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Original Research

"Coal-to-Oil Substitution": New Energy Vehicles and Electricity Carbon Emissions – Based on "Ten Cities, Thousand Vehicles" Pilot Project

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Abstract

This study analyzes the impact of New Energy Vehicle (NEV) promotion on electricity sector carbon emissions using panel data from 50 Chinese cities (2006-2020) and a multi-period DID model. NEV promotion, while reducing transportation sector emissions, has increased carbon emissions in the electricity sector due to reliance on coal-based power generation. Results indicate that (1) In "Ten Cities, Thousand Vehicles" pilot cities, NEV adoption increased power sector carbon emissions by an average of 1.19%. Furthermore, the "Ten Cities, Thousand Vehicles" plan generated significant spatial spillover effects, elevating power sector emissions in neighboring regions. (2) Through China's "West-to-East Power Transmission" project reveals that the use of electricity by NEVs also places carbon reduction pressure on the power generation sector. This pressure can shift through local and cross-regional electricity transmission, thereby creating a "regional transfer" effect of carbon emissions; (3) Mechanism analysis indicates that NEV usage increases regional electricity demand and fossil energy consumption while synergistically enhancing regional renewable energy technological innovation. Policy implementation has also accelerated advancements in "three-electric systems" (battery, motor, electronic control) and V2G technologies, which improve NEV energy efficiency though require further refinement; (4) Under policy synergies between NEV demonstration cities and low-carbon city initiatives, NEV promotion effectively mitigates carbon emission transfers to power sectors while amplifying environmentally positive externalities. This study provides

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a comprehensive assessment of the negative environmental externalities of NEV promotion, offering a new perspective on NEV development.

Keywords: new energy vehicles, negative environmental externalities, electricity carbon emissions, "Ten Cities, Thousand Vehicles" pilot project, DID model

Introduction

In 2006, China introduced and implemented the "National Medium- and Long-Term Science and Technology Development Plan (2006-2020)", explicitly identifying the development of non-fossil energy as a key measure to diversify the energy structure and emphasizing the development of electric vehicles as a focal point in cultivating strategic emerging industries, with a focus on transforming transportation energy sources. In 2009, China launched a demonstration and promotion pilot for energy-saving and new energy vehicles, known as the "Ten Cities, Thousand Vehicles" pilot project, to further implement the State Council's strategic directive on "energy conservation and emissions reduction" and "enhancing efforts to save oil and electricity". The "Ten Cities, Thousand Vehicles" pilot project is one of China's earliest demonstration initiatives aimed at promoting energy conservation and emissions reduction through the adoption of NEVs and addressing air pollution. This initiative mainly targeted public sectors such as public transport, taxis, government vehicles, municipal services, and postal services, all of which are directly associated with energy consumption and carbon emissions in transportation, warehousing, and postal industries.

However, existing research generally overlooks the potential environmental negative externalities associated with NEVs. While NEVs have a carbon reduction effect during their operation, the extent of this effect also depends on the carbon emissions of upstream power plants that supply electricity for their use. Huo et al. (2010) argue that the role of NEVs in carbon reduction is limited; in the process of their widespread adoption, the impact only alters the pathway of energy consumption and carbon emissions, shifting emissions from the transportation sector to the electricity production sector. This phenomenon arises because the NEV industrial chain is embedded in two high-carbon-emission sectors: upstream electricity production (indirect carbon emissions) and downstream transportation (direct carbon emissions). As the penetration rate of NEVs increases, energy consumption shifts from petroleum-based fuels to electricity. At this point, carbon emissions do not completely disappear but are redistributed along the production network. The extent of this redistribution effect depends on the carbon emission coefficient of the electricity sector, i.e., the marginal carbon emission change caused by a unit increase in electricity demand. However, this phenomenon has rarely been discussed in the academic literature. Given that China's power production is undergoing a clean transformation, data from the National Bureau of Statistics of China indicate that the share of non-fossil fuel electricity generation reached 34.6% in 2021, while the number of NEVs exceeded 7.84 million. Based on Huo et al.'s (2010) [1] hypothesis of carbon emission transfer from NEVs, it can be argued that when the marginal increase in electricity demand is primarily met by coal-fired power plants, the additional electricity demand generated by the promotion of NEVs may cause a "sectoral transfer" effect on urban carbon emissions. Therefore, it is necessary to investigate whether the environmental positive externality of NEVs comes at the expense of increased carbon emissions in the electricity production sector, and to clarify its pathway and mechanisms.

As a quasi-natural experiment in energy conservation and emissions reduction within the transportation sector, the "Ten Cities, Thousand Vehicles" policy has achieved considerable success. However, while NEVs exert carbon reduction effects downstream in the fuel cycle, the upstream segment – electricity production – faces substantial new demand for power, thereby imposing significant pressure on carbon emissions control in the electricity production sector amid large-scale NEV deployment. This initiative, therefore, links not only to the transportation sector but also directly impacts the electricity production sector. Consequently, the "Ten Cities, Thousand Vehicles" policy provides a new perspective for examining the relationship between NEV usage and the electricity sector carbon emissions. In addition, it should be noted that battery electric vehicles (BEVs) and hybrid electric vehicles (HEVs) dominate the international market. The International Energy Agency's "EV Outlook" exclusively reports sales figures for these two vehicle types, reinforcing their market recognition and classification rationality. Similarly, statistical data from the China Passenger Car Association and the Energy-saving and New Energy Vehicle Yearbook also emphasize these two vehicle categories, further highlighting their market prominence. Therefore, in this paper, the conceptual scope of NEVs specifically encompasses BEVs and HEVs. Moreover, considering data availability and continuity, this study employs panel data covering 50 Chinese cities from 2006 to 2020 to empirically quantify and evaluate the actual impacts of NEV promotion on carbon emissions in the electricity sector, thereby enriching the theoretical discourse on NEVs' environmental externalities.

The marginal contributions of this paper are as follows: (1) It establishes a connection between the "low-carbon or zero-carbon" emissions of new energy vehicles and their "carbon emission transfer"; (2) It provides theoretical foundations and empirical evidence for carbon emission transfers in the fuel cycle of NEVs, clarifying the impacts of regional power generation structures and cross-regional electricity transmission on carbon emission transfers within the fuel cycle; (3) It empirically demonstrates a critical mechanism by which the surging electricity demand from NEV adoption exacerbates carbon emissions in the power sector by increasing coal consumption for power generation. (4) In addition to uncovering the phenomenon of carbon emission transfer from the promotion and adoption of NEVs to the electricity production sector, this study also finds that such emission transfer effects can be mitigated through various combinations of environmental regulations. Furthermore, beyond directly increasing electricity consumption and stimulating renewable energy technology innovation, NEV promotion indirectly fosters innovation in core NEV technologies and vehicle-to-grid (V2G) technologies via demand-induced innovation. This mechanism provides valuable insights for the long-term optimization of regional electricity consumption and production structures. To ensure methodological rigor and robustness, this study extends the baseline regression analysis by incorporating advanced econometric techniques, including propensity score matching combined with difference-in-differences (PSM-DID) and high-dimensional fixed-effect interactions, to effectively address potential endogeneity concerns. Additionally, we verify the radiative spillover effects of NEV promotion on carbon emissions in the electricity sector from a spatial effects perspective, further deepening the causal understanding of this relationship.

The innovations of this paper lie in: (1) Leveraging the quasi-natural experiment characteristics of policy implementation and utilizing the advantages of the multi-period DID model, including its low estimation bias, flexibility, and scalability. Through the "Ten Cities, Thousand Vehicles" pilot project, a policy for promoting NEV adoption, the study examines the actual impact of NEV promotion on upstream carbon emissions in the power sector within the fuel cycle. It validates the carbon emission transfer pathways of NEVs in the fuel cycle, evaluates the policy's impact on regional power sector emissions before and after implementation, and investigates whether carbon emissions are "exported" across regions via the grid, particularly in the context of China's "West-to-East Power Transmission" project and regional power generation structures. The study also calculates the net effect of NEV promotion on power sector carbon emissions from an economic perspective; (2) From a direct perspective, it establishes a pathway between NEV promotion and power sector carbon emissions, while from an indirect perspective, it provides empirical insights to mitigate carbon emission transfers caused by NEV promotion.

Policy Background, Literature Review, and Theoretical Hypothesis

Policy Background

The promotion of New Energy Vehicles (NEVs) initially focused on public service sectors such as buses, taxis, official vehicles, sanitation, and postal services. In 2009, fiscal policies, including one-time subsidies, were introduced to promote NEVs in these sectors. Relevant policies included initiatives such as the "Energy-Saving and New Energy Vehicle Demonstration Pilot Program", the "Ten Cities, Thousand Vehicles" plan, and the "Provisional Administrative Measures for Fiscal Subsidy Funds". The pilot cities included Beijing, Shanghai, Chongqing, Changchun, Dalian, Hangzhou, Jinan, Wuhan, Shenzhen, Hefei, Changsha, Kunming, and Nanchang.

In 2010, NEVs were recognized as one of the seven strategic emerging industries and a critical measure for advancing energy conservation and emissions reduction. The Ministry of Finance, Ministry of Science and Technology, Ministry of Industry and Information Technology, and the National Development and Reform Commission issued a joint notice to expand NEV demonstration efforts in public services, adding Tianjin, Haikou, Zhengzhou, Xiamen, Suzhou, Tangshan, and Guangzhou as pilot cities, increasing the number to 20. Later that year, another notice from the same ministries added Shenyang, Hohhot, Baotou, Chengdu, and Xiangyang as the third batch of pilot cities, broadening the scope of NEV promotion in public services.

NEV promotion also expanded into the private vehicle sector. A joint notice, "On the Pilot Subsidy Program for Private Purchases of New Energy Vehicles", selected six cities, all of which overlapped with the first batch of public service pilot cities. By this point, the market subsidy framework for NEVs was fully established. By 2023, China's NEV ownership had reached 20.41 million vehicles, reducing carbon emissions by as much as 50 million tons during use compared to traditional fuel vehicles. However, the additional electricity consumption and its impact on carbon emissions in the electricity sector remain underexplored. The "Ten Cities, Thousand Vehicles" pilot project provides an ideal quasi-natural experiment to study the upstream carbon emission effects of green consumption.

Literature Review

Existing studies have examined the efficiency of NEVs in replacing fuel vehicles but have largely overlooked the emissions generated by additional new NEVs. NEVs are not zero-emission vehicles; their production, particularly in the manufacturing of power batteries, results in significant carbon emissions, creating a "use-to-production" pollution transfer effect. Qiao et al. (2017) [2] estimated that the carbon emissions during the production phase of battery electric vehicles (BEVs) in China are approximately 50% higher than those of traditional fuel vehicles, primarily due to the carbon footprint of battery production. Consequently, large-scale NEV adoption in China may not only transfer carbon emissions through the grid during electricity consumption but also generate emissions from battery production. Additionally, electricity consumption during NEV use entails pollution transfer effects [3].

The government's large-scale NEV promotion has facilitated widespread adoption but has also indirectly driven up electricity demand. While NEVs produce zero emissions during use, electricity generation involves carbon emissions through energy conversion. Studies show that NEV emissions vary with the electricity mix [4]. For instance, NEV electricity consumption may rely on interregional grid transfers. Holland et al. (2016) [3] developed a general equilibrium model based on discrete choice to estimate the utility a consumer derives from purchasing and driving a car over its lifetime. Their findings suggest that consumers generally do not account for the environmental externalities of driving in their purchase decisions. The study also revealed significant regional differences in NEV environmental benefits, which can be positive or negative depending on the location. For example, NEVs show substantial environmental advantages in California due to relatively high pollution from fuel vehicles and a cleaner local power grid. However, in northern Midwest regions such as North Dakota, NEVs have notable negative environmental impacts. Moreover, the study found that driving NEVs has a significant externality, as most electricity consumed comes from other regions via grid transfers. In this scenario, 91% of pollution from driving NEVs is "transferred" to other regions, compared to only 19% for fuel vehicles.

Li and An (2023) [5] reached similar conclusions. Using panel data from 285 Chinese cities (2003-2019) and a DID model, they analyzed the impact of NEV promotion policies on carbon emissions. Their findings suggest that, given China's current electricity mix, which has not yet achieved decarbonization, NEV use primarily shifts carbon emissions from vehicle operation to electricity production, effectively turning NEVs into "coal-powered cars". Guo and Xiao (2023) [6] further demonstrated that, under a scenario where all electricity is produced from coal, NEVs would have higher per-unit emissions than fuel vehicles, leading to negative externalities from NEV adoption. Additionally, many key industries in China remain heavily reliant on coal and thermal power, leaving limited room for reducing vehicle emissions through structural energy changes in the short term [7]. Given the dual goals of "carbon peaking" and "carbon neutrality", assessing the effectiveness of NEV promotion in achieving energy savings and emissions reduction is increasingly critical. However, few studies have thoroughly examined and clarified the fundamental nature of carbon emission changes associated with NEV promotion or explored the phenomenon of carbon emission transfer resulting from NEV adoption.

