

Study on the Spatial Distribution of China's New Energy Vehicle Fleet and Its Influencing Factors

Xunnan Liu*, Liping Du

North China University of Science and Technology, Tangshan, Hebei 050000, China

*Corresponding Author

Abstract

Against the backdrop of the "Dual Carbon" strategy, the new energy vehicle (NEV) industry has become a key driver of China's green and low-carbon transition and the upgrading of its automotive sector. This paper takes China's 31 provinces (autonomous regions and municipalities) in 2017, 2020, and 2023 as the units of analysis. By integrating data on NEV ownership and socioeconomic development, and employing spatial autocorrelation analysis and spatial econometric models, this study investigates the spatial agglomeration characteristics and influencing mechanisms of NEV ownership. The results show that: ① the national NEV stock exhibits significant spatial agglomeration characteristics; the global Moran's I index shows an overall upward trend, indicating that the degree of spatial agglomeration is continuously increasing; ② the NEV stock displays a distinct pattern of regional imbalance, with high-value areas primarily concentrated in the eastern coastal regions, while the central and western regions lag behind overall, though regional disparities are gradually narrowing; ③ Regional economic development levels, urbanization levels, permanent resident population size, and per capita disposable income of urban residents all have a significant impact on the number of new energy vehicles in circulation. Among these, the spatial spillover effects of regional economic development levels and resident income gradually strengthen as the industry develops, and the intensity of the various influencing factors varies to some extent across different stages; ④ As the new energy vehicle industry continues to mature, spatial interconnections among regions are strengthening, and the development of new energy vehicle markets is shifting from localized agglomeration to cross-regional collaborative expansion. Based on this, efforts should be made to strengthen regional coordinated development, refine differentiated support policies, optimize resource allocation, promote the coordinated development of the new energy vehicle industry, and advance the transition to a green and low-carbon economy.

Keywords

New Energy Vehicle Fleet; Charging Infrastructure; Spatial Durbin Model; Spatial Spillover Effects.

1. Introduction

In recent years, driven by the nation's "Dual Carbon" strategic goals, continued support from industrial policies, and the automotive industry's transition to electrification, China's new energy vehicle (NEV) fleet has grown rapidly, with its industrial scale ranking among the world's largest for consecutive years. That said, looking at the national level as a whole, NEV development across regions has hardly followed an even, balanced spread. Instead, there are clear regional gaps and a pronounced pattern of spatial clustering^[1]. The eastern coastal belt stands out most - places like Guangdong, Jiangsu, Zhejiang, Shanghai, and Beijing have stayed near the top of national NEV ownership rankings for years, driven by strong local economies,

mature industrial chains, higher consumer purchasing power, and better charging infrastructure. On the other hand, the number of new energy vehicles in many places in the northwest, southwest and northeast is low. The economic base of these regions is relatively weak, the population density is not high, and the charging network has not been widely rolled out. In this way, a clear spatial distribution is formed : the permeability in the eastern region is significantly higher, while that in the western region is much lower ; the coastal area is more concentrated, and the more inland the more sparse.

In general, the development of new energy vehicles in China is still very uneven, the gap between regions is quite prominent, and the spatial aggregation tendency is also obvious. The speed of the promotion of new energy vehicles depends not only on the big economic trend, but also on the population size, the speed of urbanization, the level of household income, the transportation network and the construction of charging facilities^[2]. The economic situation of a place will not only affect the actual ability of people to buy a car, but also largely determine the size of the entire market demand. The total population is basically framed the upper limit of potential car buyers. The degree of urbanization will change the scenarios in which these cars can be used and how efficient the promotion is. At the same time, the charging network plays a fundamental supporting role, which can effectively alleviate people 's concerns about mileage, thus promoting the acceptance of new energy vehicles more generally. However, the economic development stages of different regions are different, and the endowments of resources are different. When these driving forces fall into specific regions, the size of the role will be very different, which will show different spatial distribution characteristics. Because of this, it is necessary for us to use some analytical tools in spatial econometrics to explore this issue in depth.

