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# How does adoption of electric vehicles reduce carbon emissions? Evidence from China

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ABSTRACT

We investigate the effect of the adoption of electric vehicles (EVs) on $CO_2$ emissions using spatial econometric models and have three findings. First, there are spatial spillover effects of EV adoption on $CO_2$ emissions, implying that the $CO_2$ mitigation of a city depends on local sales of EVs and sales of EVs in neighboring cities. A 1% increase in the sale of EVs in a city can reduce $CO_2$ emissions locally by 0.096% and by 0.087% in a nearby city. Second, EVs indirectly impact $CO_2$ emissions through the substitution effect, energy consumption effect, and technological effect. The overall impact of EV adoption on $CO_2$ emissions is negative. Finally, we demonstrate the moderating effect of urban energy structure on EVs' $CO_2$ emissions mitigation. A 1% increase in the proportion of renewable energy generation increases the decarbonization of EVs by 0.036%. These findings provide policy implications for the coordinated development of EV market and energy system.

## 1. Introduction

Internal combustion engine vehicles (ICEVs) bring great convenience to human society but also cause serious greenhouse effects. In 2020, the global transport sector accounted for 22.3% of energy-related $CO_2$ emissions and 15.5% of energy consumption[1] [1,2]. To meet the important commitments made in the Paris Agreement as well as to deal with the greenhouse effects, the Chinese government has released a long-term plan to achieve the "carbon peak" by 2030 and "carbon neutrality" by2060.[2] The transportation sector has emerged as a prominent decarbonization goal [3,4]. The Chinese government places a high value on electrifying the transportation industry to minimize $CO_2$ emissions. To accelerate the market penetration of EVs, China's policymakers have developed some industrial incentive policies since 2009 [1]. As a result, EV sales in China have increased from 480 in 2009 to 3.521 million in 2021 [5].

Although the widespread adoption of EVs is regarded as a feasible strategy for decarbonization, scholars are still divided on whether or not EVs reduce emissions. Whether EVs really contribute to decarbonization and gradually alleviate the greenhouse effects

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[1] Data source: Statistical Review of World Energy 2021, BP (British Petroleum).
[2] Data source: Opinions of the Communist Party of China Central Committee and the State Council on Fully Implementing the New Development Concept and Doing Well in Carbon Peak and Carbon Neutrality, State Council of China, October 2021.

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is still a yet-to-be-verified question. Many scholars have attempted to answer this question [6–8]. Holland et al. [9] provided a perspective on externalities and studied regional differences in the environmental effects of EVs. The study also demonstrates that EVs may increase electricity consumption and “export” $CO_2$ to neighboring areas through the electricity grid. Therefore, it is crucial to understand the inherent cause-and-effect relationship between EVs and $CO_2$ emissions.

To fill the gap in existing research, we use a spatial econometric model to study the environmental effect of EVs. Based on EV sales and $CO_2$ emissions in 50 Chinese cities from 2010 to 2020, we empirically study the spatial spillover effect and influencing mechanisms of EV adoption on $CO_2$ emissions. The substitution effect, energy consumption effect, and technological effect are three ways that EVs influence $CO_2$ emissions.

First, under the constraint of a purchase restriction policy for ICEVs, the widespread adoption of EVs, as the main substitute for ICEVs, can reduce the market share of ICEVs. Much literature has shown that an EV’s $CO_2$ emission is significantly lower than that of an ICEV [10–13]. Therefore, we make a reasonable assumption that the increase in EV adoption can significantly reduce $CO_2$ emissions by reducing the market share of ICEVs. The decline in ICEVs’ market share due to the increase in EV adoption is defined as the “substitution effect”. Second, Holland et al. [9] found an interesting conclusion: EVs “export” $CO_2$ to neighboring areas through the electricity grid. Although the $CO_2$ emissions per EV are lower than that of an ICEV, driving EVs still consumes electricity. As EV sales increase, the residents’ electricity consumption significantly increases. The literature shows that to date, more than 50% of China’s electricity is still generated by fossil fuel combustion [14], and the combustion of fossil fuels is the key factor producing the greenhouse effect. Consequently, the widespread adoption of EVs significantly increases $CO_2$ emissions by increasing the consumption of fossil fuels. The expansion of fossil fuel usage is defined as the “energy consumption effect”. Third, the widespread adoption of EVs is conducive to promoting transportation technology innovation. The increase in EV sales also improves the financial performance of manufacturers. Using the revenue from the sales of EVs, manufacturers can further boost R&D investment to enhance the level of transportation technology. As transportation technology advances, urban traffic congestion will be lessened, and vehicles’ exhaust emissions will decrease as a result [15]. Furthermore, the advancement of transportation technologies may also have a spatial spillover effect. For example, airplanes, railways, and high-speed railways can improve connectivity between different regions and improve transportation efficiency. The overall effect of EVs on $CO_2$ emissions is unknown. Therefore, an empirical study of the aforementioned mechanism is still required.

The marginal contribution of this study is as follows: First, we study the effect of EV adoption on $CO_2$ emissions, which provides a meaningful examination of the causal relationships between EVs and $CO_2$ emissions, as well as confirms the existence of externalities in the environmental effects of EVs. Our findings not only provide new evidence for the argument on the environmental effects of EVs but also provide a theoretical basis for policymakers to adjust and optimize the industrial layout of EVs. Second, based on the substitution effect, energy consumption effect, and technological effect, the feasibility path of EV diffusion emission reduction is explored. More policies can be formulated to accelerate the diffusion of EVs and decarbonization. Third, by constructing the interaction term between EVs and energy structures, we demonstrate the moderating effect of urban energy structures on the $CO_2$ emissions mitigation effect of EVs. This finding has important policy implications for the coordinated growth of the EV market and energy structure. Finally, by grouping regression (cities with net power generation or net power consumption), we demonstrate that urban energy consumption can “export” $CO_2$ through the electricity grid. Based on this, by constructing the interaction term between the proportion of renewable energy generation and urban power consumption, we demonstrate that a higher proportion of renewable production can offset the energy consumption effect, which also means that the “exported” $CO_2$ can be reduced by optimizing the energy structure. This finding not only offers a reasonable explanation for optimizing the distribution of the electric power grid and EV industry but also provides a new perspective for the coordinated growth of the EV market and energy structure.

The rest of our study is structured as follows: The related literature is reviewed in Section 2 along with the literature’s gaps. Section 3 describes our empirical strategy and data. Section 4 presents the empirical results and analysis of this paper. The moderating effect and influence mechanism of EV adoption on $CO_2$ emissions are further discussed in Section 5. Section 6 presents the conclusion and policy implications.