Theoretical Analysis of New Energy Vehicles and Electricity Carbon Emissions

Current research defines the carbon emission transfer effect as the phenomenon where carbon emissions reduction or increase does not fully occur within a region but is transferred to other regions through cross-regional electricity flows, industrial chain shifts, and other mechanisms. This concept is derived from the Environmental Kuznets Curve theory. Some studies (William, 2019) [8] suggest that with globalization, pollutants such as CO_2 may be "transferred" to other countries or regions, leading to the ineffectiveness of global pollution control. Thus, carbon emission transfer is the result of regional carbon emission flow influenced by factors such as energy structure differences and policy variations. Regarding energy structure differences, regional disparities in energy production are a major cause of carbon emission transfer. Some rapidly developing regions face geographical constraints and cannot build large-scale energy production facilities. As a result, they rely on cross-regional energy imports to meet their energy demand. The carbon intensity of energy production varies across regions, and when electricity is exchanged between them, carbon emissions are also transferred. If an energy-importing region receives power from a high-carbon-emission region, it creates a scenario where economic growth in the importing region comes at the expense of increased emissions in the exporting region, leading to a cross-regional carbon emission transfer. Policy differences also play a crucial role in carbon emission transfer. Regions with stricter carbon regulations may drive high-carbon industries to move to regions with more lenient policies, causing a transfer of emissions. Additionally, globalization exacerbates the spatial transfer of carbon emissions. Developed countries, while reducing emissions domestically, may transfer the "cost" of emissions to developing countries (Wang et al., 2020 [9]). This transfer occurs not only in international trade but also through regional electricity exchanges and industrial shifts. As cross-regional electricity flow increases, regions with high energy demands may import electricity from regions with resource advantages, indirectly increasing emissions in power-producing areas (Liu and Han, 2024 [10]). Therefore, carbon emission transfer is closely linked to globalization, regional economic structures, and energy supply and demand.

Theoretically, replacing traditional fuel vehicles with NEVs reduces carbon emissions in the transportation sector, and many scholars acknowledge NEVs' long-term environmental benefits. NEVs rely on electric power, which does not emit pollutants or harmful gases during use. Electricity generated from clean sources such as hydropower, wind, and nuclear energy results in lower emissions. Additionally, coal and oil combustion by thermal power plants, typically located in low-population-density areas, can be centrally managed to mitigate harmful gas emissions.

However, from the perspective of full lifecycle theory, although electric vehicles (EVs) are characterized as "zero-emission" during their operation, in actuality, they transfer carbon emissions to stages such as vehicle production, electricity generation, and charging. Whether this constitutes genuine carbon reduction or merely a shifting of emissions remains to be substantiated. Numerous scholars have applied lifecycle assessment methods and models such as GaBi to study the complete vehicle, fuel lifecycle, and relevant components and processes of vehicle powertrains in order to obtain a more precise estimation of the carbon emissions of EVs from production to disposal. However, due to differences in the delineation of lifecycle boundaries, inventory data, and selection of research subjects, two contradictory conclusions have emerged. Naranjo et al. (2021) found that in Spain, although EVs reduce pollutant emissions during on-road operation by utilizing electricity, their lifecycle carbon emissions (including the phases of vehicle production, manufacturing, transportation, distribution, use, and disposal) are 46% lower than those of conventional fuel vehicles [11]. Li et al. (2017) analyzed the lifecycle carbon emissions of electric buses and found that their CO_2 emissions could be reduced by 19.7% [12], whereas Feng et al. (2017) discovered that over the full lifecycle (comprising the fuel cycle, vehicle cycle, and supporting infrastructure cycle), the heavy reliance on coal may actually lead to an increase in carbon emissions [13]. Yang et al. (2020), based on the current situation in China, conducted a full lifecycle analysis of EVs and conventional fuel vehicles and concluded that EVs exhibit higher carbon emissions due to high energy consumption and battery production [14]. Petrauskienė et al. (2020) reported that in Lithuania, the full lifecycle carbon emissions of EVs are 26% higher than those of conventional fuel vehicles [15]. Moreover, a study by the European Environment Agency (2017) indicated that if charging is performed using electricity from coal-fired power plants, EVs do not exhibit a carbon reduction effect over their full lifecycle, with carbon emission intensities exceeding 300 g/km (compared to less than 240 g/km for conventional fuel vehicles) [16]. Wang et al. (2013), through lifecycle assessment, concluded that the full lifecycle carbon emissions of EVs are slightly higher than those of conventional fuel vehicles [17], while Yu et al. (2018) found, based on a full lifecycle carbon emission analysis of the powertrain systems of EVs and conventional fuel vehicles, that the current lifecycle carbon emissions of EV powertrains are higher than those of conventional fuel vehicles [18].

Therefore, given that China's current power production structure is predominantly based on thermal power generation, the promotion of new energy vehicles may significantly increase the carbon emission levels of power plants. This shifts energy consumption and carbon emissions from the transportation sector to electricity production. As a result, the carbon reductions in transportation may be offset by increases in the electricity sector, limiting the overall impact of NEV promotion on emissions. Furthermore, the rise in electricity demand caused by NEV adoption may exacerbate regional power shortages. To meet this increased demand in the short term, thermal power production must increase, requiring more coal combustion. Thus, from an energy lifecycle perspective, "driving on electricity" effectively becomes "driving on coal". This transition undermines the low-carbon potential of NEVs, turning the electrification of transportation into a "coal-for-oil" substitution. Some scholars argue that NEV promotion must be coupled with decarbonization in power generation. Only by decarbonizing electricity production can NEV adoption truly reduce the transportation sector's reliance on oil and contribute to CO_2 reduction. Based on this, the hypothesis of this study is proposed:

Hypothesis 1: At the current stage, where electricity production has not achieved "carbon decoupling", the market promotion of NEVs will increase carbon emissions in the electricity sector.

Pathway Analysis of the Impact of New Energy Vehicles on Electricity Carbon Emissions

The market for NEVs in China has been rapidly expanding, and the resulting increase in electricity demand, coupled with the need for power system stability, is likely to create short-term carbon emission pressure. Thermal power generation plays a "ballast" role in ensuring power supply due to its controllability and stability (Joskow, 2011 [19]). When demand fluctuations occur, the ability of thermal power plants to respond quickly becomes crucial for maintaining grid stability. This technical characteristic means that during the transition period for renewable energy development, the installed capacity of thermal power may actually increase, leading to an "excessive capacity" phenomenon. In other words, as more renewable energy infrastructure is built, the scale of thermal power infrastructure often increases as well. As the energy demand from NEVs continues to surge, this power supply constraint directly contributes to an increase in the carbon emission intensity of the electricity industry.

Porter's hypothesis (Porter and Linde, 1995) [20] suggests that appropriate environmental regulations can stimulate technological innovation in enterprises. NEVs are not only tools for energy consumption but also serve as mobile storage units. Their widespread adoption changes the demand-side characteristics of the electricity system. Research by Sioshansi (2011) [21] indicates that intelligent charging of NEVs can enhance renewable energy absorption by 15-20%. In addition, according to the demand-induced innovation theory, changes in market demand constitute a key driver of technological innovation. When consumer and market demand for environmentally friendly and efficient transportation options increase, enterprises along the entire new-energy industrial chain allocate resources toward technological research and innovation to satisfy these emerging demands. Consequently, rising sales of new energy vehicles continually expand the energy consumption market scale, positively influencing the business performance of firms throughout the energy production chain. Leveraging increased revenue from NEV sales, related enterprises can intensify investment in technological research and development, thus enhancing innovation capabilities. Moreover, as green and low-carbon concepts spread and market orientation evolves, traditional automobile manufacturers are increasingly shifting towards NEV production in response to higher market penetration and competition pressures, thereby reinforcing their commitment to NEV technological innovation. Taking the electric control technology – one of the "three electric systems" (battery, motor, and electronic control) – as an example, this technology forms the core of the NEV power management system, encompassing battery management systems (BMS), motor controllers, and vehicle controllers. Specifically, the battery management system optimizes charging and discharging strategies and thermal management systems, extending battery lifespan, improving energy efficiency, and reducing energy losses during usage. Advanced electronic control technology further optimizes operational efficiency and energy utilization, dynamically adjusting power output in real-time according to road conditions and driving behavior, thereby enhancing the overall energy efficiency of electric vehicles. Thus, electronic control technology serves as a critical mechanism for reducing NEV energy consumption and maximizing energy utilization efficiency.

This demand-side response mechanism amplifies market incentives for renewable energy technology innovation, promoting breakthroughs in energy storage and smart-grid technologies. Driven by the directional returns of technology-biased innovation, expanding market demand for NEVs can create path dependencies that further stimulate renewable energy technology development. Concurrently, improvements in renewable energy technologies can alleviate carbon emission factors within the electricity grid, progressively enabling cleaner electricity production and thus enhancing the positive environmental externalities associated with NEVs. Based on this, the following hypotheses are proposed:

Hypothesis 2: The expansion of NEV adoption increases electricity demand and induces the electricity industry to rely on thermal power for supply, thereby raising the carbon emissions level of the electricity sector.

Hypothesis 3: The expansion of NEV adoption stimulates renewable energy technology innovation, thereby reducing the carbon emissions level of the electricity sector.

Materials and Methods

Variable Selection and Data Sources

Dependent Variable

This section primarily investigates the actual impact of NEV promotion on carbon emissions in the regional electricity production sector, measured by the carbon emissions level of each city's electricity production sector (denoted as *EC*). Drawing on Wang et al. (2022) [22], we allocate provincial-level electricity carbon emissions from the MEIC database to the city level using night-time light data, as constructed by Wu et al. (2021) [23]. This approach is based on two main considerations: first, night-time light intensity data is spatially and temporally consistent, allowing for carbon emissions data comparability across different regions and time periods. Second, night-time light intensity data is widely adopted by scholars for estimating carbon emissions at a more granular level [24-26]. Verification against the Global Power Plant Database from WRI confirms that all 50 sample cities contain a varying number of power plants, thus validating the use of city-level electricity production carbon emissions data as meaningful. Third, this study compares the carbon emission trends derived from our calculations with data from the China City Greenhouse Gas Emissions Dataset (CCG). It should be noted that the CCG dataset does not separately categorize carbon emissions from the electricity production sector; therefore, we could only conduct correlation analyses using data from the broader energy sector. The results indicate a high consistency between the electricity sector carbon emissions data calculated in this study and the corresponding data from the CCG dataset, with a correlation coefficient of 0.7412. This further confirms that the city-level electricity sector carbon emissions data derived from nighttime lighting data in this study are both reliable and methodologically rigorous.

Independent Variable

Based on the policy context outlined earlier, the key independent variable in this study is the "Ten Cities, Thousand Vehicles" pilot project. The implementation of this project serves as a policy shock, allowing us to quantify the impact of NEV promotion by the government on carbon emissions within urban transportation sectors. If city i was selected for the "Ten Cities, Thousand Vehicles" pilot project in year t (as indicated in Table 1), it is classified as part of the treatment group, assigned a value of 1; otherwise, it is part of the control group, assigned a value of 0. Overall, considering the availability and continuity of data,

Table 1. Pilot cities for the ‘Ten Cities, Thousand Vehicles’ pilot project.

Experimental Group		Control Group
Policy Implementation Time	City	City
2009	Beijing, Shanghai, Chongqing, Changchun, Dalian, Hangzhou, Jinan, Wuhan, Shenzhen, Hefei, Changsha, Kunming, Nanchang	Nanjing, Xi’an, Shijiazhuang, Xining, Urumqi, Lanzhou, Yinchuan, Nanning, Fuzhou, Taiyuan, Harbin, Guiyang, Yangzhou, Yancheng, Ningbo, Jinhua, Xinxiang, Foshan, Qingdao, Shaoxing, Huzhou, Wuhu, Dongguan, Mianyang, Deyang
2010	Tianjin, Haikou, Zhengzhou, Xiamen, Suzhou, Tangshan, Guangzhou	
2011	Shenyang, Chengdu, Hohhot, Nantong, Xiangyang	

this study selects 50 cities, including 25 pilot cities and 25 non-pilot cities. These 50 cities accounted for 73.4% of the national average annual sales of new energy vehicles from 2006 to 2020, making them representative of the broader national trend. Additionally, the overall level of economic and social development in the experimental (pilot) and control (non-pilot) cities is nearly identical, meeting the selection criteria for the experimental and control groups in a DID model.

Control Variables

Following the approach of Cao et al. (2021) [27], this section selects a set of factors potentially influencing production and carbon emissions in the electricity sector as control variables, including economic level (*pGdp*), population density (*Density*), level of industrial development (*Ind_gdp*), scale of industrial enterprises (*Ind_corp*), and the size of the secondary (*s_Ind*) and tertiary (*t_Ind*) industries. Existing research suggests that economic and social development, as well as regional population size, are positively correlated with changes in electricity demand [28-30]. Rising economic strength and population concentration continuously drive electricity demand, thereby increasing carbon emissions in the electricity sector. Therefore, this section uses per capita GDP of each city in the given year to measure economic and social development and population density to represent regional population size.

Furthermore, changes in industrial structure are closely linked to electricity demand [31, 32]. During China’s drive for industrial restructuring and optimization, adjustments within the secondary and tertiary industries impact electricity production and carbon emissions control. For example, Wen and Diao (2022) [33] found that the rapid development of the tertiary industry in China has reduced electricity consumption levels. Accordingly, this study represents changes in the secondary and tertiary industry structures by the ratio of their respective added values to the city’s GDP. Additionally, as the industrial sector remains the largest consumer of electricity in China (China Electricity Council, 2024), this section also uses each city’s industrial gross output and number of industrial enterprises to depict the development of local industrial sectors.