So far, many scholars have discussed this issue from different perspectives on the research of new energy vehicles. Everyone 's attention has been extended from the characteristics of spatial distribution, the driving factors affecting purchase intention, to the actual effects of forecasting methods and policies, as well as the dynamic changes of supply chain, which can be said to cover a wide range. Liu Y Q et al. ^[3]By using the two models of SAR and SEM, we verify that there is a significant positive spatial spillover effect in the promotion of new energy vehicles. Moreover, factors such as R & D investment and economic development level also show obvious differences in the role played by different urban agglomerations; Huang X T et al.^[4], based on micro-level enterprise data covering the full industrial chain, found that the clustering characteristics of upstream and downstream enterprises diverge, with economic factors, innovation, and industrial policies serving as the core drivers of their distribution; Fang Y P et al. ^[7]and Wang X N^[8], using the Pearl River Delta and Changzhou as case studies, respectively, revealed that industrial innovation exhibits spatial evolution patterns characterized by core-periphery radiation pattern and industry-research synergy, with geographic proximity and industrial chain division of labor jointly shaping regional industrial patterns. In terms of methodology, Xiong P P^[5] built a grey prediction model that takes nonlinear disturbances into account, making it possible to forecast the sales volume of new energy vehicles with a high degree of accuracy. From the perspectives of policy and consumption, Xing W B^[6] developed a discrete choice model, confirming that differences in consumer income and regional preferences lead to divergent outcomes in the implementation of purchase tax policies. From a supply chain perspective, Zou H^[9] developed a game theory model centered on consumer range anxiety and found that the adoption of blockchain technology faces cost barriers; within a reasonable cost range, both corporate profits and social welfare can be enhanced simultaneously.

Overall, existing research has systematically analyzed the spatial distribution, industrial agglomeration, demand behavior, and forecasting methods for new energy vehicles; however, studies on the dynamic evolution and regional heterogeneity of the spatial spillover effects of

new energy vehicle stock remain relatively scarce. Based on this, this paper argues that the development of NEV ownership in China is no longer a process of independent evolution within individual regions, but rather a spatial evolutionary process shaped by the combined effects of regional economic linkages, industrial synergy, infrastructure interconnectivity, and policy interactions. Therefore, this paper first employs spatial autocorrelation methods to examine whether spatial agglomeration exists in NEV ownership, and, building on this, constructs a spatial Durbin model to further analyze the direct effects and spatial spillover effects of factors such as economic development level, population size, urbanization level, and charging infrastructure on the NEV stock. By combining panel data from three time periods to conduct a time-series heterogeneity analysis, this study aims to reveal the regional linkage mechanisms underlying China's NEV development, thereby providing a theoretical basis and empirical support for optimizing the industrial layout of the NEV sector, scientifically allocating charging infrastructure, and formulating policies for regional coordinated development.

2. Variable Selection and Research Methods

2.1. Variable Selection

Outcome variable: Count of new energy vehicles by province ev_{it} . In this analysis, the annual stock of new energy vehicles in each province is used to indicate the scale of local promotion. How many of these vehicles are actually in circulation says a lot about where the regional NEV market stands - both its development level and penetration rate - and it serves as one of the primary measures for evaluating how well the industry is progressing. To address concerns around data volatility and heteroscedasticity, the variables were log-transformed ahead of the empirical estimation. The observation year variable, in turn, is $ev_{2017}, ev_{2020}, ev_{2023}$;

Key Explanatory Variable: Scale of Charging Infrastructure by Province chg_{it} . The level of charging infrastructure development is measured by the number of public charging stations at the provincial level. Charging infrastructure is a key pillar supporting the promotion of new energy vehicles, and its level of development directly affects the convenience of vehicle use and consumers' willingness to purchase such vehicles; therefore, the number of public charging stations is selected as the core explanatory variable. Prior to empirical analysis, this variable is transformed using the natural logarithm, and the corresponding year-on-year variable is $chg_{2017}, chg_{2020}, chg_{2023}$;

Control Variables: To reduce omitted variable bias, and based on existing research findings and the factors influencing the development of new energy vehicles, the following control variables were selected: ①Regional economic development level gdp_{it} , Measured by regional gross domestic product (GDP), this reflects a region's economic strength and level of market development; ②Size of the permanent resident population pop_{it} , measured by the permanent resident population of each province, reflecting the size of the potential consumer market; ③Level of urbanization urb_{it} , measured by the urbanization rate, reflects a region's level of urban development and the environment for promoting new energy vehicles; ④Per capita disposable income of urban residents inc_{it} , reflecting residents' consumption capacity and purchasing power. All scale-related variables are uniformly log-transformed.

Spatial Weight Matrix: To pick up on spatial patterns in how new energy vehicles develop across regions, we use a Queen's adjacency matrix as our spatial weight matrix. If two areas share any kind of geographic border, the corresponding entry gets a 1. No shared boundary, and it stays at 0. Once the matrix is set up, we run it through row normalization so each row's weights total exactly 1. Doing this keeps the spatial lag terms comparable across the board and helps with stability in the estimates.

