variable Name	First-stage regression result lnEV	Second-stage regression result lnC
	(1)	(2)
$lnCharger_{(t-1)}$	0.2153*** (0.0175)	
lnEV		-0.0768*** (0.0297)
Cragg-Donald Wald F statistic	150.59(16.38)	
Kleibergen-Paap Wald rk F statistic	133.34	
Control Variable	YES	YES
City Fixed Effect	YES	YES
Time Fixed Effect	YES	YES
Observations	1050	1050

Note: (1) ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The numbers in parentheses indicate robust standard errors. (2) The weak instrument F-statistic values are reported inside parentheses, showing the critical value for identifying the instrument's weak error margin

Heterogeneity analysis

Vehicle type heterogeneity analysis

To further explore the impact of different types of new energy vehicles on urban carbon emissions, this paper divides new energy vehicles into two categories: pure electric vehicles (BEV) (denoted as *lnBEV*) and hybrid electric vehicles (HEV) (denoted as *lnHEV*). These variables are introduced into model (1) to replace *lnEV* and regress separately. The results are shown in columns (1) and (2) of *Table 6*. The coefficient for *lnBEV* is significant at the 1% level, indicating that for every 1% increase in the sales of pure electric vehicles, local carbon emissions decrease by 0.0674%. However, the coefficient for *lnHEV* is not significant, which is consistent with existing research (Yang et al., 2021). The main reason is the fundamental difference in the driving mechanisms between the two types of vehicles. The term HEVs generally refers to gasoline-electric hybrids, which utilize both a conventional internal combustion engine (diesel or gasoline) and an electric motor as power sources. In some cases, the internal combustion engine is modified to operate on alternative fuels, such as compressed natural gas, propane, or ethanol. However, given that the energy conversion efficiency of electric motors is significantly higher than that of internal combustion engines (Faria et al., 2012), electric motors can deliver more mileage per unit of energy input, thereby further reducing carbon emissions.

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Table 6. *Heterogeneity analysis of carbon reduction effects of BEV and HEV*

Variable Name	**BEV**	**HEV**
	(1)	**(2)**
lnBEV	-0.0674***	
	(0.0153)	
lnHEV		-0.0081
		(0.0134)
	(0.0245)	(0.0249)
Constant	6.5159***	6.0446***
	(0.9447)	(0.9528)
Control Variable	YES	YES
City Fixed Effect	YES	YES
Time Fixed Effect	YES	YES
Observations	1125	1125
Adj-R^2	0.9489	0.9475

Note: (1) ***, **, * represent statistical significance at the 1%, 5%, and 10% levels, respectively. The values in parentheses are robust standard errors

Heterogeneity analysis of vehicle energy consumption levels

New energy vehicles with different fuel consumption levels may have varying impacts on urban carbon emissions (Miotti et al., 2016). For pure electric vehicles, the carbon reduction effect depends on energy consumption levels (Nordelöf et al., 2019). For hybrid vehicles, it depends on both the energy consumption in non-depleted battery states and the fuel consumption at minimum charge states.

To examine this, interaction terms for pure electric vehicle energy consumption (*lnBEV*×*lnEEC*) and hybrid vehicle consumption levels (*lnHEV*×*lnCD*, *lnHEV*×*lnCS*) are added to the baseline model. The sample is also grouped based on mean energy consumption levels for each type (*Group_BEV*/*Group_HEV* = 1 for above the mean, 0 for below). Data is sourced from the "Annual Report on Fuel Consumption of Chinese Passenger Vehicles."

Results in *Table 7* show that in columns (1) and (2), *lnBEV*×*lnEEC* and *lnBEV*×*Group_BEV* are positive and significant at the 1% level, indicating that higher energy consumption in pure electric vehicles reduces their carbon reduction effect.

In columns (3) to (5), the coefficients of *lnHEV*×*lnCD*, *lnHEV*×*lnCS*, and *lnBEV*×*Group_HEV* are significant, with *lnCD* and *lnCS* having opposite signs to *lnHEV*, confirming the significant impact of energy consumption and fuel use on hybrid vehicles' carbon reduction. Reducing energy consumption and advancing clean power grids is crucial for maximizing the carbon reduction effects of new energy vehicles.