## 2. Literature review

### *2.1. Spatial spillover effects of $CO_2$ emissions*

Many researchers have proven that $CO_2$ emissions have a regional spillover impact. To illustrate the dynamic spatial spillover impact of EV industry regulations on $CO_2$ emissions, Zhao et al. [16] built a dynamic spatial panel data model. Fang et al. [17] assessed the $CO_2$ emissions of 282 Chinese cities from 2004 to 2018 using data on nighttime lighting, along with the $CO_2$ emissions efficiency (CEE). Their findings demonstrate the sizeable and advantageous geographical spillover effects of CEE in Chinese cities. When Liu et al. [14] calculated the $CO_2$ emissions efficiency of 30 Chinese provinces, they discovered that the provinces with high or low $CO_2$ emissions efficiency tend to cluster over time and that the spatial distribution of $CO_2$ emissions efficiency changes to be ordered. Based on data from China’s provinces from 2000 to 2018, Huo et al. [18] explored the network structure features of $CO_2$ emissions in the building industry. They discovered that China’s building $CO_2$ emissions show the network structure. The significance and durability of the spatial linkages steadily increased between 2000 and 2018.

### *2.2. Impact of the transport sector on $CO_2$ emissions*

Although many scholars have studied the effect of the transport sector on $CO_2$ emissions, there is no agreement in the research about how much emissions are reduced by EVs [19].

First, some scholars have studied the negative impact of ICEVs and the positive impact of EVs on decarbonization. On the one hand, ICEVs will hinder decarbonization. For instance, to examine transportation-related energy consumption and $CO_2$ emissions, Yin et al. [20] used the comprehensive energy model that is nested in the Global Change Assessment Model (GCAM). According to this research, the transportation industry will continue to be highly dependent on fossil fuels and future transportation energy consumption and $CO_2$ emissions will rise quickly. According to Li et al. [10], urban passenger transport is now a significant contributor to the consumption of energy and $CO_2$ emissions due to the continued rise in automobile ownership caused by economic growth and urbanization. Böhm et al. [21] used GPS traces and a microscopic model to analyze the emissions of four air pollutants. They found that the emissions across the vehicles and roads are well approximated by heavy-tailed distributions, and as a result, they identified the existence of gross polluters—vehicles with the highest emissions—and grossly polluted roads—which are subject to the highest emissions. Ten gasoline, four diesel, and six fully hybrid light-duty passenger vehicles (LDPVs) were examined by He et al. [22] in Macao, China, using portable emissions measuring systems (PEMS). Due to the deliberate removal of after-treatment systems, they discovered that diesel vehicles are the study's highest polluters. HEVs, on the other hand, could reduce carbon emissions by about 30% (i.e., by consuming less fuel and producing less $CO_2$).

On the other hand, EVs are conducive to decarbonization. For instance, Zheng et al. [23] discovered that 682,047 battery electric vehicles (BEVs) sold in the five provinces between 2011 and 2017, totaling 18.3 billion kilometers driven by EVs. 3.0 TWh of electricity was used, which decreased the amount of $CO_2$ emitted by 611,824 tons and the amount of gasoline used by 1.6 billion gallons. According to Gan et al. [24], PHEVs have a significant deal of potential to decarbonize the transportation industry. Even though all future expansions of the electric sector's capacity will be powered by fossil fuels, Ou et al. [25] determined that widespread adoption of EVs would reduce net $CO_2$ emissions until 2050. Best et al. [26] used a life-cycle evaluation and discovered that under most circumstances, electric cars emit less pollution than ICEVs. In a life cycle approach, Yu et al. [27] estimated the GHG emissions of powertrain cars with a focus on the effects on energy and the environment. The findings demonstrated that compared to ICEVs, all electric cars (EVs)—of which BEV is the least—have lower life-cycle total energy and GHG emissions. Li et al. [28] found that promoting the use of electric vehicles contributes to a reduction in national-level nitrogen oxide emissions, as well as greenhouse gas and PM2.5 emissions in most provinces of China. Based on a suite of scenarios with a chemistry transport model, Schnell et al. [29] found that the electrification of heavy-duty vehicles (HDVs) contributes to sustained improvements in air quality, specifically in reducing $NO_2$ and fine particulate matter ($PM_{2.5}$) pollution. Based on the integrated assessment model combining the regional air pollution model WRF-Chem and epidemiological concentration-response relationships, Peng et al. [30] found that the electrification of the transportation sector can lead to significant health benefits.

Second, based on various models of engineering technology, some scholars have estimated the negative effect of EVs on the environment. To estimate the $CO_2$ from the producing vehicle, Yang et al. [13] used the life cycle assessment (LCA). Their findings showed when compared to ICEVs, BEVs and PHEVs reduced $CO_2$, VOC, and NOX emissions but increased $PM_{2.5}$ and $SO_2$. Qiao et al. [31] discovered that, in the context of China, BEV manufacturing has emissions of greenhouse gases and energy that are around 50% greater than those of an ICEV. Experimental research on exhaust and non-exhaust emissions from gasoline and diesel ICEVs was conducted by Woo et al. [32]. They discovered that when just main exhaust PM emissions were taken into account in cars fitted with non-asbestos organic (NAO) brake pads, the total $PM_{10}$ of the EVs was 10–17% higher than those of the gasoline ICEVs and diesel ICEVs. By analyzing the age and distribution of NEVs, Yu et al. [27] built on the prior research. They discovered that the $CO_2$ emissions of BEV and PHEV total life cycle are greatly increased by the short lifespan, making them much higher than those of conventional cars. Using portable emissions monitoring devices, McCaffery et al. [33] discovered that compressed natural gas vehicles and liquefied petroleum gas vehicles had lower emissions, while conventional diesel engines still exhibited significant distance-specific NOx benefits. Shen et al. [34] found that the electrification of transportation brings significant benefits to national energy security, but the climate benefits remain uncertain.

Finally, previous studies had explored the effect of transportation infrastructure on decarbonization. For instance, Ensslen et al. [4] found that customized smart charging services are a persuasive technique to lower $CO_2$ emissions unique to EVs as $CO_2$ emissions intensities alter over time according to the electric power networks. Based on empirical information from the operations of ride-hailing services, Li et al. [35] modeled the travel and charging patterns of shared autonomous electric vehicles (SAEVs). According to their research, shared autonomous electric cars often emit less $CO_2$ per mile than contemporary ICEVs under the Californian power system.