Given that each city’s electricity demand and its associated carbon emissions are driven by regional socio-economic factors, changes in the output and emissions of a single power plant are unlikely to influence city-wide conditions or the status of policy implementation. Thus, both the core explanatory variable and control variables can be regarded as strictly exogenous. Moreover, the control variables selected in this study have a direct and close association with regional electricity carbon emissions, and are unlikely to exhibit lagged effects or reverse causality. Therefore, all control variables in our empirical analysis are represented by their contemporaneous values.

Methods

Since the “Ten Cities, Thousand Vehicles” pilot project selected three batches of cities with varying participation times, this section employs a staggered Difference-in-Differences (DID) model to assess the true carbon reduction effect on the urban transportation sector from this initiative. By comparing cities selected as NEV pilot cities (treatment group) with non-selected cities (control group), the design satisfies the prerequisites for using a staggered DID model. Meanwhile, by employing the STIRPAT model constructed by Dietz and Rosa in 1997, which offers notable advantages in evaluating environmental benefits and the effects on air pollutants, the specific econometric model is defined as shown in Equation (1):

$$lnECE_{it} = \rho_0 + \rho_1 Treat_i \times Time_t + \sum_k \alpha_k C_{it} + \mu_i + \gamma_t + \varepsilon_{it} \tag{1}$$

In this model, subscripts i and t represent city i and year t, respectively. $Treat_i$ is a dummy variable distinguishing the treatment group from the control group; for cities in the treatment group, $Treat_i$ takes the value 1, otherwise 0. $Time_t$ is a dummy variable distinguishing the policy period; it takes the value 0 before the policy is implemented and 1 after the policy takes effect. The interaction term $Treat_i \times Time_t$

represents the policy variable, capturing the impact of the "Ten Cities, Thousand Vehicles" pilot project as a policy shock.

In the equation, the coefficient ρ_1 measures, in an average sense, the overall impact of the "Ten Cities, Thousand Vehicles" pilot project on the carbon emission level of the local electricity sector. Since most cities across the country have power supply facilities to ensure local electricity usage, it is reasonable to use a multiple-period DID model to assess the relationship between the promotion of NEVs and carbon emissions in the electricity sector. If the creation of the "Ten Cities, Thousand Vehicles" pilot project cities has led to an increase in the carbon emission levels of the electricity sector, then ρ_1 should be significantly positive. Additionally, C_{it} represents a set of control variables affecting urban carbon emissions, with α_k as the coefficients for these control variables. μ_i and γ_t denote city and time fixed effects, respectively, and ε_{it} captures other random factors influencing regional carbon emissions.

Sample Data Introduction and Descriptive Statistics

The sample data for this section consists of panel data from 50 Chinese cities spanning 2006 to 2020. Following the logarithmic transformation approach of the STIRPAT model, and to eliminate heteroscedasticity and dimensional discrepancies among the variables, this study applies logarithmic transformations to each of the explanatory variables, the explained variable, and the control variables. Table 2 provides names, symbols, definitions, and data sources for each variable.

Results and Discussion

An analysis of potential multicollinearity in the model using the Variance Inflation Factor (VIF) reveals (as shown in Table 3) that the variable with the highest VIF value is 7.54 (*lnInd_gdp*). All variables have VIF values below the critical threshold of 10, and 1/VIF values are all greater than 0.1, indicating that there is no serious multicollinearity issue in the model. The results of the unit root test show that all variables are first-order difference stationary.

Baseline Regression Results

Table 4 reports the impact of the implementation of the "Ten Cities, Thousand Vehicles" pilot project on carbon emissions in the regional electricity production sector, based on Equation (1). Column (1) of Table 4 presents the regression results with only the core explanatory variable, using a two-way fixed effects model. Columns (2) and (3) progressively add fixed effects to the regression. Combining the results from columns (1) to (3), it is found that, compared to cities not participating in the "Ten Cities, Thousand Vehicles" pilot project, the carbon emissions from the electricity production sector in participating cities increased by 1.19%. After including a series of control variables in the regression, the coefficient of the policy effect *Treat×Time* remains negative and significant at the 1% level. In addition, to preliminarily address potential endogeneity issues in the model, all control variables in the explanatory variables set are lagged by one period, and the regression is re-estimated. The results are shown in column (4). It can be observed that the coefficient

Table 2. Variable names, symbols, definitions, and data sources.

Variable name	Symbol	Definition	Data Source
Carbon Emission Level of City Electricity	*ECE*	Carbon emissions from the electricity production sector in each city, measured in tons	Calculated in this study
"Ten Cities, Thousand Vehicles" pilot project	*Treat*Time*	Policy impact indicator based on the "Ten Cities, Thousand Vehicles" pilot project	National Development and Reform Commission
Economic Level	*pGdp*	Per capita GDP in each city for the given year, measured in 10,000 yuan	China City Statistical Yearbook
Population Density	*Density*	Population per square kilometer for each city in the given year	China City Statistical Yearbook
Industrial Development Level	*Ind_gdp*	Industrial output value for each city in the given year, measured in 10,000 yuan	China City Statistical Yearbook Regional statistical yearbooks Websites of City Statistical Bureaus
Industrial Enterprise Scale	*Ind_corp*	Number of large-scale industrial enterprises in each city for the given year	China City Statistical Yearbook Regional statistical yearbooks Websites of City Statistical Bureaus
Scale of Secondary Industry	*s_Ind*	Proportion of secondary industry output to city GDP in the given year	China City Statistical Yearbook
Scale of Tertiary Industry	*t_Ind*	Proportion of tertiary industry output to city GDP in the given year	China City Statistical Yearbook

Table 3. Multicollinearity analysis results.

Variable name	VIF	1/VIF
*Treat*Time*	1.37	0.7298
lnpGdp	3.63	0.2754
lnDensity	1.91	0.5229
lnInd_gdp	7.54	0.1326
lnInd_corp	4.80	0.2082
lns_Ind	4.96	0.2014
lnt_Ind	5.81	0.1720

of the independent variable remains significantly negative at the 1% level, with its magnitude showing no substantial change compared to columns (2)-(3). The significance, sign direction, and magnitude of the other control variables also remain largely unchanged. These results further confirm the robustness of the baseline model, indicating that the baseline regression does not suffer from obvious endogeneity or reverse causality. They also provide preliminary evidence of a positive association between NEV promotion and regional power sector carbon emissions. The above findings suggest that between 2006 and 2020, the promotion and adoption of NEVs in pilot cities indeed exerted considerable pressure on regional carbon emissions in the electricity sector. In the long term, however, driven by the mechanism of demand-induced innovation, the synergistic advancement of NEV technologies and clean energy technologies will positively impact power generation and structural optimization. Such advancements will, in turn, alleviate the carbon emission transfer from NEV adoption to the electricity production sector.

Robustness Tests

Parallel Trend Test

The validity of the DID method requires that the treatment and control groups satisfy the parallel trend assumption. Following the approach of Beck et al. (2010)

Table 4. Evaluation of the policy effect of the 'Ten Cities, Thousand Vehicles' pilot project.

Variable name	Baseline Regression: *lnECE*			Lagging the control variables by one period
	(1)	(2)	(3)	(4)
Treat×Time	0.0587***	0.0172***	0.0119***	0.0111***
	(0.0055)	(0.0034)	(0.0027)	(0.0027)
lnpGDP	-	0.1805	0.1945*	0.1357
	-	(0.1553)	(0.1127)	(0.0932)
lnDensity	-	0.2487***	0.0158	0.0261
	-	(0.0500)	(0.0303)	(0.0300)
lnInd_gdp	-	0.4986***	0.6624***	0.7181***
	-	(0.0662)	(0.0911)	(0.0755)
lnInd_corp	-	0.3402***	0.1757***	0.1419**
	-	(0.0576)	(0.0680)	(0.0584)
lns_Ind	-	0.1077	0.1560	0.1606
	-	(0.1737)	(0.1614)	(0.1728)
lnt_Ind	-	-0.1215	-0.3342***	-0.3252***
	-	(0.1997)	(0.1170)	(0.1229)
Constant	0.5294***	0.4771***	0.4734***	0.4697
	(0.0404)	(0.0396)	(0.0529)	(1.0239)
City Fixed Effects	YES	NO	YES	YES
Time Fixed Effects	YES	YES	YES	YES
Observations	750	750	750	700
Adj-R^2	0.5660	0.8546	0.9617	0.9637

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

[34], it is necessary to establish relative time dummy variables for the implementation of the "Ten Cities, Thousand Vehicles" pilot project in each pilot city. Therefore, this study constructs the following Model (2):

$$lnECE_{it} = \rho_0 + \sum_{k\in[2006,2020]} \rho_k D_{t_{i0}+k} + \sum_r \alpha_r C_{it} + \mu_i + \gamma_t + \varepsilon_{it} \quad (2)$$

The estimated results are then used to plot a staggered DID parallel trend graph. As shown in Fig. 1, before the implementation of the "Ten Cities, Thousand Vehicles" pilot project, there was essentially no difference in carbon emissions levels in the electricity production sectors between pilot and non-pilot cities. Starting from the fifth period after the project's implementation, the carbon emissions level in the electricity production sector of pilot cities began to significantly exceed that of non-pilot cities. However, as China subsequently extended and reinforced its NEV promotion efforts, the large-scale adoption of NEVs led to a surge in electricity demand, significantly increasing carbon emissions in the electricity production sector. This trend continued until the end of the sample period, indicating that the parallel trend test was satisfied.

Placebo Test

The estimation results from the staggered DID model indicate that the "Ten Cities, Thousand Vehicles" pilot project increased carbon emissions in the electricity sector of cities. However, other unobservable factors may also influence the policy effect of the "Ten Cities, Thousand Vehicles" pilot project, potentially leading to omitted variable bias in the DID model's identification framework. To address this, this study follows the approach of Bai et al. (2022) [35] and conducts a double-randomization placebo test. Fig. 2 presents the kernel density plot of the policy effect estimates for pilot cities under double randomization and compares it with the true estimated coefficient from Table 5 (0.0119).

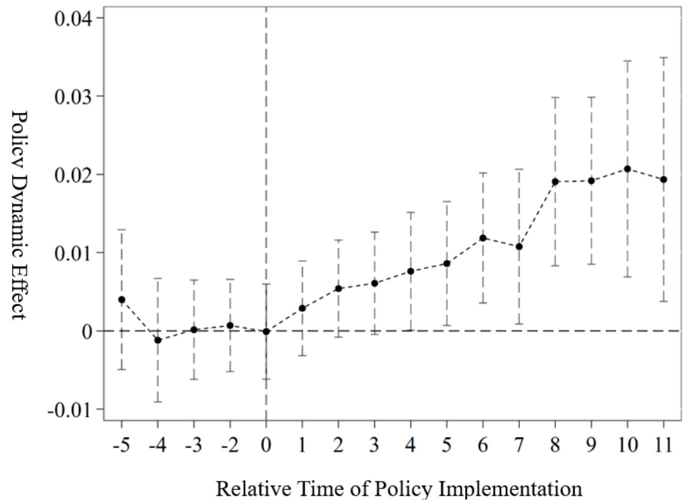

Fig. 1. Parallel Trend test.

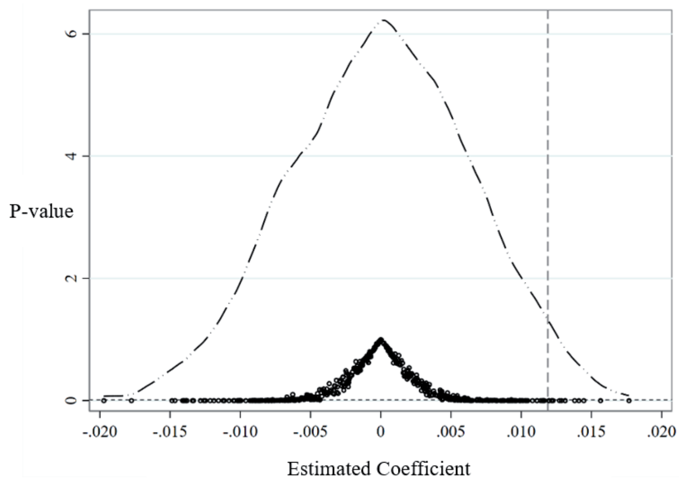

Fig. 2. Placebo Test.

The randomized policy effect exhibits a normal distribution centered around zero, with the majority of P-values exceeding 0.1. Furthermore, the randomized coefficients are predominantly located to the left of the true value of 0.0119, indicating that, after double randomization, both the significance and effect strength of the policy impact are substantially weakened. This result supports the robustness of the baseline regression findings, showing that the observed increase in carbon emissions in the electricity production sector due to the “Ten Cities, Thousand Vehicles” pilot project is not a random event. Thus, the effect of the “Ten Cities, Thousand Vehicles” pilot project on increasing carbon emissions in the regional electricity production sector is robust.

Multi-Period DID Weight Proportion Test

To address the potential instability in the multi-period DID estimates for the “Ten Cities, Thousand Vehicles” pilot project, this study employs the Goodman-Bacon decomposition method [36]. From the estimation results (as shown in Fig. 3), it can be seen that the test estimate of 0.0119 is consistent with the result in column (3) of Table 5. The decomposition results indicate that 87.50% of the effect is derived from comparisons with groups that were never treated, suggesting that the bias caused by negative weights in the baseline model’s estimate is minimal. This further confirms the robustness of the results.