The spatial weight matrix is defined as follows:

$$W_{ij} = \begin{cases} 1, & \text{If regions } i \text{ and } j \text{ are adjacent} \\ 0, & \text{Otherwise} \end{cases}$$

In the equation: W_{ij} a cell in the spatial weight matrix; i, j representing different provincial research samples, the matrix was standardized by row to ensure the comparability of the estimated spatial lag terms.

2.2. Research Methods

The number of new energy vehicles in a province depends not only on its own socio-economic status, but also on the impact of the surrounding areas. Such as the spillover effect of economic growth, the cross-regional flow of personnel, the construction of infrastructure, and the correlation between local industries, these are likely to spread outward, resulting in ripple effects. In our analysis, a spatial Durbin model is specially constructed to explore these spatial dynamic characteristics behind the ownership of new energy vehicles. Compared with the more common spatial autoregressive model or spatial error model, the Dubin model has a very prominent advantage : it can not only capture the spatial dependence of the dependent variables, but also extract the spatial spillover effects carried by the independent variables in the same model framework. That's what makes it better suited for showing just how interconnected NEV development really is across provinces.

The spatial Durbin model can be expressed as:

$$y_{it} = \rho \sum_{j=1}^n w_{ij} y_{jt} + X_{it}\beta + \sum_{j=1}^n w_{ij} X_{jt}\theta + \varepsilon_{it}$$

Here, y_{it} represents the number of new energy vehicles in the $i - th$ province in year t ; X_{it} is the set of independent variables consisting of all explanatory variables and control variables; w_{ij} represents the elements of the standardized spatial weight matrix; ρ is the spatial lag coefficient of the dependent variable; β is the regression coefficient of the independent variables; θ is the spatial lag coefficient of the independent variables, representing the coefficient of the effect of independent variables from neighboring provinces on the dependent variable of the current province; ε_{it} is the random disturbance term of the model.

2.3. Data Sources

Our study draws on 31 provincial-level regions across China's mainland - Hong Kong, Macao, and Taiwan are not included in the sample. We did not use the data for each year from 2017 to 2023, but selected three representative years : 2017, 2020 and 2023. The purpose is to see how the spatial pattern and influencing factors of the industry change in different stages of development. In 2017, the industry is still in the promotion period, and the growth is mainly driven by policies. 2020 is a turning point, starting from policy-driven to market-driven. By 2023, the industry has entered a stage of large-scale and high-quality development, and the scale of vehicles and charging facilities on the road is high. These three years basically cover the main development stages, which can better reflect the phased evolution of spatial pattern and influencing factors.

In addition, the ownership and charging facilities have a strong cumulative effect and path dependence, and the spatial pattern has little interannual change. With continuous year data, it is easy to cause high correlation in time and produce a lot of redundant information. Comparing the cross sections every 3 years, it is easier to see the spatial differences in stages, and the results are more representative and comparable.

Data sources : new energy vehicle ownership from industry statistics and public yearbook. Regional economic indicators, such as GDP, resident population, per capita disposable income, and urbanization rate, mainly come from the ' China Statistical Yearbook ' and provincial statistical yearbooks. The data of charging facilities are from the China Electric Vehicle Charging Infrastructure Promotion Alliance and related industry reports. In order to unify the caliber and ensure comparability, we have done price deflator and logarithmic processing on monetary and scale variables, and removed Hong Kong, Macao and Taiwan samples. The final dataset covers 31 provincial units.

3. Empirical Analysis

3.1. Descriptive Statistics for Variables

In order to find out the distribution and degree of change of each variable, we first make a natural logarithmic transformation of all variables, remove the interference of heteroscedasticity, and then carry out descriptive statistics. The results are listed in the table below.