### *2.3. Research gaps*

Based on the above studies, first, many studies have focused on the positive effect of EVs on $CO_2$ emissions and the spillover effect of $CO_2$ emissions, which ignores discussing the possible channels of EVs increasing $CO_2$ emissions. Second, although many studies have estimated the negative effect of EVs on the environment based on various models of engineering technology, there is still no study on the causal relationship between EVs and $CO_2$ emissions based on economic theories and methods, especially the channels through which EVs may increase $CO_2$ emissions. Therefore, it is of great importance to reveal the internal impact mechanism between EVs and $CO_2$ emissions based on the research paradigm of economics. Based on the substitution effect, energy consumption effect, and technological effect, this paper studies the negative, positive, and net effects of EV adoption on $CO_2$ emissions. Third, the research objective of most scholars is $CO_2$ emissions. The dependent variable we used is $CO_2$ emissions intensity with more economic significance. Fourth, scholars often ignore the synergy between EVs and energy structure when studying the decarbonization effect of EVs. By constructing the interaction term between EVs and energy structures, this paper demonstrates the moderating effect of urban energy structures on the $CO_2$ emissions mitigation effect of EVs. This paper also demonstrates that more optimized energy structures will be conducive to mitigating $CO_2$ "exported" by EVs through the electricity grid.

## 3. Empirical strategy and data

### 3.1. Variable and data

We employ balanced panel data from 50 Chinese cities from 2010 to 2020 for empirical analysis. Transportation-related $CO_2$ emissions intensity (*$CO_2$*) is the core dependent variable of this study. It is measured by the ratio of $CO_2$ emissions to transportation-related output values [15,36]. To further study the geographic distribution of China's $CO_2$ emissions, we draw distribution maps of China's $CO_2$ emissions in 2010, 2015, and 2020, respectively. These maps are shown in Fig. 1. In 2010, the $CO_2$ emissions of the southeast coastal and northwest cities were relatively high. While $CO_2$ emissions in the west of the southeast coastal cities decreased significantly in 2015. Finally, in 2020, except in a few cities, for example, Beijing and Shanghai, other cities' $CO_2$ emissions have decreased to a low level. The $CO_2$ emissions data is obtained from the China Emissions Accounts and Datasets (CEAD, 2022). As a core independent variable, the data on EV sales is obtained from the Statistical Yearbook of China's Energy Conservation and Electric Vehicles 2011–2021.

Furthermore, related literature also shows that $CO_2$ emissions are affected by the following variables [36]. The ratio of foreign direct investment to GDP serves as a proxy for the degree of openness (*Open*). *Open* is measured by the proportion of foreign direct investment to GDP. The energy consumption level (*ES*) is measured by 10,000 tons of coal consumption. The ratio of the tertiary sector's production value to that of the secondary industry serves as a proxy for industrial structure upgrading (*Ind*). The ratio of the total urban population to the urban area is used to measure population density (*Density*). The level of urbanization (*Urban*) is measured by the ratio of urban residents to the total local population. The data for *GDP*, *Open*, *Ind*, and *Density* is derived from the China City Statistical Yearbook 2011–2021. The data for ES is derived from the statistics bureaus of Chinese cities. We logarithmic all the variables except *Urban*. Table 1 shows the descriptive statistics of variables.

### 3.2. Econometric model

#### 3.2.1. Spatial autocorrelation analysis

Before employing spatial econometric methods, we first examine whether there is a spatial dependency between data. Spatial autocorrelation is defined as those regions with similar positions having similar variable values [37]. An overall measure of spatial autocorrelation is provided by Global Moran's I (Moran, 1950). Moran's I is given by:

$$I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}\omega_{ij}(x_i-\bar{x})(x_j-\bar{x})}{s^2\sum_{i=1}^{n}\sum_{j=1}^{n}\omega_{ij}} \tag{1}$$

where $s^2 = \frac{\sum_{i=1}^{n}(x_i-\bar{x})}{n}$; $\omega_{ij}$ is the (i, j) element of the spatial weight matrix; $\sum_{i=1}^{n}\sum_{j=1}^{n}\omega_{ij}$ is the sum of the weights of the space; n is the number of cities; $x_i$ and $x_j$ are the $CO_2$ emissions of the city i and j.

According to LeSage et al. [38], the choice of a spatial weight matrix significantly influences the test for spatial autocorrelation. Thus, based on our data and previous literature analysis, we employ a geographical weight matrix based on economic distance. To be more specific, we first analyze the Shp-file at the city level in China to obtain longitude, latitude, and other city-specific information. Second, we match the latitude and longitude with the data used in this paper. Finally, based on the gross product of the transportation sector, we construct a spatial weight matrix of economic distance through STATA 16. Global Moran's I, however, only assesses the

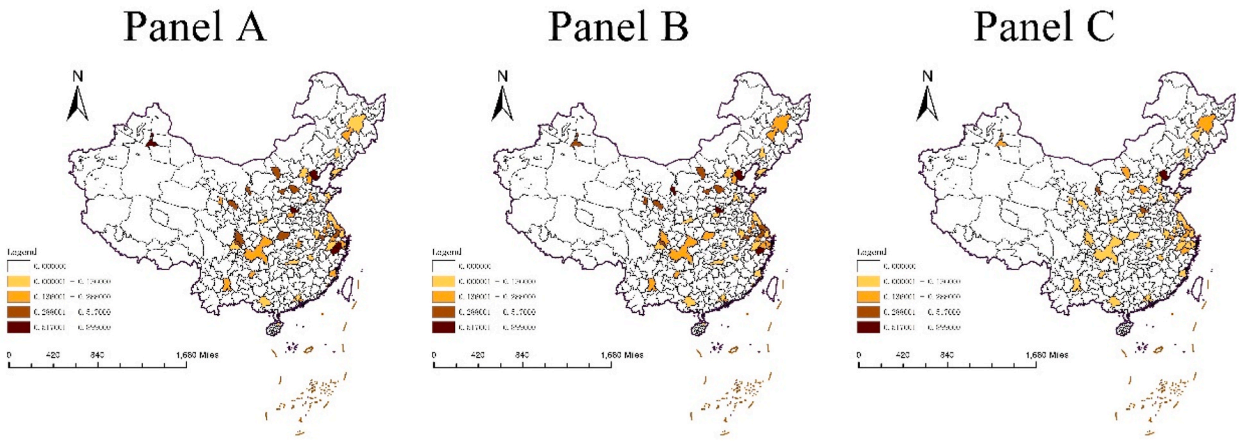


**Fig. 1.** Spatial-temporal Trends of CO2 emissions intensity from China's Transport Sector in 2010 (Panel A), 2015 (Panel B), and 2020 (Panel C).