Addressing Endogeneity Issues

Instrumental Variable Estimation

Considering the potential endogeneity between the “Ten Cities, Thousand Vehicles” pilot program and regional electricity sector carbon emissions, this section further addresses the issue using an instrumental variable approach. Since the establishment of the pilot program was based on the local foundation for NEV development and promotion, the number of NEV enterprises in each city serves as an important reference for the Chinese government in selecting pilot cities. In this regard, the number of NEV enterprises in a region can, to a certain extent, reflect the development of its NEV industry. A higher number of NEV enterprises indicates a stronger industrial foundation for NEVs, greater attention from the local government, and better alignment with the criteria for inclusion in the “Ten Cities, Thousand Vehicles” program. Therefore, using the number of NEV enterprises at the prefecture level as an instrumental variable satisfies the relevance condition, while the carbon emissions level of the electricity sector is not directly affected by the number of NEV enterprises, thus meeting the exogeneity requirement.

Furthermore, to eliminate the effects of regional scale differences and heteroskedasticity, the variable is processed as the natural logarithm of the number of NEV enterprises per 10,000 people in each region (denoted as *lnnev_corp*), and then a two-stage instrumental variable regression analysis is conducted. The results in Table 5 show that, in column (1), the regression coefficient of *lnnev_corp* is significantly positive at the 1% level, indicating that the number of NEV enterprises is correlated with the establishment of the “Ten Cities, Thousand Vehicles” pilot program; in column (2), the coefficient of *Treat×Time* remains significantly negative at the 5% level, and the model passes both the weak instrument test and the under-identification test, confirming the validity of the instrumental variable. Overall, the results indicate that after addressing the potential endogeneity between the pilot program and

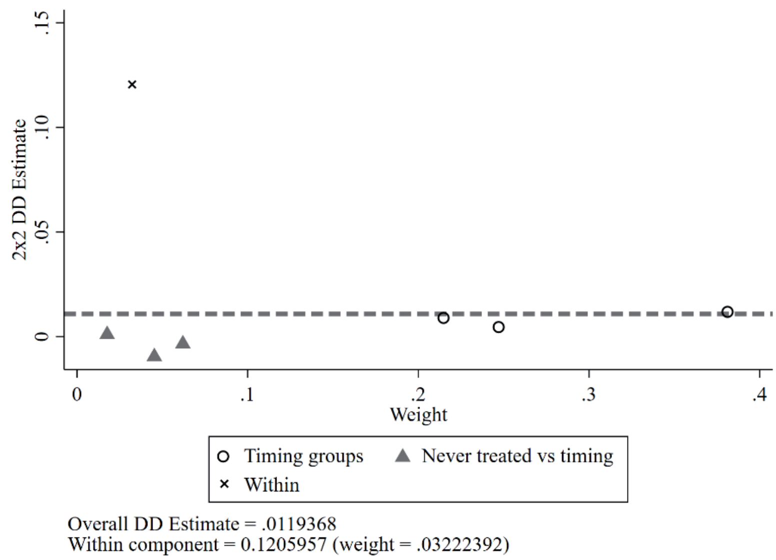

Fig. 3. Multi-period DID weight proportion test.

Table 5. 2SLS estimation results using instrumental variables.

Variables name	First-Stage Regression *Treat×Time*	Second-Stage Regression *lnECE*
	(1)	(2)
lnnev_corp	0.1846***	
	(0.0376)	
Treat×Time		0.0319**
		(0.0143)
Constant	6.7168***	
	(1.7828)	
Cragg-Donald Wald F statistic	64.496***	
Anderson canon. corr. LM statistic	70.027(16.38)	
Control Variables	YES	YES
City Fixed Effect	YES	YES
Year Fixed Effect	YES	YES
$Adj\text{-}R^2$	0.4837	0.3067
Observations	750	750

Note: (1) ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Robust standard errors are reported in parentheses. (2) The F-statistic for the weak instrument test is reported, with the critical value for a 10% maximal IV size shown in parentheses.

carbon emissions in the electricity sector, the main findings remain valid: the “Ten Cities, Thousand Vehicles” pilot program significantly increases carbon emissions in the electricity sector, confirming the objective existence of carbon emission transfer from the transportation sector to the electricity sector resulting from NEV promotion.

PSM-DID

The “Ten Cities, Thousand Vehicles” pilot project selected participating cities based on local applications and central government assessments, meaning chosen cities typically possessed a stronger foundation in NEV promotion and related infrastructure construction. To address potential identification biases arising from sample selection and endogeneity, this study employs PSM to match individuals in the treatment group with those in the control group, followed by DID regressions using matched samples. During propensity score matching, all control variables from the baseline regression model are included as covariates. Radius matching, kernel matching, and nearest-neighbor matching (1:4) methods are employed to match the samples. Table 6 presents the balance test results for the covariates. It shows that after matching, there are no significant differences between the treatment and control groups across the covariates. Fig. 4 illustrates the changes in standardized bias for each covariate before and after propensity score matching. As shown in Fig. 4, the standardized bias for most variables decreases significantly after matching, and the standardized bias for all covariates falls below 10%, indicating that no systematic bias exists between the treatment and control groups post-matching. These results confirm that the matching process performed as expected, and the matching quality is satisfactory. Column (1) of Table 7 presents regression results based on radius matching, which confirm that the “Ten Cities,

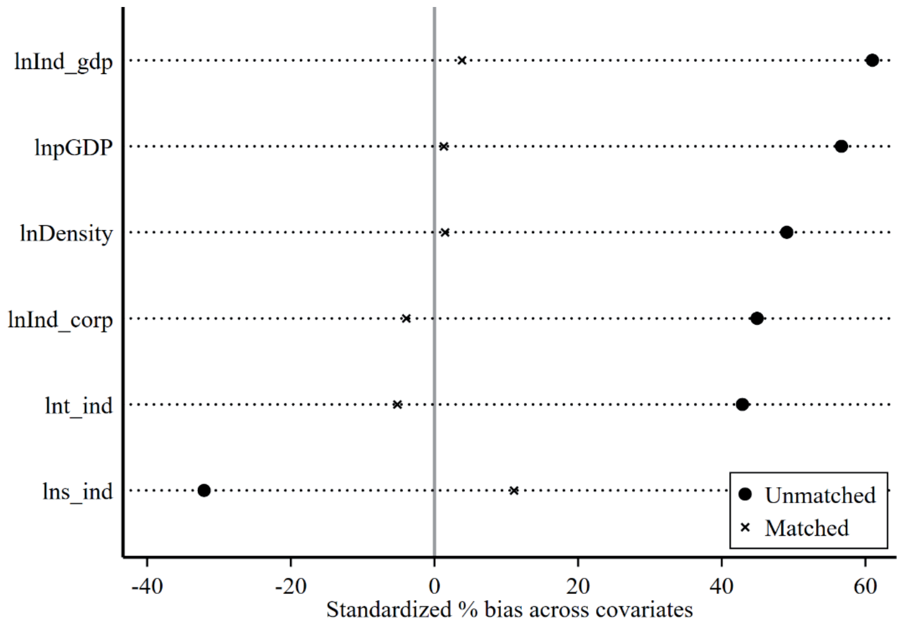

Fig. 4. Distribution of standardized bias for covariates before and after PSM matching.

Table 6. Balance test.

Variables name		Mean		Bias	Reduct bias	t	t-test (p>t)
		Treated	Control				
lnpGDP	Unmatched	18.072	17.467	61.0	93.7	8.35	0.000
	Matched	17.904	17.867	3.8		0.51	0.612
lnDensity	Unmatched	11.183	10.867	56.7	97.7	7.76	0.000
	Matched	11.101	11.094	1.3		0.17	0.862
lnInd_gdp	Unmatched	-2.496	-2.862	49.1	97.0	6.72	0.000
	Matched	-2.693	-2.704	1.5		0.19	0.848
lnInd_corp	Unmatched	3.749	3.826	-32.1	65.5	-4.39	0.000
	Matched	3.796	3.770	11.1		1.32	0.187
lns_Ind	Unmatched	3.919	3.824	42.9	87.9	5.87	0.000
	Matched	3.877	3.888	-5.2		-0.70	0.487
lnt_Ind	Unmatched	7.823	7.369	44.9	91.2	6.15	0.000
	Matched	7.644	7.684	-3.9		-0.50	0.617

Thousand Vehicles” pilot project significantly increased carbon emissions in urban electricity sectors, consistent with prior findings.

To further validate the robustness of our conclusions and the reliability of the PSM-DID approach, we repeated the analysis using alternative matching methods, specifically kernel matching and 1:4 nearest-neighbor matching. Columns (2) and (3) of Table 5 display regression results from these two alternative matching methods. In both columns, the coefficient for the “Ten Cities, Thousand Vehicles” variable remains positive and significant at the 1% level, reaffirming the robustness of our baseline regression findings after addressing potential sample selection bias and endogeneity concerns.

Excluding Alternative Explanations

Existing research suggests that the establishment of New Energy Demonstration Cities also contributes to reducing urban carbon emissions, indicating that policies promoting new energy development improve urban carbon quality and reduce carbon emissions in the electricity production sector [37, 38]. To test alternative explanations, a policy dummy variable for New Energy Demonstration Cities was added to model (1). Column (1) of Table 8 shows the estimation results when controlling the establishment of New Energy Demonstration Cities. Compared to the results in column (3) of Table 4, where this variable was not included, the regression coefficient remains positively significant, with little change from

Table 7. PSM-DID regression results.

Variable name	Radius Matching	Kernel Matching	Neighbor Matching (1:4)
	(1)	(2)	(3)
Treat×Time	0.0126***	0.0119***	0.0088***
	(0.0026)	(0.0027)	(0.0027)
Constant	1.2951	0.8537	2.3369
	(1.4517)	(1.1778)	(1.4952)
Control Variables	YES	YES	YES
City Fixed Effect	YES	YES	YES
Time Fixed Effects	YES	YES	YES
Observations	667	709	320
Adj-R^2	0.9579	0.9607	0.9499

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

the baseline results in Table 8 column (3). The coefficient for New Energy Demonstration Cities, however, is not statistically significant. This further confirms the negative impact of participation in the "Ten Cities, Thousand Vehicles" pilot project on carbon emissions in the electricity production sector of pilot cities.

Policy Exogeneity

Following the assumptions for evaluating the multi-period DID model, a counterfactual analysis was conducted. The policy implementation time $Time_i$ was advanced by one and two years for each city, generating pseudo-time variables $Time_{t-1}$ and $Time_{t-2}$, which were then interacted with $Treat_i$ for regression analysis. This was done to test the exogeneity of the NEV pilot city policy and to verify that the observed effects on carbon emissions in the electricity production sector were not "pseudo-events". As shown in columns (2) and (3) of Table 8, the coefficients for the pseudo-policy effects $Treat \times Time_{t-1}$ and $Treat \times Time_{t-2}$ are not significant, indicating that the positive impact of the "Ten Cities, Thousand Vehicles" project on carbon emissions in the electricity sector is real, confirming the robustness of the baseline regression results.

Considering Time-Varying Factors Across Cities

To control for inherent time trends across groups that could affect carbon emissions in the electricity sector, this section incorporates city-specific time trends into model (1). Column (4) of Table 8 shows the results after controlling time-varying factors across different cities. The findings indicate that, even with the inclusion of city-specific time trends, the effect of the "Ten Cities, Thousand Vehicles" pilot project on increasing carbon emissions in the electricity sector remains robust, further validating the reliability of the empirical results presented in Table 4.

Adjusting the Sample Structure

Firstly, considering that the COVID-19 pandemic may have caused fluctuations in regional power-sector carbon emissions in 2020, the time window for regression analysis is restricted to the period from 2006 to 2019. The corresponding regression results are shown in column (5) of Table 8. After accounting for external shocks to policy implementation, the effect of NEVs on increasing carbon emissions in the power generation sector remains significant.

Secondly, given differences in economic development, provincial capital cities, due to their political status, may exhibit a more pronounced relationship between NEV promotion and carbon emissions from the power generation sector. To address this, provincial capital cities were excluded from the sample, and the regression was conducted again. The results, presented in column (6) of Table 8, show that the coefficient of the core explanatory variable – the "Ten Cities, Thousand Vehicles" pilot project – remains positive and significant at the 5% level.

Third, to further verify the robustness of our baseline regression results, we replaced the core explanatory variable – "Ten Cities, Thousand Vehicles" pilot project – with the logarithmic transformation of both the scale of NEV adoption per 10,000 people (denoted as *lnEV*) and the one-period-lagged number of installed charging infrastructures (denoted as $lnCharger_{t-1}$) for each sample city. The data were sourced from the Energy-saving and New Energy Vehicle Yearbook. The regression results are presented in columns (7) and (8) of Table 8. The findings demonstrate that the scale of NEV adoption and the corresponding infrastructure expansion continue to have a significantly positive impact on regional carbon emissions in the electricity production sector, further confirming the robustness of the baseline regression results.