Heterogeneity analysis of public sector and subfields

Public transportation plays a major role in urban travel. In cities with higher levels of new energy transformation in the public sector, the carbon footprint of public transportation is lower, aiding carbon reduction. This study divides cities based on the mean share of new energy vehicles in the public sector (*Public* = 1 if above the mean, *Public* = 0 if below) and adds an interaction term with the core variable into the baseline model (denoted as *lnEV*×*Public*) for regression. The results are in column (1) of *Table 8*. The public sector is further divided into five areas: buses (denoted as *lnBus*), government

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vehicles (denoted as *lnGov*), taxis (denoted as *lnTaxi*), car rentals (denoted as *lnLease*), and logistics vehicles (denoted as *lnLogistics*), with the private sector as a comparison (denoted as *lnPrivate*). Results are shown in columns (2) to (7).

Table 7. *Differences in the impact of energy consumption levels on carbon reduction effects for different vehicle types*

Variable Name	**BEV**		**HEV**		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
lnBEV	-0.2967*** (0.0787)	-0.0688*** (0.0152)			
lnEEC	0.9925*** (0.2265)				
lnBEV×lnEEC	0.0838*** (0.0282)				
lnBEV×Group_BEV		0.0351** (0.0164)			
lnHEV			-0.4577*** (0.1050)	-0.2529*** (0.0575)	-0.0172 (0.0135)
lnCD			0.9796*** (0.3068)		
lnHEV×lnCD			0.1436*** (0.0333)		
lnCS				0.8447*** (0.2976)	
lnHEV×lnCS				0.1269*** (0.0290)	
lnHEV×Group_HEV					0.0551*** (0.0144)
Constant	9.9192*** (1.4078)	7.2029*** (1.0242)	9.6424*** (1.6943)	8.2058*** (1.3939)	6.6514*** (1.0235)
Control Variable	YES	YES	YES	YES	YES
City Fixed Effect	YES	YES	YES	YES	YES
Time Fixed Effect	YES	YES	YES	YES	YES
Observations	1125	1125	1125	1125	1125
Adj-R^2	0.9495	0.9492	0.9488	0.9489	0.9485

Note: (1) ***, **, * represent statistical significance at the 1%, 5%, and 10% levels, respectively. The values in parentheses are robust standard errors

As shown in column (1) of *Table 8*, regions with higher public sector electrification levels show better carbon reduction effects for new energy vehicles. In columns (2) to (6), except for *lnGov* and *lnLease*, *lnBus*, *lnTaxi*, and *lnLogistics* are significantly negative, indicating a strong link between electrification in these areas and carbon reduction. By the end of 2020, new energy buses, taxis, and logistics vehicles numbered 466,000, 132,000, and 430,000, respectively, with significantly higher annual mileage than private or government cars (Lin et al., 2009). The public sector, led by buses, taxis, and logistics vehicles, has great potential for carbon reduction. As the share of new energy vehicles in these areas increases, the carbon reduction effect will grow. Additionally, column (7) shows that new energy private cars remain key to carbon reduction.

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Table 8. *Heterogeneity analysis of carbon reduction effects of new energy transformation in the public sector and its subfields*

Variable Name	**Public Sector New Energy Transformation Level**	**New Energy Buse**	**New Energy Government Vehicle**	**New Energy Taxi**	**New Energy Rental Vehicles**	**New Energy Logistics Vehicles**	**New Energy Private Cars**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
lnEV	-0.0295*** (0.0081)						
lnEV×Public	-0.0247*** (0.0096)						
lnBus		-0.0102** (0.0048)					
lnGov			0.0043 (0.0049)				
lnTaxi				-0.0117*** (0.0045)			
lnLease					-0.0078 (0.0048)		
lnLogistics						-0.0109** (0.0049)	
lnPrivate							-0.0198*** (0.0062)
Constant	6.3554*** (0.9942)	6.0912*** (0.9968)	6.0459*** (0.9933)	6.3151*** (0.9936)	6.1324*** (0.9918)	6.1349*** (0.9898)	6.4930*** (0.9944)
Control Variable	YES	YES	YES	YES	YES	YES	YES
City Fixed Effect	YES	YES	YES	YES	YES	YES	YES
Time Fixed Effect	YES	YES	YES	YES	YES	YES	YES
Observations	1125	1125	1125	1125	1125	1125	1125
Adj-R^2	0.9487	0.9475	0.9475	0.9479	0.9477	0.9479	0.9482