**Table 1**
Descriptive statistics of variables.

| Variable | N | Mean | Std | Min | Max |
|---|---|---|---|---|---|
| *LnCO*$_2$ | 550 | −9.055651 | 0.8479215 | −11.3740 | −6.71603 |
| *LnEV* | 550 | 6.50396 | 2.864217 | 0.693147 | 11.70439 |
| *LnGDP* | 550 | 8.360369 | 1.007169 | 5.652026 | 10.57038 |
| *LnOpen* | 550 | −1.14234 | 1.218428 | −8.08187 | 0.870852 |
| *LnES* | 550 | 5.930918 | 0.925420 | 3.888691 | 8.313852 |
| *LnInd* | 550 | 0.192983 | 0.460780 | −.867916 | 1.677097 |
| *LnDensity* | 550 | 6.347876 | 0.566769 | 5.067646 | 8.252316 |
| *Urban* | 550 | 0.705812 | 0.129014 | 0.386 | 1 |

general distribution and trends of $CO_2$ emissions and does not provide details on the geographical connection of specific units [15]. The degree of spatial autocorrelation of specific locations can be determined using the local indicator of spatial association (LISA) [39]. LISA is given by:

$$LISA_i = \frac{x_i - \overline{x}}{s^2}\sum\nolimits_{i=1}^{n}\omega_{ij}(x_i - \overline{x}) \tag{2}$$

where $LISA_i$ is the local Moran's I for the city i. In the LISA spatial pattern, there are four different types of clusters: the homogeneous low-low and high-high clusters (L-L and H–H), as well as the heterogeneous high-low and low-high outliers (H-L and L-H).

### 3.2.2. Construction of spatial effect model

The degree of economic growth and energy structure in various areas of China varied significantly, which offered a suitable experimental setting for researching the regional spillover impact of $CO_2$ emissions. To be more specific, the GDP of the southeast coastal regions of China is higher than that of the central and western regions. Second, China's power generation industry is clustered in the western cities. However, electric consumption is clustered in the central and eastern cities. As a result, the spatial interaction effect is not taken into account by the typical econometric model, which might result in a biased model configuration and biased conclusions. The assumptions of geographical irrelevance and homogeneity are refuted by spatial econometrics [16]. Therefore, we set up the following spatial econometric model:

$$ln\ CO_{2it} = \alpha + \beta\ ln\ EV_{it} + \sum\nolimits_{i=2}^{7}\beta_i\ ln\ X_{it} + \varepsilon_{it} \tag{3}$$

In equation (3), $CO_{2it}$ represents $CO_2$ emissions of each city in year t; $EV_{it}$ is the sales of EVs in each city in year t; $X_{it}$ is the control variable matrix; $\varepsilon_{it}$ is a random disturbance. Specifically, by introducing the spatial weight matrix of economic distance, we employ the spatial fixed effect for spatial econometrics and make a comparative analysis of the above three methods.[3] The specific three econometric models are as follows:

$$ln\ CO_{2it} = \alpha_1 + \gamma\sum\nolimits_{j=1}^{n}W_{ij}CO_{2it} + \beta\ ln\ EV_{it} + \sum\nolimits_{i=2}^{7}\beta_i\ ln\ X_{it} + \alpha_i + \varepsilon_{it} \tag{4}$$

In equation (4), $\gamma$ represents the spatial correlation coefficient; $W_{ij}$ represents spatial matrix; $W_{ij}CO_{2it}$ represents spatial lag term; $\alpha_i$ represents spatial fixed effects; $EV_{it}$ represents the core explanatory variable. The SAR is to test the spatial correlation of the explanatory variables, i.e., whether neighboring cities' $CO_2$ emissions can affect those of the local city.

$$\begin{cases} ln\ CO_{2it} = \alpha_2 + \beta\ ln\ EV_{it} + \sum\nolimits_{i=2}^{7}\beta_i\ ln\ X_{it} + \alpha_i + u_{it} \\ u_{it} = \lambda\sum\nolimits_{j=1}^{n}W_{ij}u_{it} + \epsilon_{it} \end{cases} \tag{5}$$

In equation (5), $\lambda$ represents the error term's coefficient; $W_{ij}$ represents the spatial error term; $\epsilon_{it}$ represents random error. The meanings of other variables are the same as those in the above equation. The purpose of SEM is to test whether there is spatial dependency in the error term, i.e., whether the error term has a spatial spillover effect. However, the disadvantages of SAR and SEM are that the spatial effect must be explained not only by endogenous variables and error terms but also by the interaction of endogenous and exogenous variables. The SDM can make up for the above shortcomings, and it is given by:

$$ln\ CO_{2it} = \alpha_3 + \gamma\sum\nolimits_{j=1}^{n}W_{ij}CO_{2it} + \theta\sum\nolimits_{j=1}^{n}W_{ij}\ ln\ EV_{it} + \sum\nolimits_{i=2}^{7}\beta_i\ ln\ X_{it} + \alpha_i + \varepsilon_{it} \tag{6}$$

In equation (6), $\theta$ represents the spatial correlation coefficient.

[3] SDM: Spatial Durbin Model; SEM: Spatial Error Model; SAR: Spatial Autoregressive Model.

## 4. Empirical results and analysis

### 4.1. Spatial autocorrelation test

We check for spatial dependencies between the data using equation (1) and the model analysis in Section 3.2.1. The results of the test are displayed in Table 2. We find that there is a stronger autocorrelation in Urban $CO_2$ emissions, as shown by the fact that all results in Table 2 are positive and pass the significance test of 1%. In addition, the results in Table 2 also prove the necessity of constructing and using a spatial econometric model.

Based on equation (2), we use the software STATA 16 to estimate the local Moran's I of $CO_2$ emissions from the transportation sector in 50 cities from 2010 to 2020. The Moran scatter is displayed in Fig. 2. In Fig. 2, the first and third quadrants indicate that the high $CO_2$ emissions of the region are surrounded by high $CO_2$ emissions and the low $CO_2$ emissions of the region are surrounded by low $CO_2$ emissions, respectively. Specifically, in 2010, 16 of the 50 cities are in the first quadrant, indicating that the $CO_2$ emissions of these cities show a high-high cluster. 14 of the 50 cities are in the third quadrant, showing a low-low $CO_2$ emissions cluster. In 2015, the number of high-high $CO_2$ emissions clusters in the first quadrant decreased to 14, and the number of clusters with low-low $CO_2$ emissions in the third quadrant increased to 18. By 2020, the number of high-high $CO_2$ emissions clusters in the first quadrant had decreased to 11, and the number of low-low $CO_2$ emissions clusters in the third quadrant had increased to 21. In the first and third quadrants, as shown in Fig. 2, there are more than 65% of the cities. Consequently, this result still proves that it is feasible and scientific for us to use spatial econometric models. Moreover, we find that over time (2010–2020), the spatial cluster of $CO_2$ emissions gradually mitigated, and $CO_2$ emissions have been alleviated to some extent.

### 4.2. The test of model

This paper uses Hausman, LR, and LM tests to test the econometric model taking into account spatial effects to choose the right model, as shown in Table 3 [14,16]. First off, the LM test result suggests that the spatial econometric model should be used in this study based on the geographic weight matrix of economic distance, which is also consistent with the findings of the spatial autocorrelation in Section 4.1. Second, the LR spatial lag test demonstrated that the SDM used in this study is robust since it does not degenerate into SAR or SEM. Moreover, the Hausman test results also indicate that the random effects model is rejected. Finally, the temporal and spatial double fixed effect panel model should be used, according to the findings of the LR test.