Fourthly, to test whether NEV promotion has led to intersectoral carbon emission transfers, the explained variable was replaced with carbon emissions from the transportation sector in each sample city. The results, shown in column (8) of Table 8, demonstrate that NEV promotion significantly facilitates the green and low-carbon transformation of urban transportation sectors. However, this beneficial transformation comes at the expense of increased carbon emissions in the power sector in the short term, establishing a clear carbon emission transfer pathway from the transportation sector to the electricity production sector.

Fifth, to further control for potential omitted variable bias, we incorporated additional control variables relevant to regional electricity carbon emissions into the model, aiming to verify the robustness of our baseline regression results. Specifically, these variables include urban consumption vitality (denoted as *lnConsume*), represented by the ratio of annual retail sales to GDP; openness to foreign investment (denoted as *lnOpen*), represented by the proportion of foreign capital utilization relative to GDP; and market share of internal combustion engine vehicles (ICEVs, denoted as *lnIcev_share*), represented by the proportion of ICEV sales relative to total annual vehicle sales. To reduce dimensional discrepancies and heteroscedasticity effects, logarithmic transformations were applied to all these variables. Regression results are presented in column (10) of Table 8. The results indicate that, even after accounting for these additional control variables, the baseline regression outcomes remain robust. NEV adoption continues to significantly contribute to increased carbon emissions in the electricity sector. Additionally, greater economic and social consumption vitality also exacerbates electricity-related emissions, whereas an increased ICEV market share helps to alleviate carbon emission pressures on the electricity sector. In other words, the carbon emission transfer from NEV adoption to the electricity production sector demands immediate policy attention.

Table 8. Robustness Tests

Variable Name	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Treat×Time	0.0115***	-	-	0.0077***	0.0116***	0.0114**	-	-	-0.0777***	0.0125***
	(0.0036)	-	-	(0.0025)	(0.0033)	(0.0049)	-	-	(0.0296)	(0.0031)
New Energy Demonstration City	-0.0283	-	-	-	-	-	-	-	-	-
	(0.0406)	-	-	-	-	-	-	-	-	-
$Treat{\times}Time_{t-1}$	-	0.0109	-	-	-	-	-	-	-	-
	-	(0.0088)	-	-	-	-	-	-	-	-
$Treat{\times}Time_{t-2}$	-		0.0102	-	-	-	-	-	-	-
	-		(0.0087)	-	-	-	-	-	-	-
lnEV	-	-	-	-	-	-	0.0907***	-	-	-
	-	-	-	-	-	-	(0.0189)	-	-	-
$lnCharger_{t-1}$	-	-	-	-	-	-	-	0.0294***	-	-
	-	-	-	-	-	-	-	(0.0093)	-	-
lnConsume	-	-	-	-	-	-	-	-	-	0.3406***
	-	-	-	-	-	-	-	-	-	(0.0877)
lnOpen	-	-	-	-	-	-	-	-	-	0.0051
	-	-	-	-	-	-	-	-	-	(0.0214)
lnIcev_share	-	-	-	-	-	-	-	-	-	-0.0470**
	-	-	-	-	-	-	-	-	-	(0.0196)
Constant	0.8160***	0.9396***	1.1361***	-1.2396***	0.5020	3.2089**	1.1385	0.4009	0.4051	1.1911
	(0.2392)	(0.2176)	(0.3257)	(0.3900)	(1.1978)	(1.3479)	(1.2241)	(1.3011)	(0.9912)	(1.4141)
Control Variables	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
City Fixed Effect	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
City×Time Trends	NO	NO	NO	YES	NO	NO	NO	NO	NO	NO
Observations	750	750	750	750	700	300	750	700	750	750
$Adj\text{-}R^2$	0.9623	0.9618	0.9616	0.9691	0.9674	0.9845	0.9630	0.9590	0.9599	0.9674

Note: (1) ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively, with robust standard errors in parentheses.

Mitigating Sample Self-selection Bias

Accurately identifying the policy effects of the “Ten Cities, Thousand Vehicles” pilot project relies on the exogeneity of the core explanatory variable within the econometric model. Ideally, cities selected as pilot cities for the “Ten Cities, Thousand Vehicles” project would be randomly assigned. However, according to policy documents issued three times by China’s National Development and Reform Commission, the selection of pilot cities was based on factors such as the foundational development of the NEV industry, regional environmental pollution status, and local transportation infrastructure development. This implies that the designation of pilot cities was not random, but rather closely related to inherent city attributes such as geographic location, economic development level, population density, environmental constraints, and degree of openness. These attributes can lead to differences between cities that may impact carbon emissions from their power sectors differently over time, thereby introducing estimation bias.

To control the influence of these city attributes on the policy effects of the “Ten Cities, Thousand Vehicles” pilot project, this study adds interaction terms between city characteristics and polynomial time trends into the baseline regression model. Specifically, four categories of city attributes were selected as proxies for these prerequisite factors: resource-based cities, environmentally protected cities, transportation hub cities, and megacities (including large cities and Type I megacities). This approach is intended to mitigate the estimation bias resulting from the non-random selection of pilot cities to a certain extent.

Table 9 presents the regression results accounting for the non-random selection of cities participating in the “Ten Cities, Thousand Vehicles” pilot project. Columns (1) through (3) report the results after adding interaction terms between the four types of city attribute dummy variables and linear, quadratic, and cubic polynomial time trends, respectively, into the baseline model. As shown in Table 9, the estimated coefficients for the core explanatory variable – the “Ten Cities, Thousand Vehicles” pilot project – range between 0.0110 and 0.0114, all statistically significant at the 1% level. Despite slight variations in coefficient magnitudes, their signs and significance levels remain consistent with previous findings, further confirming that NEV promotion increases carbon emissions from the power sector.

Heterogeneity Analysis

Analysis of Spatial Carbon Emission Transfer Based on Regional Electricity Exchange

The “West-to-East Power Transmission” project is one of China’s four major projects of the new century. Its purpose is to convert the abundant water and coal resources in the western regions into electricity and deliver it to the eastern regions, which face electricity shortages, limited primary energy resources, and concentrated electricity demand [39]. This project not only ensures a stable power supply for the eastern regions to support their economic and social development but also facilitates the full utilization and development of the western regions’ power resources, thereby promoting regional economic growth. Thus, the “West-to-East Power Transmission” project provides a new cross-regional perspective for exploring the carbon emission transfer between the transportation and electricity production sectors. Based on this, the 50 cities in this study are further classified into output

Table 9. Regression results for non-random selection of pilot cities in the “Ten Cities, Thousand Vehicles” pilot project.

Variable name	(1)	(2)	(3)
Treat×Time	0.0110***	0.0113***	0.0114***
	(0.0026)	(0.0026)	(0.0027)
Constant	-1.4857	-2.7411*	-3.0240**
	(1.1789)	(1.4162)	(1.4186)
Control Variables	YES	YES	YES
City Fixed Effect	YES	YES	YES
Time Fixed Effects	YES	YES	YES
City Attributes × Linear Time Trends	YES	YES	YES
City Attributes × Quadratic Time Trends	NO	YES	YES
City Attributes × Cubic Time Trends	NO	NO	YES
Observations	750	750	750
Adj-R^2	0.9721	0.9728	0.9733

Note: (1) ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively, with robust standard errors in parentheses.

Table 10. Analysis results of the carbon emission transfer in the fuel cycle of New Energy Vehicles based on cross-regional electricity transmission.

Variable name	"West-to-East Power Transmission" Project		
	Northern Corridor	Central Corridor	Southern Corridor
	(1)	(2)	(3)
Treat×Time	0.0196***	0.0111**	0.0383
	(0.0047)	(0.0056)	(0.0878)
Treat×Time×EWE	0.0337***	0.0916*	0.0370
	(0.0888)	(0.0531)	(0.0245)
Constant	2.0201***	2.0336***	2.8851***
	(0.2298)	(0.4566)	(0.3468)
Control Variables	YES	YES	YES
City Fixed Effect	YES	YES	YES
Time Fixed Effects	YES	YES	YES
Observations	225	285	120
$Adj\text{-}R^2$	0.9543	0.9015	0.9695

Note: (1) ***, **, * indicate statistical significance at the 1%, 5%, and 10% levels, respectively, with standard errors in parentheses.

regions and input regions (denoted as *EWE*, where *EWE* = 1 for output regions and *EWE* = 0 for input regions). An interaction term *Treat×Time×EWE* is introduced into model (1), with further tests conducted along the northern, central, and southern transmission corridors (as shown in Table 11). The results are shown in columns (1) to (3) of Table 10.

In columns (1) to (3) of Table 10, the estimation results show that the interaction term coefficient for NEV promotion and the "West-to-East Power Transmission" project is significant at the 10% level or higher for both the northern and central corridors.

Firstly, for the northern corridor, the coefficient of the interaction term *Treat×Time×EWE* is positive, and the policy effect *Treat×Time* is also positive and statistically significant at the 1% level. This indicates that in the output regions of the northern corridor, NEV promotion not only increases carbon emissions in the local electricity production sector but also, through cross-regional power transmission, adds further emission reduction pressure on the region's electricity sector. Conversely, in the input regions of the northern corridor, NEV adoption helps alleviate the carbon emission pressure in local power departments. The reason for this phenomenon lies in the fact that the output regions of the north corridor, such as Inner Mongolia, Shanxi, and Shaanxi in the northwest, are rich in coal resources. Due to the rigid energy structure and comparative advantage, the marginal cost of coal-fired power generation in these areas is relatively low, and electricity production is largely based on thermal power generation. For input regions like Beijing, Hebei, and Tianjin, these areas are constrained by factors such as air pollution control, leading to relatively passive attitudes toward the construction of thermal power projects, with a stronger emphasis on renewable energy generation projects. As the penetration of new energy vehicles continues and electricity demand surges, there is greater reliance on the electricity grid from the output regions of the corridor, for "power supply assurance". While the electricity imported to meet the demand for new energy vehicles in the input regions reduces local electricity supply pressure and departmental carbon emissions, it simultaneously increases the carbon emissions from electricity production in the upstream output regions. This results in a reduction in the carbon reduction effect of new energy vehicles in the output regions, creating a cross-regional carbon emission transfer phenomenon

Table 11. Input and output regions of the "West-to-East Power Transmission" project.transmission.

Corridor	Output Regions	Input Regions
Northern	Inner Mongolia, Shanxi, Shaanxi, Ningxia, Qinghai, Xinjiang, Gansu	Beijing, Tianjin, Hebei, Shandong, Liaoning
Central	Hubei, Sichuan, Chongqing	Shanghai, Jiangsu, Zhejiang, Fujian
Southern	Yunnan, Guizhou, Guangxi	Guangdong, Hainan

between the "transportation sector" and the "electricity production sector".

Secondly, for the central corridor, NEV promotion similarly exerts a significant positive impact on carbon emissions in the electricity sector of the output regions, while power exchange benefits the input regions by reducing local carbon emissions in the power sector. The output regions of the central corridor – Hubei, Sichuan, and Chongqing – have a thermal power generation ratio lower than the national average and are situated between China's second and third geographic tiers. Their favorable natural conditions allow for the construction of large-scale hydropower facilities. In contrast, the input regions of the central corridor are located in the southeastern coastal and Yangtze River Delta areas, where rapid socio-economic development has heightened pressure on power supply. The Yangtze River Delta, with relatively flat terrain and a persistently high regional power deficit (as shown in Fig. 5), has limited self-sufficiency in power production, relying substantially on external electricity sources. The regulatory capacity of hydropower is constrained by the storage capacity of reservoirs, and this rigid constraint means that during peak electricity demand seasons in the Yangtze River Delta, there is an increased reliance on thermal power generation in the output regions for peak shaving. Therefore, the additional electricity demand created by the growing scale of new energy vehicle adoption leads to a carbon emission "export" phenomenon between electricity output and input regions. Although the carbon emission factor of the electricity grid in the upstream output regions is lower, the growing electricity demand in the downstream regions still increases the carbon emission pressure on the power production side. This reduces the inherent low-carbon emission reduction effect of new energy vehicles in those areas and forms a carbon emission transfer path, facilitated by cross-regional electricity exchanges.

Finally, regarding the southern corridor, the heterogeneous impact of NEV promotion on carbon emissions in the output regions is not statistically significant. A possible explanation is that the input regions along the southern corridor are situated between China's first and second geographic tiers or between the second and third tiers. For example, Yunnan's Hengduan Mountains feature high elevations and deep valleys, with significant topographical variations. The region is located in a monsoon climate zone, with abundant and concentrated rainfall in summer, providing exceptional conditions for hydropower generation. In 2020, thermal power accounted for only 11.28% of Yunnan's electricity production, while hydropower represented as much as 80.57%. Therefore, whether supplying electricity for local NEV usage or exporting electricity to Guangdong and Hainan to meet their NEV-related demand, the increased electricity consumption does not place substantial carbon emission pressure on power production in the output regions of the southern corridor.