Note: (1) ***, **, * represent statistical significance at the 1%, 5%, and 10% levels, respectively. The values in parentheses are robust standard errors

Spatial spillover effects analysis

Due to the regional interactions in the transportation sector, and based on spatial interaction theory, new energy vehicles, like other vehicles, are highly mobile, with consumers potentially coming from both local and neighboring regions (Hu et al., 2020). This requires considering the spatial spillover effects of new energy vehicle promotion on carbon emissions. Using the sample data and previous analysis, a spatial weight matrix combining economic and geographic distances is created. The spatial distances between cities are obtained from the *Shp* file, and the latitude and longitude are matched to the data. Additionally, a geographically nested matrix, *W1*, is built based on the per capita GDP of the cities. Before testing the spillover effect with a spatial econometric model, Moran's I is used to identify spatial correlation (Moran, 1950), as shown in *Table 9*. The global Moran's I index for carbon emissions and new energy vehicle promotion from 2006 to 2020 has consistently been greater than zero, showing an increasing trend, indicating significant spatial correlation.

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Table 9. *Global Moran's I index for carbon emission levels and new energy vehicle promotion across regions*

Year	lnC		lnEV	
	Moran's I	P Value	Moran's I	P Value
2006	0.1738	0.0320	0.1936	0.0183
2007	0.2147	0.0091	0.1107	0.0489
2008	0.2428	0.0034	0.0878	0.0347
2009	0.2321	0.0050	0.1419	0.0749
2010	0.2302	0.0052	0.2139	0.0099
2011	0.2607	0.0018	0.2441	0.0034
2012	0.2720	0.0012	0.1791	0.0269
2013	0.2579	0.0020	0.2881	0.0006
2014	0.2539	0.0023	0.4074	0.0000
2015	0.2779	0.0009	0.3690	0.0000
2016	0.3145	0.0002	0.2773	0.0010
2017	0.3060	0.0003	0.2883	0.0007
2018	0.3098	0.0003	0.3153	0.0002
2019	0.2728	0.0011	0.3048	0.0003
2020	0.2708	0.0012	0.3101	0.0003

Before conducting spatial econometric regression, the spatial effect model must be tested using the LM, LR, Wald, and Hausman tests (Liu et al., 2020). The results in *Table 10* show that the spatiotemporal double fixed SDM model used in this paper is robust.

Table 10. *Spatial econometric model testing results*

Methods	Statistic	P Value
LM-Error	48.92	0.000
Robust LM-Error	4.74	0.029
LM-Lag	52.43	0.000
Robust LM-Lag	8.25	0.004
LR-SDM-SEM	53.12	0.000
LR-SDM-SAR	59.68	0.000
LR-Time Fixed	41.85	0.000
LR-Spatial Fixed	46.32	0.000
Hausman	92.70	0.000
Wald-SDM/SEM	53.48	0.000
Wald-SDM/SAR	55.52	0.000

The SDM model is shown in *Equation (2)*, where α is the constant, ρ is the spatial autocorrelation coefficient (ranging from [-1,1]), ω_{it} is the spatial weight matrix, and θ is the coefficient vector. Other variables are defined in *Equation (1)*.

$$lnC_{i,t} = \alpha + \rho \sum_{j=1}^{n} \omega_{i,t} lnC_{i,t} + \beta \left(lnEV_{i,t} + \sum_{i=1}^{n} X_{i,t} \right) + \theta \sum_{j=1}^{n} \omega_{i,t} \left(lnEV_{i,t} + \sum_{i=1}^{n} X_{i,t} \right) + \mu_i + \gamma_t + \varepsilon_{it} \tag{Eq.2}$$

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Regression results based on *Equation (2)* are in *Table 11*. Column (1) shows results using the geographically nested matrix *W1*, where *lnEV* and *WlnEV* are significantly negative at the 1% level, and the spatial spillover effect ρ is significantly positive, indicating the carbon reduction effect of new energy vehicle promotion has spatial spillover characteristics. Column (2) replaces the spatial weight matrix with a geographic distance matrix. Column (3) re-estimates *lnC* after trimming at the 1% and 99% quantiles. Column (4) adds a city × time trend term to the baseline model, and the results show the coefficients remain robust.