### 4.3. The total spatial effects

We employ the SDM to study the spillover effect of EV sales on $CO_2$ emissions in light of the findings in Section 4.2. Our baseline regression results based on the economic distance matrix are presented in Table 4. Table 4 shows that all the remaining variables except *LnOpen* and *LnUrban* are significant at the 1% level. To be more specific, the results of model (1) total effect show that *LnEV* has a significant inhibitory effect on $CO_2$ emissions, which means that the net effect of the substitution effect, energy consumption effect, and technological effect is negative. Those results are also consistent with previous research [40,41].

As far as the control variables are concerned in model (1), *LnGDP* fails to pass the significance test, proving that the effect of GDP on $CO_2$ emissions is not significant. This result does not agree with earlier research. The following are some possible explanations: GDP is a very macro indicator, which can affect the three channels of influence we mentioned. Firstly, many studies have shown that the GDP will significantly and rapidly increase energy consumption [42], which will increase $CO_2$ emissions. Secondly, the increase in GDP will promote the level of science and technology, which will decrease $CO_2$ emissions. Thirdly, the effect of GDP on the "substitution effect" may not be very obvious due to the complex impact mechanism. As a result, the effects of GDP on energy consumption and technology may offset each other. The estimated coefficient of *Open* is not significant, indicating that higher FDI over the study period is not expected to significantly increase $CO_2$ emissions. *ES* has a significant positive effect on $CO_2$ emissions. This result is also consistent with the fact that energy consumption will directly lead to an increase in $CO_2$ emissions. *LnInd's* coefficient is $-0.750$ at a 1% level, indicating that the larger the ratio of the tertiary sector to the secondary sector, the lower the $CO_2$ emissions. Population density exerts a positive effect on $CO_2$ emissions. The result is in line with our expectation, because the higher the population density, the higher the overall emissions from commuter traffic. *Urban* also has a positive impact on $CO_2$ emissions, because urbanization is often accompanied by industrialization, which increases energy consumption.

### 4.4. The direct and indirect spatial effects

The spatial spillover effect cannot be demonstrated in the SDM using point estimates. The indirect impacts can be thought of as a spatial spillover effect, and partial differentiation should be employed to estimate both the direct and indirect effects [10]. The results of direct and indirect effects are shown in models (2–3) of Table 4. The estimated coefficients of *LnEV* are both negative (direct effect: $-0.096$; indirect effect: $-0.087$). On the one hand, a 1% increase in EV sales in a city reduces local $CO_2$ emissions by 0.096%. On the other hand, significant negative spillovers indicate that a 1% increase in EV sales in the surrounding city will reduce the $CO_2$ emissions of the local city by 0.087%. The diffusion of EVs will not only benefit the local environment but also help improve the environment of nearby cities. A possible reason is that neighboring cities with high EV market penetration affect the environmental quality of local cities through advanced technology diffusion. In other words, the market diffusion of EVs in adjacent cities promotes the spillover of transport technology and transport efficiency, thereby significantly mitigating local $CO_2$ emissions.

**Table 2**
Spatial autocorrelation test——Global Moran's I.

| Year | Moran' s I | Z | P |
|---|---|---|---|
| 2010 | 0.308 | 2.667 | 0.008 |
| 2011 | 0.362 | 3.100 | 0.002 |
| 2012 | 0.372 | 3.189 | 0.001 |
| 2013 | 0.425 | 3.645 | 0.000 |
| 2014 | 0.420 | 3.586 | 0.000 |
| 2015 | 0.383 | 3.289 | 0.001 |
| 2016 | 0.367 | 3.156 | 0.002 |
| 2017 | 0.365 | 3.158 | 0.002 |
| 2018 | 0.280 | 2.479 | 0.013 |
| 2019 | 0.261 | 2.316 | 0.021 |
| 2020 | 0.325 | 2.844 | 0.004 |

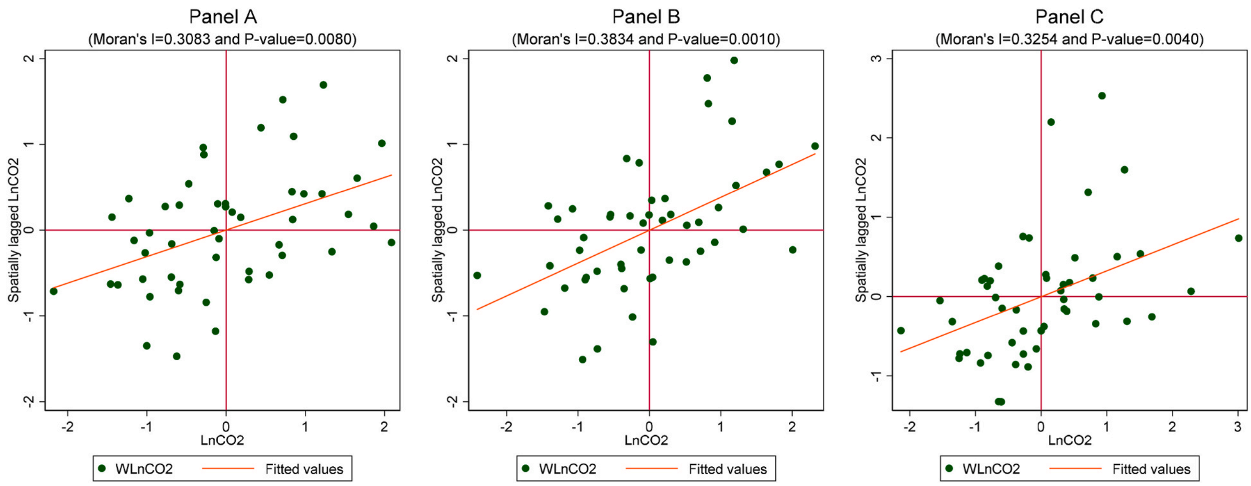


**Fig. 2.** Local Moran's I and Moran's scatter in 2010 (Panel A), 2015 (Panel B), and 2020 (Panel C).

**Table 3**
The results of model identification.

| Test method | Test results | P-value |
|---|---|---|
| Hausman | 88.63 | 0.000 |
| LR- space fixed | 23.99 | 0.006 |
| LR- space fixed | 976.79 | 0.000 |
| LR-SDM-SEM | 41.08 | 0.000 |
| LR-SDM-SAR | 41.02 | 0.000 |
| LM-Lag | 11.764 | 0.001 |
| LM-Error | 6.360 | 0.012 |
| Robust LM-Lag | 5.688 | 0.017 |
| Robust LM- Error | 4.231 | 0.040 |

As far as control variables are concerned in models (2–3), the direct and indirect effects of the GDP offset each other, which validates the reasons mentioned above. The explanation of the level of opening and population density is the same as in Section 4.3. In addition, we find an interesting result, i.e., the coefficient of energy consumption in the model (2–3). This result suggests that an increase in energy consumption in nearby cities increases the $CO_2$ emissions of local cities, which validates the conclusion of previous studies [9], i.e., EVs may "export" $CO_2$ through the electricity grid. The direct impact and indirect effects of industrial structures are both negative. This finding shows that local industrial upgrading will be conducive to decarbonization. The positive spillover effect of industrial upgrading in neighboring regions may be the result of the coordinated development of the industrial structure. The industrial upgrading of neighboring cities can provide an advanced development mode and management for neighboring cities, and a model of coordinated development with the industrial upgrading itinerary of local cities. The direct impact of the level of urbanization is negative, but the indirect impact of the level of urbanization is positive. This finding suggests that the more urbanized neighboring cities are, the more energy they consume, increasing the power generation load of the local cities because some of this energy is generated locally and some of it is generated in nearby cities.