Although Guangdong, a key output region in the southern corridor, is both China's largest NEV sales hub – accounting for 12.17% of national NEV sales in 2020, ranking first nationwide – and the province with the largest electricity deficit in the same year, two key factors mitigate its carbon emission impact. First, Yunnan's surplus electricity supply aligns well with Guangdong's power demand, while Hainan maintains a balanced power supply-demand structure. Second, both Guangdong and Hainan have relatively low grid carbon emission factors nationwide. As a result, even with large-scale NEV adoption, the clean energy-dominated power structure in exporting regions and the low carbon intensity of local grids ensure that NEV

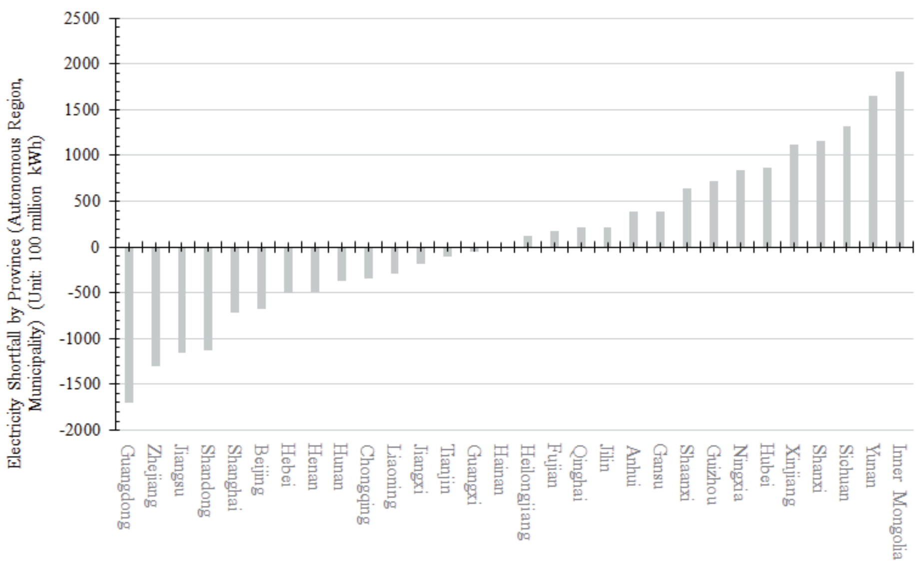

Fig. 5. Electricity shortfall in 30 provinces (autonomous regions, municipalities) in China.

deployment does not generate heterogeneous carbon emission effects.

In summary, under the "West-East Power Transmission" framework, our analysis reveals. Firstly, when exporting regions rely predominantly on thermal power, carbon reduction benefits from NEV adoption in receiving areas occur at the expense of increased emissions in exporting regions, manifesting as cross-regional carbon transfer through power transmission based on inter-sectoral shifts between transportation and power generation sectors. Secondly, for clean energy-dominated exporting regions, when receiving regions' aggregate electricity deficit exceeds exportable surplus, NEV adoption significantly enhances local emission reductions but partially exports carbon costs to upstream power producers. When regional deficits align with exportable surpluses, NEV deployment imposes minimal additional pressure on exporting regions' power production emissions. These findings demonstrate that while NEV promotion generally reduces urban and transportation sector emissions, its electricity demand creates decarbonization pressures on power generation systems. Such pressures undergo spatial redistribution through local and cross-regional power transmission networks, with differential impacts on fuel-cycle emission transfers contingent upon regional variations in power mix characteristics and electricity supply-demand patterns.

Based on Regional Grid Pressure and NEV Promotion Levels

China's vast territory encompasses diverse natural conditions, socio-economic foundations, and development statuses across regions. Consequently, the country is divided into four regions – East, Central, West, and Northeast – based on geographical location, economic foundation, and natural and human geography (National Bureau of Statistics, 2021). Under this classification: (1) The promotion and application levels of NEVs vary across regions, leading to heterogeneous impacts on carbon reduction. For example, the promotion effectiveness of NEVs in the Northeast region is relatively poor. (2) Each region shares certain characteristics in power production structure and power supply-demand features. For instance, the Eastern region generally includes provinces with significant power deficits and high reliance on thermal power, while the Western region consists primarily of provinces with power surpluses and a focus on renewable energy generation. This regional differentiation offers a valuable perspective for examining the carbon reduction effects of NEVs across different regions, further verifying the robustness of previous conclusions regarding carbon emissions transfer within the fuel cycle. Based on the above analysis, this study divides the sample cities into the four regions of East, Central, West, and Northeast (denoted as *Region*), interacts with the core explanatory variable, and includes them in model (1) for regression analysis. The results are shown in columns (1) to (4) of Table 12.

We can find that from columns (1) to (4) in Table 12. First, the policy effect coefficients for all four regions are statistically significant at the 1% level, indicating that NEV promotion increases carbon emissions in the electricity sector in each region. Second, with the exception of the Northeast region, the interaction coefficients between the "Ten Cities, Thousand

Table 12. Heterogeneity analysis results based on regional grid pressure and NEV promotion levels.

Variable name	Heterogeneity Analysis: East, Central, West, Northeast			
	East	Central	West	Northeast
	(1)	(2)	(3)	(4)
Treat×Time	0.0224***	0.0107***	0.0109***	0.0119***
	(0.0028)	(0.0031)	(0.0027)	(0.0027)
Treat×Time×Region	-0.0138***	0.0073**	0.0188***	0.0014
	(0.0035)	(0.0032)	(0.0061)	(0.0054)
Constant	1.2285***	0.8438***	0.5696***	0.4719***
	(0.1226)	(0.1421)	(0.1436)	(0.1541)
Control Variables	YES	YES	YES	YES
City Fixed Effect	YES	YES	YES	YES
Time Fixed Effects	YES	YES	YES	YES
Observations	750	750	750	750
Adj-R^2	0.9361	0.9618	0.9625	0.9615

Note: (1) ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively, with robust standard errors in parentheses.

Vehicles" pilot project and the Eastern, Central, and Western regions are statistically significant at the 5% level. Specifically, the coefficient for the Eastern region is negative, indicating that NEV promotion helps reduce carbon emissions in the electricity sector in this region. In contrast, the coefficients for the Central and Western regions are positive, suggesting that NEV promotion further increases carbon emissions in their respective electricity sectors.

The underlying reason for this is that the 10 provinces (municipalities) in the Eastern region generally have significant power shortages, and, except for Fujian and Hainan, the remaining 8 provinces (municipalities) have a high reliance on thermal power. Consequently, some of the additional electricity demand generated by NEV promotion is met through cross-regional grid transmission, thereby reducing the carbon emission pressure on the local electricity sector. The 12 provinces (regions, municipalities) in the Western region, on the other hand, are rich in power resources, including areas abundant in both renewable and fossil energy. Under the national trend of NEV promotion, the Western region not only needs to meet local power demand but also to fulfill the task of supplying electricity across regions. This results in increased pressure on the electricity sector's carbon emissions in the Western region.

These findings further confirm the phenomenon of sectoral transfer of carbon emissions associated with NEV promotion, indirectly revealing that the electricity production structure of a region affects the actual carbon reduction effectiveness of NEVs and, to some extent, determines the degree to which carbon emissions shift from the transportation sector to the electricity sector. In the Central region, the heterogeneity in the carbon emissions impact of NEV promotion on the electricity sector is due to significant differences in the power production structure among the 6 provinces. For example, Shanxi, Anhui, and Henan have a high proportion of thermal power, while Hubei and Hunan have a lower share of thermal power. This structural variation leads to a heterogeneous impact of NEV promotion on carbon emissions in the Central region's electricity sector.

The insignificance of the interaction coefficient for the Northeast region may be attributed to the poor effectiveness of NEV promotion in this region, as discussed in the previous analysis on temperature heterogeneity. The Northeast region is likely constrained by temperature-related issues, limiting the effectiveness of NEV promotion, and thus, the impact of regional heterogeneity on carbon emissions in the electricity sector is not pronounced.

Policy Synergy Effect Analysis

During the implementation of the "Ten Cities, Thousand Vehicles" pilot program, the Chinese government successively introduced policies such as the "New Energy Demonstration City Pilot" policy, "Low-Carbon City Pilot" policy, and "Smart City Pilot" policy to promote a green transition in economic and social development. According to the previous analysis, the positive environmental externalities of NEVs depend on green and low-carbon transformation across all lifecycle stages. Based on the findings of Han et al. (2024) [40], the "New Energy Demonstration City Pilot" policy, "Low-Carbon City Pilot" policy, and "Smart City Pilot" policy, when combined with the "Ten Cities, Thousand Vehicles" policy, generate policy synergy effects, either offsetting or amplifying the carbon emissions transferred to the power sector due to NEV usage. Referring to the approach of Han et al. (2024) [34], if a city in the given year or subsequent years qualifies as a "dual pilot" city – "New Energy Demonstration-"Ten Cities, Thousand Vehicles" Pilot", "Low-Carbon City-"Ten Cities, Thousand Vehicles" Pilot", or "Smart City-"Ten Cities, Thousand Vehicles" Pilot" – the $Treat_i$ variable is reassigned a value of 1, and the city is included in the treatment group; otherwise, it is assigned 0 and categorized as part of the control group. The $Posti_t$ variable is set to 1 for treatment group cities in the year of policy implementation and subsequent years, and 0 otherwise. This study introduces the dummy variables *EVNE*, *EVLC*, and *EVSC* to represent the three dual pilot policies, which are incorporated into model (1) to replace the $Treat{\times}Time$ interaction term for regression analysis.

Table 13, columns (1)-(3), presents the estimation results considering the synergy effects of the three policies. The results show that the synergy between the "Ten Cities, Thousand Vehicles" policy and either the low-carbon city or new energy demonstration city policies effectively mitigates the carbon emissions transferred to the power sector. However, when combined with the smart city policy, the "Ten Cities, Thousand Vehicles" policy further increases carbon reduction pressure on the power sector. This may be because smart city development is centered on digital and intelligent transformation, which significantly increases electricity demand, thereby intensifying the carbon emissions transferred to the power sector, coupled with NEV promotion policies.

Analysis of the Pathways Through which NEV Promotion Impacts Carbon Emissions in the Electricity Sector

Direct Impact Analysis based on the Optimization of Energy Consumption Structure

Existing research shows that NEVs reduce regional gasoline and diesel consumption from road mobile sources, optimize energy structures, and curb carbon emissions caused by fossil fuel use. However, as NEVs rely on electricity, reduced gasoline and diesel consumption is replaced by increased electricity consumption, leading to higher carbon emissions in the power sector. This study argues that the energy

Table 13. Policy synergy effect analysis.

Variable name	"Ten Cities, Thousand Vehicles" and New Energy Demonstration City	"Ten Cities, Thousand Vehicles" and Low-Carbon City	"Ten Cities, Thousand Vehicles" and Smart City
	(1)	(2)	(3)
EVNE	0.0065**	-	-
	(0.0030)	-	-
EVLC	-	0.0037*	-
	-	(0.0021)	-
EVSC	-	-	0.0178***
	-	-	(0.0034)
Constant	0.7300*	0.3937	-0.3084
	(0.9854)	(1.2202)	(1.0268)
Control Variables	YES	YES	YES
City Fixed Effect	YES	YES	YES
Time Fixed Effects	YES	YES	YES
Observations	750	750	750
Adj-R^2	0.9584	0.9580	0.9633

Note: (1) ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively, with robust standard errors in parentheses.

optimization effect of NEVs essentially shifts fossil fuel consumption from road sources to the power sector, increasing electricity demand. Since thermal power remains dominant in most parts of China, higher electricity consumption raises fossil fuel use for power generation, directly linking power sector emissions to fossil fuel consumption. Additionally, Porter's hypothesis suggests that appropriate environmental regulations incentivize enterprise innovation, enhancing competitiveness. Accordingly, the "Ten Cities, Thousand Vehicles" pilot policy not only generates positive environmental effects but also drives urban innovation. The policy emphasizes the coordinated development of the NEV industry and renewable energy-related technologies, such as fuels and batteries, directly promoting renewable energy technology innovation. Thus, this study concludes that NEV adoption synergistically enhances renewable energy technology and optimizes energy consumption.

To examine the pathway mechanism, this study draws on the methodologies of Wen et al. (2004) [41] and Baron and Kenny (1986) [42]. Using models (1), (3), and (4), the "Ten Cities, Thousand Vehicles" pilot project serves as a case to analyze the impact of NEV promotion on electricity consumption, renewable energy technology innovation, and its pathway through energy consumption in power generation.

$$M_{it} = c_0 + \alpha Treat_i \times Time_t + \sum_g \beta_g X_{it} + \mu_i + \gamma_t + \varepsilon_{it} \tag{3}$$

$$lnECE_{it} = c_1 + a_2 Treat_i \times Time_t + \lambda_n M_{it} + \sum_k \beta_k X_{it} + \mu_i + \gamma_t + \varepsilon_{it} \tag{4}$$

In models (1) and (4), the dependent variable is replaced with the energy consumption for power generation associated with carbon emissions in the electricity sector in each region, and the mechanism variable M_{it} is set as the electricity consumption and renewable energy technology innovation in each city. Here, the annual total electricity consumption in each city is used to represent the city's electricity consumption level (denoted as *lnElec*). Following Cheng and Yao's (2021) method [43], renewable energy patent applications were manually collected and categorized by type for each city. The total number of renewable energy patents, calculated by summing the five types (hydropower, wind, solar, geothermal, and biomass), was used as a proxy for renewable energy technology innovation. The variable was transformed using the natural logarithm of (patent count + 1) and adjusted for regional scale differences, represented as patents per 10,000 people (denoted as *lnNETec*). Due to the difficulty in obtaining precise data on energy consumption specifically for power generation in each city, the total annual energy consumption in each city is used as a proxy (denoted as *lnEnergy*), following the data calculation methods of Wang et al. (2011) [44] and Zhong et al. (2007) [45]. Relevant data are sourced from the China City Statistical Yearbook, provincial statistical yearbooks, statistical bulletins, and prefecture-level city statistical yearbooks.