Table 11. *Regression results of the spatial effects of new energy vehicle promotion on carbon emissions*

Variable Name		Baseline Regression	Change Spatial Weight Matrix	Remove Outliers	Consider Time-Varying Factors Across Different Cities
		(1)	(2)	(3)	(4)
lnEV		-0.0471***	-0.0488***	-0.0503***	-0.0525***
		(0.0153)	(0.0153)	(0.0150)	(0.0154)
WlnEV		-0.0507***	-0.0414**	-0.0398**	-0.0515**
		(0.0186)	(0.0184)	(0.0188)	(0.0204)
rho		0.1966**	0.3135**	0.2005**	0.2179*
		(0.1001)	(0.1422)	(0.1009)	(0.1305)
sigma2_e		0.0293***	0.0292***	0.0280***	0.0291***
		(0.0015)	(0.0015)	(0.0014)	(0.0015)
lnEV Spatial effect decomposition	Direct effect	-0.0491***	-0.0490***	-0.0495***	-0.0515***
		(0.0158)	(0.0158)	(0.0154)	(0.0160)
	Indirect effect	-0.0372***	-0.0227*	-0.0277**	-0.0303**
		(0.0130)	(0.0136)	(0.0135)	(0.0139)
	Total effect	-0.0863***	-0.0717**	-0.0771**	-0.0818***
		(0.0282)	(0.0334)	(0.0367)	(0.0316)
Control Variable		YES	YES	YES	YES
City Fixed Effect		YES	YES	YES	YES
Time Fixed Effect		YES	YES	YES	YES
City×Time Trend		NO	NO	NO	YES
Observations		1125	1125	1125	1125
R^2-*within*		0.0058	0.0028	0.0401	0.0198

Note: (1) ***, **, * represent statistical significance at the 1%, 5%, and 10% levels, respectively. The values in parentheses are robust standard errors

The spatial effect decomposition shows that the carbon reduction effect of new energy vehicle promotion has a spatial spillover effect. This is due to the replacement of traditional vehicles and optimization of energy use, which improves high-pollution development models (Dong and Liu, 2020). From the ratio of indirect effects to total effects (43.11%), the spillover effect plays a critical role in the low-carbon transformation of the transportation sector and cities. The feedback effect of *lnEV* is -0.0020 (Feedback effect refers to the influence of the independent variable *X* in region A on the dependent variable Y_b in neighboring region B, which in turn affects the dependent variable Y_a in region A. The calculation formula is: Feedback effect = Direct effect - Spatial econometric model regression coefficient), meaning that as neighboring regions' new

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energy vehicle numbers grow, it also reduces emissions in the original region, creating a positive feedback loop for sustainable development, aligning with the virtuous cycle of sustainability.

Mechanism test

Based on the method of Baron and Kenny (1986), this paper constructs the following pathway test models (shown as *Equations (3) and (4)*).

$$M_{it} = c_0 + \alpha lnEV_{it} + \sum_g \beta_g X_{it} + \mu_i + \gamma_t + \varepsilon_{it} \tag{Eq.3}$$

$$lnC_{it} = c_1 + a_2 lnEV_{it} + \lambda_n M_{it} + \sum_k \beta_k X_{it} + \mu_i + \gamma_t + \varepsilon_{it} \tag{Eq.4}$$

Here, M_{it} represents the path variables for the impact of new energy vehicle promotion on urban carbon emissions, including the share of gasoline and diesel consumption (denoted as *lnGas_Share*) and the level of innovation output (denoted as *lnPatent*). Other variables are defined in equation (1). The results of testing the energy structure optimization effect and technological innovation effect are shown in *Table 12*.