**Table 4**
Spatial spillover effect of EV adoption on $CO_2$ emissions.[41]

| Variable | SDM | | |
|---|---|---|---|
| | Total effect (1) | Direct effect (2) | Indirect effect (3) |
| *LnEV* | −0.183*** | −0.096*** | −0.087** |
| | (-3.43) | (-3.92) | (-2.42) |
| *LnGDP* | −0.008 | −0.534*** | 0.526*** |
| | (-0.05) | (-7.98) | (4.14) |
| *LnOpen* | −0.021 | 0.011 | −0.032 |
| | (-0.49) | (0.51) | (-0.84) |
| *LnES* | 0.616*** | 0.413*** | 0.203*** |
| | (11.35) | (3.96) | (2.60) |
| *LnInd* | −0.750*** | −0.452*** | −0.297** |
| | (-4.15) | (-7.09) | (-1.99) |
| *LnDensity* | 0.827*** | 0.357*** | 0.471*** |
| | (4.55) | (6.17) | (3.21) |
| *Urban* | 0.731*** | 0.313* | 0.418** |
| | (3.42) | (1.96) | (2.37) |
| Observations | 550 | 550 | 550 |
| $R^2$ | 0.772 | 0.772 | 0.772 |

We also carry out robustness tests based on various spatial matrices. The regression utilizing the spatial weight matrices for geographic adjacency and distance is robust.

## 5. Further discussion

### 5.1. The influence mechanism of EV sales on $CO_2$ emissions

#### 5.1.1. Mediating model

Here, we continue to examine the impact mechanism of EV adoption on $CO_2$ emissions, building on the study from Section 1 of this paper. Specifically, we contend that rising EV sales have an impact on $CO_2$ emissions by impacting substitution effects, energy consumption effects and technology effects. Accordingly, the market share of EVs (*LnShare*), electricity consumption in cities (*LnElectric*),[5] and the quantity of transportation-related patent applications (*LnPatent*) are used as proxies for the substitution impact, energy use effect, and technological effect. We use the following mediation effects equations (7)–(9):

$$\begin{cases} ln\ Share_{it} = \alpha_1 + \partial_1\ ln\ EV_{it} + \sum_{i=2}^{7} \beta_i\ ln\ X_{it} + \varepsilon_{it} \\ ln\ CO_{2it} = \alpha + \rho_1 lnShare_{it} + \sigma_1\ ln\ EV_{it} + \sum_{i=2}^{7} \beta_i\ ln\ X_{it} + \varepsilon_{it} \end{cases} \tag{7}$$

$$\begin{cases} ln\ Electric_{it} = \alpha_2 + \partial_2\ ln\ EV_{it} + \sum_{i=2}^{7} \beta_i\ ln\ X_{it} + \varepsilon_{it} \\ ln\ CO_{2it} = \alpha + \rho_2\ ln\ Electric_{it} + \sigma_2\ ln\ EV_{it} + \sum_{i=2}^{7} \beta_i\ ln\ X_{it} + \varepsilon_{it} \end{cases} \tag{8}$$

$$\begin{cases} ln\ Patent_{it} = \alpha_3 + \partial_3\ ln\ EV_{it} + \sum_{i=2}^{7} \beta_i\ ln\ X_{it} + \varepsilon_{it} \\ ln\ CO_{2it} = \alpha + \rho_3 llnPatent_{it} + \sigma_3\ ln\ EV_{it} + \sum_{i=2}^{7} \beta_i\ ln\ X_{it} + \varepsilon_{it} \end{cases} \tag{9}$$

#### 5.1.2. The influence mechanism of EV sales on $CO_2$ emissions

Table 5 displays the regression results of the mediating effect between EV sales and $CO_2$ emissions. In models (1), (3), and (5), the coefficients of *LnEV* in models (1), (3), and (5) all are significantly positive, indicating that EV sales have a positive impact on the substitution effect, energy consumption effect, and technological effect. An increase in EV sales by 1% can increase the market share of EVs by 0.0136%, electricity consumption in cities by 0.041%, and the quantity of transportation-related patent applications by 0.217%. Accordingly, the market diffusion of EVs has the most obvious effect on the substitution effect. In addition, the coefficients of *LnShare* and *LnPatent* in models (2), (4), and (6) all are significantly negative, while *LnElectric* is significantly positive. This finding shows that the market share of EVs and patent applications in the transportation sector can significantly decrease $CO_2$ emissions, while electricity consumption in cities can significantly increase $CO_2$ emissions. Specifically, the widespread adoption of EVs can hinder the

[5] The electricity consumption data mentioned here refers to direct emissions, specifically measured in billions of kilowatt-hours (GWh) for each city. This measurement unit represents the amount of electricity consumed by the respective cities.