The regression results are presented in columns (1) to (5) of Table 14. As shown in columns (1) to (3), NEV promotion has led to an increase in regional electricity consumption, which in turn raises the energy consumption level for power generation, further driving up carbon emissions in the electricity sector. A power generation structure predominantly based on fossil fuels exacerbates the carbon emissions transfer effect associated with NEV usage. From columns (4) and (5), NEV promotion synergistically enhances regional renewable energy technology innovation, thereby reducing energy consumption in electricity production. This mitigates the carbon emission transfer effect caused by NEV usage, allowing NEVs to fully realize their positive externalities. In addition, to enhance the robustness of the mediation effect model, the study further conducts a Sobel test and Bootstrap resampling (1,000 iterations) to re-examine the mediation effects. As shown in the table, the results from both tests support the findings of the stepwise regression approach. Specifically, the mediating effect through electricity consumption accounts for 6% (partial mediation), while the mediating effect through renewable energy technology innovation accounts for 25.6% (partial mediation). Based on the above analysis, Hypotheses 2 and 3 are supported. Based on the above analysis, Hypotheses 2 and 3 have been validated.

Indirect Impact Analysis Based on Technological Innovation

The implementation of the "Ten Cities, Thousand Vehicles" pilot project significantly increased regional electricity consumption, thereby elevating energy consumption levels in power production. Thus, to mitigate the carbon emissions transferred to the power production sector resulting from the widespread adoption of NEVs, it is necessary, on the one hand, to fundamentally enhance the energy efficiency of NEVs; on the other hand, it is crucial to leverage the energy-storage capabilities of NEVs by accelerating V2G collaboration, intelligently optimizing charging and discharging strategies, and engaging in applications such as peak shaving and valley filling, virtual power plants, and aggregated trading, thereby comprehensively reducing both supply and carbon reduction pressures on the electricity sector. Given that the demonstration nature of the "Ten Cities, Thousand Vehicles" pilot project effectively stimulates technological innovation in the NEV industry [46, 47], reducing carbon emission pressures on the power production sector necessitates prioritizing energy conservation and consumption reduction. The core technologies of NEVs, specifically

Table 14. Direct effect pathway analysis results.

Variable name	Direct Impact Analysis				
	Energy Consumption	City Electricity Consumption	Energy Consumption	Renewable Energy Technology Innovation	Energy Consumption
	(1)	(2)	(3)	(4)	(5)
Treat×Time	0.1406***	0.0114***	0.1321***	0.6029***	0.1767***
	(0.0462)	(0.0027)	(0.0364)	(0.1277)	(0.0480)
lnElec	-	-	0.7461***	-	
	-	-	(0.0311)	-	
lnNETec	-	-	-	-	-0.0598***
	-	-	-	-	(0.0160)
Constant	7.5078***	-0.3704	7.7842***	-16.5702***	8.4984***
	(2.2682	(1.3367)	(2.1024)	(3.0323)	(2.2873)
Control Variables	YES	YES	YES	YES	YES
City Fixed Effect	YES	YES	YES	YES	YES
Time Fixed Effects	YES	YES	YES	YES	YES
Sobel Test	0.008			-0.036	
Mediation Effects	0.060**			-0.256***	
Observations	750	750	750	750	750
R^2	0.9206	0.9333	0.9576	0.7784	0.9221

Note: (1) ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively, with robust standard errors in parentheses.

Table 15. Indirect effect pathway analysis results.

Variable name	Indirect Impact Analysis							
	“Three Electric” Technology						V2G Technology	
	Battery Technology	City Electricity Consumption	Motor Technology	City Electricity Consumption	Electric Control Technology	City Electricity Consumption	V2G Technology	City Electricity Consumption
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treat×Time	0.0479***	0.0134***	0.0452***	0.0143***	0.1522***	0.0145***	0.0893*	0.0124***
	0.0117	0.0038	0.0116	0.0041	0.0524	0.0043	0.0520	0.0045
lnBattery	-	-0.0425***	-	-	-	-	-	-
	-	0.0160	-	-	-	-	-	-
lnMotor	-	-	-	-0.0642***	-	-	-	-
	-	-	-	0.0149	-	-	-	-
lnContorl	-	-	-		-	-0.0208*	-	-
	-	-	-		-	0.0118	-	-
lnV2G	-	-	-		-	-	-	-0.0111***
	-	-	-		-	-	-	0.0023
Constant	-4.7058	-0.5704	4.4150	-0.0868	10.1720***	-0.1586	15.4763***	1.3399
	4.3391	1.3057	4.4257	1.3294	2.2413	1.3831	3.0725	1.3752
Control Variables	YES	YES	YES	YES	YES	YES	YES	YES
City Fixed Effect	YES	YES	YES	YES	YES	YES	YES	YES
Time Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Sobel Test	-0.002		-0.003		-0.003		-0.001	
Mediation Effects	-0.182***		-0.264***		-0.279***		-0.087**	
Observations	750	750	750	750	750	750	750	750
Adj-R^2	0.8612	0.9340	0.8225	0.9350	0.5926	0.9334	0.4781	0.9355

Note: (1) ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively, with robust standard errors in parentheses.

Table 16. Spatial matrix calculation formula.

*W*1		*W*2	
$W_{ij}^{de} = \begin{cases} aW_{ij}^{d}(1-a)W_{ij}^{e} \\ 0 \end{cases}$	$i \neq j$	$W_{ij}^{de} = \begin{cases} \dfrac{PGDP_i \times PGDP_j}{d_{ij}^2} \\ 0 \end{cases}$	$i \neq j$
	$i = j$		$i = j$

Table 17. Moran's I value of *lnECE* from 2006 to 2020.

Year	*W1*	*W2*
2006	0.0910***	0.3197***
	(0.0052)	(0.0002)
2007	0.1110***	0.3526***
	(0.0010)	(0.0000)
2008	0.1370***	0.3746***
	(0.0001)	(0.0000)
2009	0.1256***	0.3506***
	(0.0002)	(0.0000)
2010	0.1523***	0.3835***
	(0.0000)	(0.0000)
2011	0.1543***	0.3786***
	(0.0000)	(0.0000)
2012	0.1655***	0.3855***
	(0.0000)	(0.0000)
2013	0.1549***	0.3693***
	(0.0000)	(0.0000)
2014	0.1720***	0.3764***
	(0.0000)	(0.0000)
2015	0.1882***	0.3697***
	(0.0000)	(0.0000)
2016	0.2047***	0.3614***
	(0.0000)	(0.0000)
2017	0.2024***	0.3765***
	(0.0000)	(0.0000)
2018	0.2058***	0.4028***
	(0.0000)	(0.0000)
2019	0.1759***	0.3920***
	(0.0000)	(0.0000)
2020	0.1666***	0.3744***
	(0.0000)	(0.0000)

Note: (1) ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively, with robust standard errors in parentheses.

the "three-electric system" (battery, motor, and electronic control system), collaboratively influence the energy consumption and operational efficiency of NEVs [48, 49].

In this context, this study explores the impact pathway of the "Ten Cities, Thousand Vehicles" pilot project on regional electricity consumption through an indirect perspective, focusing on "Three Electric" technology and V2G technology. To accurately identify the effect of core "Three Electric" technologies on reducing carbon emissions transferred to the power sector, we use patent application counts as proxies: IPC patent classifications H01M and H02J represent battery technology (denoted as *lnBattery*), B60L and B60K represent motor technology (denoted as *lnMotor*), and H02K represents electric control technology (denoted as *lnControl*). V2G technology innovation level is represented by the number of V2G-related patent applications (denoted as *lnV2G*).

The mechanism variable M_{it} in models (3) and (4) is replaced with "Three Electric" and V2G technologies, while the dependent variable in model (1) is substituted with city electricity consumption. The relevant data is sourced from the IncoPat patent databases. Regression results are shown in columns (4) to (11) of Table 15.

The results in columns (1), (3), (5), and (7) indicate that the promotion of the "Ten Cities, Thousand Vehicles" project has significantly spurred R&D in "Three Electric" and V2G technologies. Additionally, the regression results in columns (2), (4), (6), and (8) show that "Three Electric" and V2G technologies help improve NEV energy consumption efficiency, thereby reducing electricity demand and easing carbon emission pressure in the electricity sector. Moreover, after conducting the Sobel test and Bootstrap resampling (1,000 iterations) to further assess the robustness of the mediation effects, it is found that the Sobel test results for each mediating variable support the findings from the regression analysis. The magnitude and statistical significance of the mediation effects further confirm the transmission roles of the mediating variables. In addition, based on the regression coefficients of each mechanism variable and the magnitude of the mediation effects, it can be observed that motor and electric control technologies are crucial for enhancing NEV energy efficiency. This is because motor power determines the power output level of NEVs, while electric control technology manages the coordination among different units. Thus, future innovative efforts should particularly focus on motor and electric control technologies.

However, as V2G technology is still in its early stages, its effectiveness in balancing power demand between the grid and NEVs has not yet been fully realized.

Further Discussion

Spatial Spillover Effect Analysis

As previously mentioned, the "Ten Cities, Thousand Vehicles" pilot program influences urban energy consumption levels by increasing regional electricity demand and renewable energy innovation, ultimately affecting carbon emissions from power production. Given the high spatial mobility of NEVs, this effect is likely not confined to local areas but may extend to surrounding regions, creating spillover effects on carbon emissions from electricity production in neighboring cities. Therefore, it is necessary to consider the spatial spillover effects of the "Ten Cities, Thousand Vehicles" pilot program.

Following the approach of Shao et al. (2016) [50], first, the shapefile of China's city levels is analyzed to obtain the distance information between sample cities. Next, the latitude and longitude data are matched with the data used in this study, and two different composite economic geography matrices are applied for calculation (the matrix calculation formulas are shown in Table 16) to enhance the robustness and reliability of the results. Second, this study adopts a composite economic-geographic matrix for calculation (the matrix formula is shown in Table 14). In this matrix, $PGDP_i$ represents the per capita GDP of region i, $PGDP_j$ represents the per capita GDP of region j, and d_{ij} is the distance between regions i and j. The parameter a, ranging between 0 and 1, denotes the weight of the geographic distance matrix. To comprehensively account for both geographic location and economic spatial effects, this study follows the approach of Shao et al. (2016) and sets $a = 0.5$, meaning that the geographic distance matrix and economic distance matrix each contribute 50% to the calculation.

Table 17 reports the global Moran's I values of *lnECE* across regions from 2006 to 2020 based on both the *W1* and *W2* spatial weight matrices. It can be observed that *lnECE* values remain consistently above zero throughout the study period, showing a generally stable or increasing trend, all of which pass the significance tests. This indicates that carbon emissions from electricity production exhibit significant spatial correlation, revealing clear geographic clustering patterns and the presence of spatial spillover effects.

Due to the inherent limitations of the global Moran's I, which only reflects the average degree of overall spatial correlation, it may fail to capture localized spatial dependencies. Specifically, negative spatial correlation in some regions may offset positive spatial correlation in others, causing the global Moran's I to approach zero and potentially mask the presence of actual spatial autocorrelation. To further test spatial dependence among sample cities, this study constructs Moran scatter

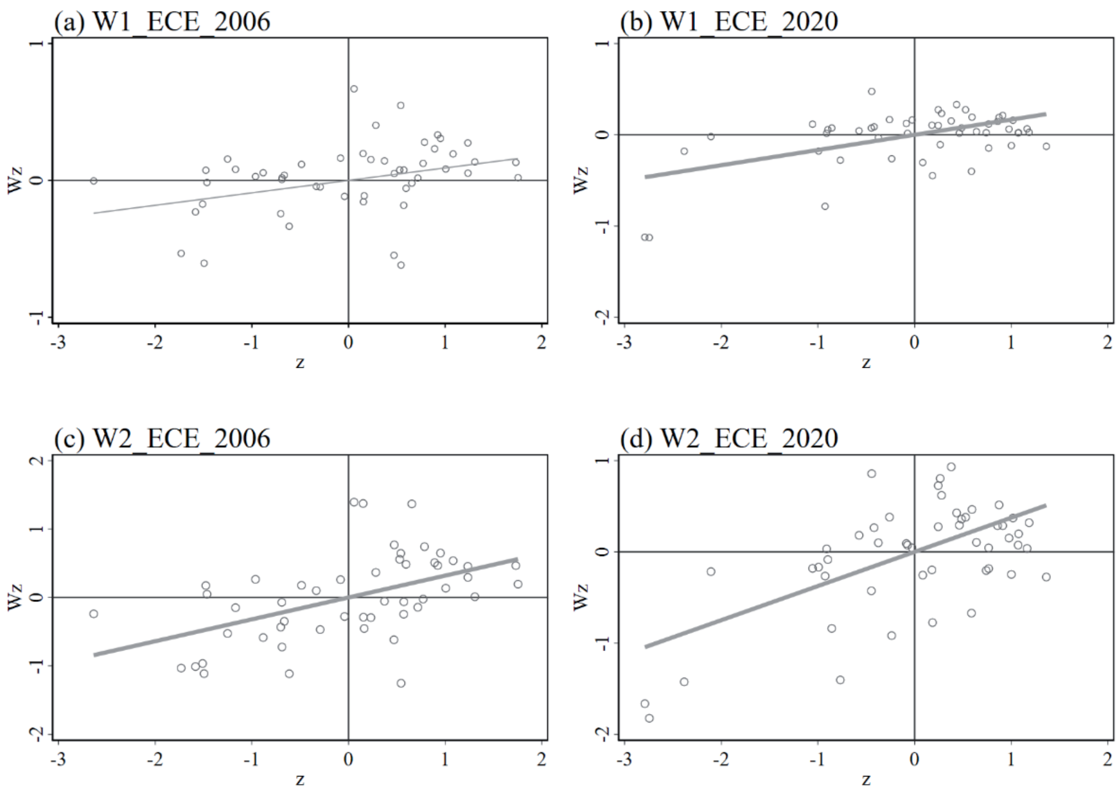

Fig. 6. Moran Scatter Plots of *lnECE* in 2006 and 2020 based on *W1* and *W2* matrices.