Table 12. *Pathway test results for energy structure optimization effect and technological innovation effect*

Variable Name	Energy Structure Optimization Effect		Technological Innovation Effect	
	lnGas_Share	lnC	lnPatent	lnC
	(1)	(2)	(3)	(4)
lnEV	-0.0251***	-0.0462***	0.3011***	-0.0443***
	(0.0076)	(0.0162)	(0.0568)	(0.0164)
lnGas_Share		0.2068***		
		(0.0583)		
lnPatent				-0.0236**
				(0.0113)
Constant	-0.7072***	6.4972***	5.9696***	6.6741***
	(0.0411)	(0.9986)	(2.2894)	(0.9957)
Control Variable	YES	YES	YES	YES
City Fixed Effect	YES	YES	YES	YES
Time Fixed Effect	YES	YES	YES	YES
Observations	1125	1125	1125	1125
Adj-R^2	0.9352	0.9482	0.8744	0.9485

Note: (1) ***, **, * represent statistical significance at the 1%, 5%, and 10% levels, respectively. The values in parentheses are robust standard errors

(1) Energy Structure Optimization Effect. As shown in columns (1) and (2) of *Table 12*, the promotion of new energy vehicles and the share of gasoline and diesel consumption (*lnGas_Share*) are significant at the 1% level. This reveals that the increase in new energy vehicle sales, through demonstration effects, improves China's energy consumption structure, reduces the use of gasoline and diesel in road transport sources, and promotes cleaner energy development, effectively lowering urban carbon emissions.

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In economics, demonstration theory posits that consumers' behavior is influenced by the consumption levels of surrounding groups. Existing research also indicates that, beyond income level, individuals' consumption behavior is shaped by that of others. For instance, seeing a popular style of clothing or hairstyle on the internet may lead individuals to purchase similar apparel or adopt the same hairstyle—this phenomenon is referred to as the "demonstration effect." As a type of consumer good, NEVs are also subject to such influence, where individual decisions to adopt NEVs are shaped by observing the purchasing behavior of peers. When consumers notice that NEVs are widely adopted among those around them or across social groups, they are likely to exhibit herd behavior in making similar choices. The "others" in this context include both private consumers and public-sector users. With the increasing variety of NEV products available on the market--from compact urban models to luxury electric vehicles--functionality has diversified significantly, meeting the demands of various consumer segments. The user experience of NEVs has become comparable to, or even superior to, that of traditional internal combustion engine vehicles. As a result, NEV sales have continued to rise, and their visibility in daily transportation has grown accordingly. This increasing prevalence reinforces consumer confidence in choosing NEVs under the influence of the demonstration effect, displacing internal combustion engine vehicles, reducing fossil fuel use in the transport sector, and thereby directly contributing to the reduction of carbon emissions from fuel consumption.

(2) Technological Innovation Effect. As shown in columns (3) and (4) of *Table 12*, the coefficient for the impact of new energy vehicle promotion on the number of new energy vehicle patents is significantly positive at the 1% level, indicating that a 1% increase in new energy vehicle sales leads to a 0.3011% increase in the number of patents for new energy vehicle innovations. This confirms the demand-induced innovation theory. Additionally, the coefficient of innovation output level *lnPatent* is significantly negative at the 5% level, suggesting that an increase in patent output improves vehicle operational efficiency and energy consumption, enhances traffic sensing and smart driving capabilities, alleviates traffic congestion, and indirectly reduces exhaust emissions, achieving energy saving and emission reduction. The underlying reason lies in the fact that green transportation technology innovation provides practical means for carbon reduction from a technological perspective. It empowers the green transformation of production and lifestyles with greater efficiency, thereby reducing carbon emissions. On one hand, within enterprises, green transportation technological innovation enhances resource utilization efficiency during the production process and reduces pollution control costs. This enables enterprises to adopt low-carbon and clean energy in the development of new products, decreasing reliance on traditional energy sources at the production level and ultimately achieving emission reduction targets. As the level of green transportation innovation improves, the allocation of production factors and specialization become more rational, enhancing workers' spatial comfort and promoting the dynamic allocation efficiency and quality of production factors. This shift accelerates the transition of production methods toward high-efficiency and intensive models, thereby facilitating the green and low-carbon transformation of enterprise operations. On the other hand, green transportation technology innovation and its applications offer the public a wider array of environmentally friendly transportation products and services, thereby fostering urban green development. It increases the proportion of clean energy use in daily life, reduces reliance on traditional energy sources, and guides consumers toward low-carbon and sustainable consumption patterns. Furthermore, green transportation innovation also