**Table 5**
The Influence mechanism of EV sales on $CO_2$ emissions.

| Explained variables: *LnCO₂* in columns (2), (4), and (6), while *LnShare*, *LnElectric,* and *LnPatent* in columns (1), (3), and (5) respectively | | | | | | |
|---|---|---|---|---|---|---|
| Variable | Substitution effect | | Energy consumption effect | | Technological effect | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *LnEV* | 0.0136*** | −0.033*** | 0.041*** | −0.028* | 0.217*** | −0.037** |
| | (9.29) | (-2.94) | (3.73) | (-1.69) | (13.73) | (-2.12) |
| *LnShare* | | −0.707*** | | | | |
| | | (-3.05) | | | | |
| *LnElectric* | | | | 0.317*** | | |
| | | | | (3.86) | | |
| *LnPatent* | | | | | | −0.132*** |
| | | | | | | (-4.54) |
| *LnGDP* | 0.003 | −0.663*** | 0.640*** | −0.657*** | 1.024*** | 0.421*** |
| | (0.01) | (-10.05) | (14.39) | (-9.93) | (5.76) | (4.25) |
| *LnOpen* | 0.009*** | −0.651** | 0.032*** | −0.010 | −0.038 | −0.071*** |
| | (3.5) | (-2.18) | (2.82) | (-0.56) | (-1.29) | (-3.64) |
| *LnES* | −0.248 | 0.651*** | 0.154*** | 0.554*** | 0.143* | 0.393*** |
| | (-1.64) | (10.42) | (3.97) | (5.96) | (1.67) | (8.42) |
| *LnInd* | 0.044*** | −0.620*** | 0.206*** | −0.639*** | 0.652*** | −0.671*** |
| | (4.28) | (-9.57) | (5.19) | (-9.94) | (4.24) | (-9.59) |
| *LnDensity* | 0.442 | 0.299*** | 0.408*** | 0.292*** | 0.477 | −0.337*** |
| | (0.55) | (5.20) | (3.16) | (-5.36) | (1.05) | (-5.79) |
| *Urban* | 0.500** | −1.05*** | 0.585*** | −0.875** | −0.080 | 0.085 |
| | (2.12) | (-6.82) | (6.66) | (-5.40) | (-0.31) | (0.35) |
| Observations | 550 | 550 | 550 | 550 | 550 | 550 |
| $R^2$ | 0.215 | 0.580 | 0.894 | 0.633 | 0.728 | 0.574 |
| F | 20.8 | 100.8 | 348.97 | 94.75 | 262.94 | 43.45 |

market diffusion of ICEVs, which is conducive to reducing $CO_2$ emissions in the transportation sector; higher energy consumption will significantly increase the use of fossil fuels, which will increase $CO_2$ emissions; furthermore, some research has found that technology advancement is a significant factor influencing $CO_2$ emissions, and it has been regarded as a potential strategy for reducing China's present $CO_2$ emissions [43].

According to the above analysis, we can confirm that an indirect effect of EV sales on $CO_2$ emissions exists. In other words, the increase in EV sales affects $CO_2$ emissions by affecting the substitution effect, energy consumption effect, and technological effect. Although the increase in EV sales increases $CO_2$ emissions by increasing electricity consumption, the results of the benchmark regression show that the overall impact of EV sales on $CO_2$ emissions is negative. As a result, the effects of substitution, energy consumption, and technology interact, and eventually, the positive and negative effects partially cancel each other out. Additionally, the energy consumption effect is exceeded by the sum of the substitution effect and the technological effect. As a result, the market share of EVs, electricity consumption in cities, and the quantity of transportation-related patent applications all indirectly contributed to the achievement of the $CO_2$ emissions reduction objective.

### *5.2. The moderating effect of energy structure on CO2 emissions*

#### *5.2.1. Moderating effect*

The conclusion of 4.4 shows that the increase in EV sales in neighboring cities will reduce local $CO_2$ emissions, i.e., the "export" of EVs is not $CO_2$, but a decarbonization effect; the increase in energy consumption in nearby cities will increase local $CO_2$ emissions, i.e., the "export" of energy consumption is $CO_2$. Therefore, in Section 5.2, we will continue to explore the evidence and optimization measures on the "export" decarbonization effect of EVs and the "export" $CO_2$ of energy consumption from the perspective of energy structure.

Here, we further analyze the moderating effect of energy structure on $CO_2$ emissions. First, we find that there are big differences in the energy structure between different cities in China. There are significant differences in the proportion of power generation fuels in different regions. In addition, related studies show that energy structure is the industrial basis for $CO_2$ emissions [14]. Cities with different energy structures have different $CO_2$ emissions industry bases. Therefore, we take the proportion of renewable energy generation (*LnGenerate*) as a proxy variable for energy structure to analyze the moderating effect of energy structure on the effect of EV sales on $CO_2$ emissions. Specifically, we construct the interaction term (*LnEV* × *LnGenerate*) between the renewable energy generation ratio and *LnEV* and add it to the panel regression model. The regression results of model (1) in Table 6 show that the moderating effect is not significant.

Then, we analyze the possible reasons: on the one hand, China's power generation structure shows the characteristics of "power

[4] The value in parentheses represents the t value. *** represents 1% significance level; ** represents 5% significance level; * represents 10% significance level (the same as other tables below).

**Table 6**
The moderating effect of energy structure on the $CO_2$ emission.

| Variable | Moderating effect | Adjusted moderating effect |
|---|---|---|
| | (1) | (2) |
| *LnEV* | −0.013 | −0.036** |
| | (-0.71) | (-2.29) |
| *LnEV* × *LnGenerate* | 0.006 | 0.000 |
| | (0.95) | (0.15) |
| *LnGenerate* | −0.134*** | −0.404*** |
| | (-5.63) | (-8.99) |
| *LnEV* × *LnGenerate* × *Region* | | -0.036*** |
| | | (-3.27) |
| *Region* | | −0.186** |
| | | (-2.22) |
| *LnGDP* | −0.624*** | −0.661*** |
| | (-10.82) | (-12.09) |
| *LnOpen* | −0.061*** | −0.041** |
| | (-3.69) | (-2.37) |
| *LnES* | 0.534*** | 0.564*** |
| | (9.91) | (11.12) |
| *LnInd* | −0.666*** | −0.475*** |
| | (-10.95) | (-8.74) |
| *LnDensity* | 0.320*** | 0.403*** |
| | (6.96) | (9.23) |
| *Urban* | −1.218*** | −1.289*** |
| | (-9.13) | (-9.47) |
| Observations | 550 | 550 |
| $R^2$ | 0.650 | 0.662 |
| F | 63.82 | 62.13 |

transmission from west to east". Cities in the Midwest do most of the generating. On the other hand, China's eastern cities are major power consumers. Accordingly, based on the region of the city (*Region*, a dummy variable, east: 0; west: 1), we constructed a triple interaction term (*LnEV* × *LnGenerate* × *Region*). The results of model (2) show that the coefficients of *LnEV*, *LnGenerate*, *Region*, and the interaction term (*LnEV* × *LnGenerate* × *Region*) are significantly negative, indicating that the endogeneity problem caused by the high correlation between *LnGenerate* and *LnES* has been alleviated. The results not only show that energy structure has a positive moderating effect on the effect of EV sales on $CO_2$ emissions after *Region* is included in the interaction item, but also imply that the moderating effect is more obvious in western cities. To be more specific, an increase in *LnGenerate* by 1% will increase the decarbonization effect of EVs by 0.036%. Previous studies show that renewable energy produces significantly lower $CO_2$ emissions than non-renewable energy [44,45]. Therefore, cities with a higher share of renewable energy generate less $CO_2$.