Table 18. Results of the LM test, LR test, and Wald test.

Comparison between spatial econometric models	W_1	W_2
LM-Error	213.504	89.882
	(0.000)	(0.000)
Robust LM-Error	135.811	3.315
	(0.000)	(0.069)
LM-Lag	92.128	94.090
	(0.000)	(0.000)
Robust LM-Lag	14.435	7.524
	(0.000)	(0.006)
LR-SDM-SEM	55.18	78.42
	(0.000)	(0.000)
LR-SDM-SAR	63.87	59.63
	(0.000)	(0.000)
Wald-SDM/SEM	19.42	30.45
	(0.0035)	(0.0000)
Wald-SDM/SAR	26.50	27.50
	(0.0004)	(0.0003)
Hausman	129.30	83.88
	(0.0000)	(0.0000)

plots of electricity sector carbon emissions based on the local Moran's I calculation, using both the *W1* and *W2* spatial weight matrices, as shown in Fig. 6 (a-b) and (c-d). From these figures, it can be observed that most cities fall into the first and third quadrants, indicating strong positive local spatial correlation in electricity carbon emissions across cities. This result is consistent with the findings of the global Moran's I. Moreover, over time, the number of cities located in the first and third quadrants increases, suggesting that the local spatial dependence in electricity sector carbon emissions has been strengthening year by year. Therefore, from a local perspective, there is significant spatial correlation in both cases, and spatial factors should be taken into account – justifying the application of spatial econometric models.

Before conducting spatial econometric regressions, it is necessary to evaluate the constructed spatial effect econometric models using LM tests, LR tests, Wald tests, and Hausman tests, as shown in Table 18. First, the results for LM-Error, Robust LM-Error, LM-Lag, and Robust LM-Lag under both the *W1* and *W2* matrices are all significant at the 1% level, indicating that a spatial econometric model is appropriate for empirical analysis. Second, the LR test for spatial lag and the Wald test results both suggest rejecting the simplification of the SDM into either a SAR or SEM model. Therefore, the Spatial Durbin Model (SDM) employed in this study is robust. Finally, the Hausman test yields a p-value below 0.01, rejecting the random effects model in favor of the fixed effects model.

Table 19. Spatial spillover effect analysis results.

Variables name	SDM		SAR	
	W1	*W2*	*W1*	*W2*
	(1)	(2)	(3)	(4)
Treat×Time	0.0937***	0.1040***	0.0870***	0.0579*
	(0.0298)	(0.0318)	(0.0292)	(0.0303)
W×Treat×Time	0.2392***	0.2321***		
	(0.0905)	(0.0551)		
ρ	0.6836***	0.2840***	0.6942***	0.3654***
	(0.0639)	(0.0562)	(0.0551)	(0.0483)
Direct effect	0.0786**	0.0893***	0.0909***	0.0587*
	(0.0318)	(0.0323)	(0.0319)	(0.0322)
Indirect effect	0.5774**	0.2755***	0.2003**	0.0315*
	(0.2881)	(0.0694)	(0.0940)	(0.0190)
Total effect	0.6560**	0.3648***	0.2913**	0.0902*
	(0.2987)	(0.0761)	(0.1220)	(0.0507)
Control Variables	YES	YES	YES	YES
Observations	750	750	750	750
Adj-R^2	0.0755	0.1339	0.0886	0.1180

Note: (1) ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively, with robust standard errors in parentheses.

Following the methodology of Huang et al. (2022) [51] and based on the results of the LM, LR, and Hausman tests, the two-way fixed effects SDM is selected for analysis. Accordingly, this study constructs a difference-in-differences SDM to examine the spatial spillover effects of the "Ten Cities, Thousand Vehicles" pilot program. It is worth noting that the SAR (Spatial Autoregressive) model captures substantive spatial dependence. In this form of spatial relationship, the impact of the dependent variable can affect not only the local area, but also other regions connected to it, making it highly applicable to this research context. The model is specified as follows, where α denotes the constant term, ρ is the spatial autoregressive coefficient ranging from [-1,1], ω_{it} is the spatial weight matrix, θ is the corresponding coefficient vector, X_{it} represents control variables, c_i and μ_t are spatial and time fixed effects respectively, and ε_{it} is the random error term. All other variables maintain their previous definitions.

$$lnECE_{it} = \alpha + \rho\sum_{j=1}^{n}\omega_{i,t}lnECE_{it} + \beta\left(\beta Treat_i \times Time_t + \sum_{i=1}^{n}X_{i,t}\right) + \theta\sum_{j=1}^{n}\omega_{i,t}\left(\beta Treat_i \times Time_t + \sum_{i=1}^{n}X_{i,t}\right) + c_i + \mu_t + \varepsilon_{i.t} \quad (5)$$

Columns (1)-(2) of Table 19 present the regression results of the model (5). Additionally, to enhance the rigor and robustness of the SDM analysis, the spatial lag model is employed as a supplementary estimation method, as shown in columns (3)-(4). From columns (1)-(2), it is evident that both the spatial autoregressive coefficient ρ and the coefficient of *Treat×Time* are significantly positive. Furthermore, following the spatial effect decomposition method proposed by LeSage and Pace (2009) [52], the SDM results are decomposed into direct effects, indirect effects, and total effects. The findings indicate that the implementation of the "Ten Cities, Thousand Vehicles" pilot program has a spatial spillover effect on carbon emission transfers in the urban electricity sector. While it increases the carbon

Table 20. The impact of the 'Ten Cities, Thousand Vehicles' pilot project on carbon emissions in the electricity sector.

Time (τ)	Carbon Emissions in the Electricity Sector	Time (τ)	Carbon Emissions in the Electricity Sector
	(1)		(1)
$\tau = -5$	0.0034	$\tau = 4$	0.0076*
	(0.0054)		(0.0046)
$\tau = -4$	-0.0012	$\tau = 5$	0.0086*
	(0.0048)		(0.0048)
$\tau = -3$	0.0002	$\tau = 6$	0.0119**
	(0.0038)		(0.0050)
$\tau = -2$	0.0007	$\tau = 7$	0.0108*
	(0.0036)		(0.0060)
$\tau = 0$	-0.0001	$\tau = 8$	0.0191***
	(0.0037)		(0.0065)
$\tau = 1$	0.0029	$\tau = 9$	0.0192***
	(0.0037)		(0.0065)
$\tau = 2$	0.0054	$\tau = 10$	0.0207**
	(0.0038)		(0.0084)
$\tau = 3$	0.0061	$\tau = 11$	0.0193**
	(0.0040)		(0.0094)
Average Effect		0.0120	
Control Variables		YES	
City Fixed Effect		YES	
Time Fixed Effects		YES	
Observations		750	
Adj-R^2		0.9610	

Note: (1) ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively, with robust standard errors in parentheses.

emissions of the electricity sector in pilot cities, it also raises emissions in neighboring cities through regional traffic flows, thereby reaffirming the robustness of the baseline regression results.

Identification of the Net Effect of NEV Promotion on Carbon Emissions in Power Production

Based on the dynamic effect results shown in Fig. 1, it is evident that NEVs have a certain impact on increasing carbon emissions in the electricity sector through the fuel cycle. Therefore, to further quantify the extent to which NEVs shift carbon emissions to the electricity sector in this cycle, a dynamic test is conducted again using model (2) to calculate the average effect. The results are presented in Table 20. As seen in column (1) of Table 20, the promotion and use of NEVs have increased the carbon emission reduction pressure on the electricity production sector, with an average increase effect of approximately 1.20%. This promoting effect shows a rising trend as the market share of NEVs continues to grow, particularly after $\tau = 7$.

To be specific, this study further discusses the economic significance of the test results. In terms of carbon emissions, the use of NEVs has added 370,200 tons of carbon emissions to the electricity sector in demonstration cities. Therefore, it is roughly estimated that the net increase in carbon emissions from NEVs in demonstration cities' electricity sectors is 370,200 tons, equivalent to an annual increase of 133,600 tons (370,200/2.77) in standard coal consumption.

Conclusions

Based on NEV-related panel data from 50 Chinese cities between 2006 and 2020, this study uses a multi-period DID model to examine the impact of NEV promotion on carbon emissions in the electricity sector. The findings indicate: (1) NEVs have placed significant carbon reduction pressure on the power sector. Taking China's first NEV promotion policy as an example, cities participating in the "Ten Cities, Thousand Vehicles" pilot program experienced a 1.19% increase in carbon emissions from electricity production. Moreover, the program exhibited notable spatial spillover effects, raising carbon emissions in the power sectors of neighboring regions. This indicates that, given China's current incomplete decarbonization of electricity production, replacing traditional fuel vehicles with NEVs essentially results in a "coal-for-oil" substitution, shifting carbon emissions from the transportation sector to the power sector; (2) The analysis conducted through China's "West-to-East Power Transmission" project reveals that the effectiveness of NEV carbon reduction is significantly influenced by whether regional power production has decoupled from fossil fuel dependency. If the power generation structure in the output regions primarily relies on thermal power, then the carbon reduction effect of NEV adoption in the input regions comes at the expense of increased carbon emissions in the output regions' power production, thereby creating a "regional transfer" effect of carbon emissions. This pressure can shift through local and cross-regional electricity transmission, with variations in regional power generation structures and supply-demand characteristics leading to differing impacts on carbon emission transfers within the fuel cycle; (3) Heterogeneity analysis reveals that the impact of NEVs on carbon emissions in the electricity sector varies according to factors like regional temperature, usage patterns, and power supply-demand structure, resulting in distinct regional differences. Additionally, under the combined effects of the new energy demonstration city and low-carbon city policies, NEV promotion effectively mitigates the transfer of carbon emissions to the power sector, amplifying the positive environmental externalities of NEVs. (4) Direct impact mechanism analysis shows that NEV usage increases regional electricity demand, leading to higher energy consumption in power production and further driving up carbon emissions in the power sector. A fossil-fuel-dominated power generation structure exacerbates the carbon emission transfer effect caused by NEV adoption. However, NEV promotion also synergistically enhances regional renewable energy technology innovation, helping to reduce overall energy consumption demand; (5) Indirect impact mechanism analysis indicates that policy promotion significantly spurred R&D in "three electric" (battery, motor, and electric control) and V2G technologies. These innovations improve NEV energy efficiency, thereby reducing electricity demand and alleviating carbon emission pressure on the electricity sector.

The policy recommendations embedded in this paper are as follows.

(1) Advance structural decarbonization in the power sector. Efforts should focus on minimizing the "regional transfer effect" identified in cross-provincial electricity trade. In fossil-dependent power-exporting regions (e.g., Inner Mongolia, Shanxi), accelerate retrofitting of coal plants with advanced carbon capture technologies and institute renewable energy quotas for exported electricity. In power-importing regions (e.g., Guangdong, Zhejiang), consider carbon-embedded tariffs on imported electricity and reinvest the proceeds in local offshore wind or solar-plus-storage facilities to offset imported emissions.

(2) Strengthen behavioral incentives for green electricity adoption. Introduce time-of-use carbon premiums to guide NEV charging toward periods when renewable generation is abundant and develop "carbon liquidity accounts" allowing NEV users to earn tradable offsets through V2G discharges. Additionally, adopt battery passport standards that track lifecycle carbon footprints, offering priority grid access for retired NEV batteries in energy storage. Establish

“renewable charging corridors” with battery-swapping stations powered predominantly by nearby wind or solar resources to improve charging convenience and reduce emissions.

(3) Adopt regionally differentiated NEV deployment strategies. In colder northern provinces (e.g., Heilongjiang, Jilin), policymakers should prioritize supporting NEVs equipped with cold-weather battery technologies and maintain transitional incentives for PHEVs until local grids can reliably meet winter electricity demands. In regions with abundant renewable or hydropower resources (e.g., Sichuan, Yunnan, Guizhou), BEVs should be promoted more aggressively to leverage cleaner power generation. Additionally, cross-provincial collaboration – such as co-funding cleaner coal retrofits – can reduce the overall carbon intensity of electricity and lay the groundwork for unified vehicle-grid integration standards. Aligning NEV promotion with each region’s specific power mix, infrastructure, and climate conditions helps ensure NEVs become a catalyst for systemic decarbonization rather than an isolated policy measure.

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Conflict of Interest

Authors declare no conflict of interest.

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