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positively influences the development of renewable energy. By profoundly transforming people’s lifestyles, such innovation not only enhances convenience but also contributes positively to urban carbon emission reduction and environmental protection.

Discussion

In 2009, China launched the energy-saving and new energy vehicle demonstration pilot program, known as the "Ten Cities, Thousand Vehicles" pilot project. This project was China’s earliest initiative to promote energy saving and emission reduction through new energy vehicles and to facilitate air pollution control. The "Ten Cities, Thousand Vehicles" pilot project, as an early top-level policy design for promoting NEVs in China, not only established a testing ground for green transportation transformation at the domestic level but also showcased distinctive policy innovation value amid the global wave of green energy revolution. By mobilizing concentrated resources to drive technological validation and market cultivation, this initiative laid a foundational cornerstone for the green transition of China’s NEV industrial chain and transportation sector. Its policy framework and implementation logic have further provided a valuable reference for the international community (Li et al., 2023), resonating with efforts such as Japan’s Advanced Environmental-Friendly Vehicles Program. However, unlike Japan’s emphasis on hydrogen or Europe’s focus on battery electric vehicles, China has pursued a multi-technology strategy--supporting battery electric, plug-in hybrid, and hydrogen fuel cell vehicles in parallel. This inclusive and diversified approach highlights China’s strategic flexibility and offers a model for developing countries seeking to balance technological risk and industrial upgrading. China’s emphasis on close coordination between local governments and enterprises through pilot cities has led to the formation of regional industrial clusters, accelerating both technological iteration and large-scale application.

Notably, the pilot project was underpinned by a new form of state coordination, linking central and local governments, research institutions, and enterprises. This system not only gave rise to leading domestic firms like BYD but also reshaped the global division of labor through international technological cooperation and standard-setting--such as global patent deployments in battery technologies. Furthermore, by aligning domestic policy experimentation with global climate governance agendas, China has translated practical experience from its pilot projects--such as in charging infrastructure—into modular solutions for other countries. Its efforts in hydrogen fuel cell development also complement strategies pursued by countries like Germany. This two-way interaction of "local experimentation--global integration" has allowed the "Ten Cities, Thousand Vehicles" project to transcend its role as a mere technological demonstration, evolving into a paradigmatic case of how national capacity and market mechanisms can be integrated in the context of global energy transition.

As such, the "Ten Cities, Thousand Vehicles" pilot project provides an excellent observational setting to analyze the impact of changes in urban transportation on regional carbon emissions. This paper treats it as a natural experiment for the government’s electrification transformation of the transportation sector, further quantifying the impact of China’s new energy vehicle promotion policy on urban carbon emissions to assess its policy effectiveness.

The "Ten Cities, Thousand Vehicles" program involved three batches of selected cities (2009: Beijing, Shanghai, Chongqing, Changchun, Dalian, Hangzhou, Jinan, Wuhan,

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Shenzhen, Hefei, Changsha, Kunming, Nanchang; 2010: Tianjin, Haikou, Zhengzhou, Xiamen, Suzhou, Tangshan, Guangzhou; 2011: Shenyang, Chengdu, Hohhot, Nantong, Xiangyang), with varying participation times. Therefore, this section uses a multi-period difference-in-differences (DID) model to assess the carbon reduction effects of the "Ten Cities, Thousand Vehicles" pilot project. The specific econometric model is set as in *Equation (5)*.

$$lnC_{it} = \beta_0 + \beta_1 Treat_i \times Time_t + \sum_j k_j X_{it} + \mu_i + \gamma_t + \varepsilon_{it} \qquad \text{(Eq.5)}$$