### 5.2.2. $CO_2$ export

Based on Section 5.2.1, we further explore the externality of urban energy consumption and the offsetting effect of optimizing energy structure. To demonstrate whether energy consumption in neighboring cities increases $CO_2$ emissions in local cities, we divided the sample into two groups (Electric output: electricity generation > electricity consumption; electric input: electricity generation < electricity consumption). The grouped regression results of model (1) in Table 7 show that the coefficient of *LnES* is only 0.145, which is far less than the result of the benchmark regression (0.616). However, the grouped regression results of model (2) show that the coefficient of *LnES* is 0.659, which is close to the benchmark regression. This difference indicates that $CO_2$ emissions from electric output cities are generated by itself and other cities, validating the discussion in Section 4.4. Therefore, we believe that urban energy consumption can "export" $CO_2$ through the electricity grid.

## 6. Conclusions and policy implications

Traditional transportation and consumption modes represented by ICEVs cause serious air pollution and the greenhouse effect. The Chinese government places a high value on the electrification of the transportation industry [46]. To accelerate the adoption of EVs, the Chinese government has issued some industry support policies since 2009. From a practical standpoint, it is critical to investigate the regional spillover effect and influence mechanisms of EV adoption on $CO_2$ emissions in this environment. Based on panel data of EV sales and $CO_2$ emissions in 50 Chinese cities from 2010 to 2020, we empirically investigate the regional spillover effect and impact mechanism of EV adoption on $CO_2$ emissions. We derive the following conclusions:

Firstly, China's EV sales have rapid increased over the past ten years, effectively curbing the increase in $CO_2$ emissions. Specifically, there are direct effects and indirect effects, i.e., a 1% increase in the sale of EVs in a city can reduce $CO_2$ emissions locally by 0.096% and by 0.087% in a nearby city. Secondly, we find that the sale of EVs influences $CO_2$ emissions through the substitution effect, energy consumption effect, and technological effect. The sale of EVs increases $CO_2$ emissions by increasing the electricity consumption in cities while decreasing $CO_2$ emissions by improving the market share of EVs and the number of patent applications in the transportation sector. Thirdly, energy structure has a positive moderating effect on the effect of EV sales on $CO_2$ emissions. And the

**Table 7**
$CO_2$ export.

| Variable | Electric output | Electric input |
|---|---|---|
| | (1) | (2) |
| *LnEV* | −0.048** | −0.060*** |
| | (-2.21) | (-2.81) |
| *LnGDP* | −0.296*** | −0.734*** |
| | (-3.69) | (-10.44) |
| *LnOpen* | −0.076*** | 0.144*** |
| | (-3.59) | (2.81) |
| *LnES* | 0.145* | 0.659*** |
| | (1.82) | (11.18) |
| *LnInd* | −0.157 | −0.630*** |
| | (-1.29) | (-8.38) |
| *LnDensity* | −0.363*** | 0.431*** |
| | (-3.54) | (7.64) |
| *Urban* | −0.863** | −2.933*** |
| | (-2.39) | (-10.17) |
| Observations | 242 | 308 |
| $R^2$ | 0.619 | 0.718 |
| F | 34.68 | 51.49 |

Notes: To keep consistent with the benchmark regression, we control the urban fixed effect and time fixed effect in the model (1–2).

proportion of renewable energy generation can mitigate the “energy consumption effect”, i.e., the proportion of renewable energy generation exerts a negative moderating effect on the increase in $CO_2$ emissions caused by the energy consumption effect. The following are three policy implications:

First, the results of this paper show that the widespread adoption of EVs will be conducive to the decarbonization of the transportation sector in the local region as well as in adjacent regions. Therefore, policymakers ought to extend supporting policies and financial support for the EV industry to further accelerate the transition to electrification in the transportation sector. To be more specific, policymakers can take cities with the obvious effect of decarbonization of EVs as pilot cities to promote “carbon peaking and carbon neutrality” in the transportation sector, which can have a positive demonstration effect on the decarbonization of the transportation sector in other cities. Based on the positive demonstration role of pilot cities, other cities can learn from their advanced management, operation, and planning schemes. In this way, the regionally coordinated development of decarbonization in the transportation sector will be realized. For instance, financial support and incentives should be increased for cities with obvious decarbonization effects by electrifying transportation departments, and meanwhile, scientific punishment measures should be implemented for cities with poor $CO_2$ reduction effects.

Second, we find that the adoption of EVs can mitigate $CO_2$ emissions through the substitution effect and the technological effect. Therefore, policymakers should issue a scientific industrial plan with clear targets for EV market penetration. For instance, promote the electrification of government official vehicles, public transport, and taxis through administrative orders; increase the number of pilot cities banning the sale of ICEVs. Additionally, authorities should keep raising the operational and R&D subsidies they provide to the transportation sector, as doing so can raise transportation efficiency and lower $CO_2$ emissions overall. For example, increase R&D subsidies and operation subsidies for charging enterprises to improve the convenience of using EVs; further, support the development of hydrogen energy vehicles and fuel cell vehicle enterprises.

Third, we find that improving energy structure can reduce the impact of energy consumption on $CO_2$ emissions as a result of the moderating effect of energy structure. The improvement and transformation of the energy structure should be given top priority by policymakers. For example, continuously increase the proportion of renewable energy generation by implementing a series of policies and demonstration projects such as wind, water, and solar energy. To encourage the coordinated development of EVs and energy structures. Firstly, policymakers must pay attention to the research investment in EV charging and discharging strategies, charging facility planning, intelligent control of the power system, and other contents to reduce the impact on the safe and stable operation of the power system. Secondly, policymakers should accelerate the realization of network-wide intelligent interaction between source, network, and load storage, including improving the charging service system, forming an effective vehicle network interaction mechanism, and accelerating the market diffusion of vehicle-to-grid technology. Thirdly, the power sector should make great efforts to improve the comprehensive regulation ability of the power system and establish multiagent unified and collaborative management systems such as an EV charging network, a virtual power plant, distributed generation, and an intelligent microgrid. Fourthly, policymakers and power departments should further explore the multi-direction interaction of source networks, load and storage, virtual power plants, and other integration and aggregation modes to continuously improve the level of energy system security.

Our study still has limitations for the following reasons: on the one hand, due to the restricted access to data, our findings may be more precise if there were access to additional cities and data. In the future, we will include more cities in the data set for further research. On the other hand, our study is not yet able to predict the effect of EVs on reducing $CO_2$ emissions. In the future, we will use more diversified methods, such as scenario analysis, to refine subsequent research.

## Author contribution statement

Xiaolei Zhao: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Wrote the paper. Hui Hu: Conceived and designed the experiments; Performed the experiments; Wrote the paper. Hongjie Yuan: Analyzed and interpreted the data. Xin Chu: Wrote the paper and interpreted the data.

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## Data availability statement

Data will be made available on reasonable request.

## Lead contact

Further information and requests for resources should be directed to and will be fulfilled by the Lead Contact, Prof. Hui Hu (hui.hu@whu.edu.cn).

## Materials availability statement

No materials were used in this study.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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