In this model, $Treat_i$ is a dummy variable that distinguishes between the treatment group and the control group. For cities in the treatment group, $Treat_i$ takes the value of 1, otherwise, it takes 0. $Time_t$ is a dummy variable that differentiates between the policy period, with $Time_t$ taking 0 before the policy's implementation and 1 after the policy comes into effect. $Treat_i \times Time_t$ is the policy variable of interest, representing the policy shock from the "Ten Cities, Thousand Vehicles" program. The coefficient β_1 measures the overall impact of the program on local carbon emissions levels on average. Other variables are defined in *Equation (1)*.

Policy evaluation of the "Ten Cities, Thousand Vehicles" pilot program

Table 13 reports the impact of the "Ten Cities, Thousand Vehicles" program on urban carbon emissions. Column (1) shows the results with only the core explanatory variables included, while columns (2) to (4) include all control variables, with time-fixed effects and regional-fixed effects added step by step. According to the results in column (4), after including the full set of control variables and fixed effects, the coefficient for the core explanatory variable remains significantly negative and largely stable, indicating that the "Ten Cities, Thousand Vehicles" program significantly reduced urban carbon emissions, establishing a negative relationship between the two.

Table 13. *Policy effect evaluation of the "Ten Cities, Thousand Vehicles" pilot program*

Variable Name	Dependent Variable: lnC				Counterfactual Test
	(1)	(2)	(3)	(4)	(5)
Treat×Time	-0.0762***	-0.1839***	-0.1453***	-0.1001***	-0.0854***
	(0.0376)	(0.0430)	(0.0458)	(0.0321)	(0.0325)
PreDID					-0.0225
					(0.0403)
Constant	16.8629***	1.5218*	0.4787	15.7786***	15.7469***
	(0.0151)	(0.8259)	(0.7955)	(1.0694)	(1.0674)
Control Variable	NO	YES	YES	YES	YES
City Fixed Effect	YES	NO	NO	YES	YES
Time Fixed Effect	YES	NO	YES	YES	YES
Observations	1125	1125	1125	1125	1125
Adj-R^2	0.9227	0.5559	0.5711	0.9373	0.9373

Note: (1) ***, **, * represent statistical significance at the 1%, 5%, and 10% levels, respectively. The values in parentheses are robust standard errors

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Additionally, the multi-period difference-in-differences model requires ensuring that there were no significant anticipatory effects before the policy was implemented. Following the approach of Song et al. (2019), a dummy variable for the year before the pilot cities were established (denoted as *PreDID*), and added to the regression model (5) for further testing. As seen in column (5) of *Table 13*, the coefficient for *Treat×Time* is consistent with column (4), while the coefficient for the previous year is not significant, indicating no anticipatory effect.

Identification and hypothesis testing

The validity of the DID method relies on the parallel trend assumption for the treatment and control groups. According to the method of Beck et al. (2010), *Figure 3a* shows the parallel trend test results for the multi-period DID. Before the implementation of the "Ten Cities, Thousand Vehicles" pilot project, there was little difference in carbon emission levels between the pilot cities and non-pilot cities. After the implementation, during the second period, the carbon emission reduction in pilot cities started to significantly exceed that of non-pilot cities. This lag effect is because the energy-saving and emission-reduction effects of new energy vehicles becoming more pronounced as their market share grows. Therefore, as the promotion of new energy vehicles continues, their carbon reduction effect becomes more significant, a trend that persists until the end of the sample period. The parallel trend assumption holds.

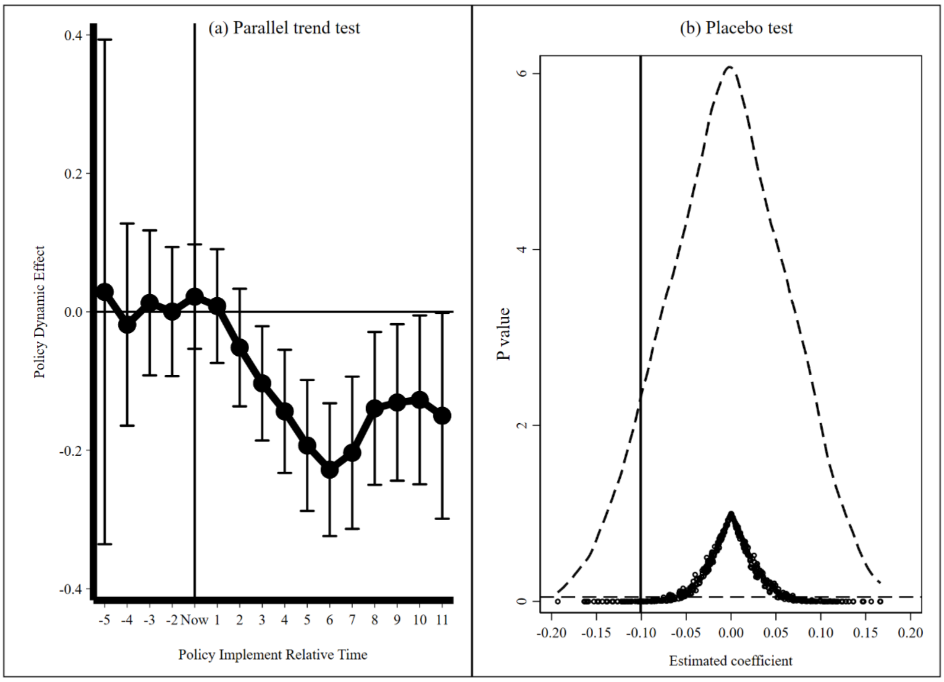

Figure 3. *Identification and hypothesis testing*

There may be omitted variables in the DID model's identification framework, which could lead to biased estimates. To address this, this paper follows the approach of Bai et al. (2022) and performs a placebo test with double randomization. As shown in *Figure 3b*, the coefficients of the randomized core explanatory variable are concentrated around 0, with most p-values greater than 0.1. Additionally, the randomized coefficients are mostly

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located to the right of the true value (-0.1001), indicating that after double randomization, the policy effect is significantly weakened in both significance and strength, indirectly confirming the robustness of the original conclusions.

Conclusion and policy recommendations

Conclusion

Based on panel data from 75 cities in China from 2006 to 2020, this paper uses a double fixed-effect model to examine the impact of new energy vehicle use on urban carbon emissions. The results show that: (1) The promotion of new energy vehicles not only significantly reduces regional carbon emissions levels and carbon emission intensity but also generates spatial spillover effects, benefiting neighboring areas by reducing carbon emissions. This conclusion holds after various robustness tests; (2) The carbon reduction effects of new energy vehicles exhibit significant heterogeneity. Pure electric vehicles have a much stronger carbon reduction effect compared to hybrid vehicles, and both vehicle types show enhanced effects as energy consumption levels decrease. Furthermore, regions with high electrification in the public sector, such as new energy buses, taxis, and urban logistics vehicles, contribute more to carbon reduction. The private car sector is also an important part of the transportation electrification transformation; (3) The mechanism analysis shows that the promotion of new energy vehicles reduces carbon emissions by lowering the share of gasoline and diesel consumption, demonstrating an "energy structure optimization effect." Additionally, it enhances corporate technological innovation, contributing to carbon reduction through a "technological innovation effect."; (4) Further analysis indicates that the implementation of the "Ten Cities, Thousand Vehicles" pilot project significantly reduces urban carbon emissions, achieving the goal of low-carbon emission reduction through the promotion of new energy vehicles.

Policy recommendations

(1) Policymakers should expand support policies and financial backing for new energy vehicles to accelerate the electrification of transportation. Cities with successful decarbonization effects can be used as models to promote carbon neutrality in other regions; (2) Policymakers should set clear targets for the adoption of pure electric vehicles, promoting the electrification of government vehicles, public transport, and taxis through regulations. Increase pilot cities that ban the sale of fuel vehicles; (3) Local governments should raise subsidies for transportation operations and R&D to improve efficiency and reduce carbon emissions. This includes increasing subsidies for charging companies and supporting hydrogen fuel cell vehicles.

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