Table 1. Descriptive Statistics for Variables

Statistical Indicators	Mean	Median	Sample standard deviation	Minimum Value	Maximum value
<i>ev</i> ₂₀₁₇	10.045	10.488	1.523	5.771	12.326
<i>ev</i> ₂₀₂₀	11.238	11.678	1.500	7.036	13.631
<i>ev</i> ₂₀₂₃	12.812	13.179	1.329	8.719	14.898
<i>chg</i> ₂₀₁₇	7.745	8.217	1.886	2.197	10.321
<i>chg</i> ₂₀₂₀	9.439	9.828	1.464	5.263	11.381
<i>chg</i> ₂₀₂₃	10.730	10.952	1.340	7.089	13.241
<i>gdp</i> ₂₀₁₇	10.901	10.750	0.385	10.279	11.822
<i>gdp</i> ₂₀₂₀	11.091	10.968	0.371	10.487	12.009
<i>gdp</i> ₂₀₂₃	11.315	11.209	0.368	10.776	12.208
<i>pop</i> ₂₀₁₇	8.139	8.270	0.853	5.855	9.404
<i>pop</i> ₂₀₂₀	8.146	8.283	0.850	5.903	9.443
<i>pop</i> ₂₀₂₃	8.145	8.284	0.843	5.894	9.449
<i>urb</i> ₂₀₁₇	-0.547	-0.571	0.211	-1.211	-0.088
<i>urb</i> ₂₀₂₀	-0.466	-0.468	0.178	-1.030	-0.113
<i>urb</i> ₂₀₂₃	-0.429	-0.431	0.161	-0.945	-0.111
<i>inc</i> ₂₀₁₇	10.103	9.993	0.330	9.646	10.985
<i>inc</i> ₂₀₂₀	10.321	10.236	0.316	9.920	11.188
<i>inc</i> ₂₀₂₃	10.514	10.411	0.326	10.127	11.344

Table 1 summarizes the descriptive statistical results of all variables in this study. From the data point of view, the dependent variable, that is, the mean and median of the new energy vehicle ownership in each province, is not much different. These two indicators have shown a steady upward trend during the study period, indicating that the overall size of the holdings is expanding year by year. However, the standard deviation of each year is still too large, reflecting that there are still many differences in the promotion level of new energy vehicles among different provinces.

In terms of key explanatory variables, the mean value of charging infrastructure has improved significantly over time. Moreover, in the three observation years, its standard deviation is the largest among all variables, and the distribution also shows obvious right-skewed characteristics. This shows that the construction of charging facilities is mainly concentrated in a few provinces, most of which are still in a relatively backward state, and the spatial imbalance is quite prominent.

On the side of control variables, the mean values of per capita disposable income and urbanization rate are increasing year by year, the mean and median are also relatively close, the standard deviation has been maintained at a low level, the inter-provincial distribution is relatively balanced, and the regional differences are not large. In contrast, the average size of the resident population changed little during the sample period and remained basically stable. In addition, the maximum and minimum values of each variable fall within a reasonable range, and there is no sign of abnormal extreme values, indicating that the quality of the data set is good, which can provide a reliable basis for the estimation of the subsequent spatial Durbin model.

In order to more intuitively show the spatial pattern and dynamic changes of China's new energy vehicle ownership at the provincial level from 2017 to 2023, we have drawn a regional distribution map based on quantiles, as shown in the figure below.

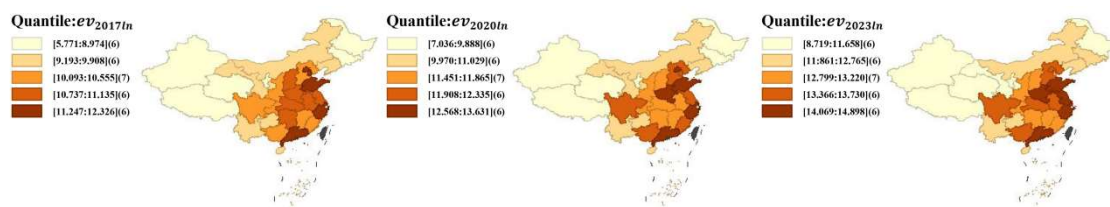


Figure 1. Heat Map Showing the Percentile-Based Classification of New Energy Vehicle Stock by Province in China, 2017–2023

On the whole, the provincial distribution presents a relatively stable spatial pattern, that is, the contrast between the eastern coastal developed areas and the western inland underdeveloped areas is obvious.

During the whole study period, Beijing, Shanghai, Jiangsu and Guangdong have been staying in the highest quantile array. The darkest areas on the figure are basically clustered in the metropolitan areas of the Yangtze River Delta, the Pearl River Delta and the Bohai Rim. In comparison, western provinces, including Xinjiang, Tibet, and Qinghai, were persistently classified in the lowest quantile category, indicating that the gap between the eastern and western regions remained evident over time.

From a temporal perspective, between 2017 and 2023, the color intensity of the provincial blocks nationwide generally continued to deepen, and the logarithmic levels of new energy vehicle ownership in each province rose in tandem. Areas with high ownership concentrations gradually expanded from a few core provinces and municipalities to neighboring provinces, clearly reflecting a significant positive spatial correlation in industrial development and

providing empirical support for the subsequent empirical analysis using spatial econometric models.

3.2. Spatial Autocorrelation Test

To identify the spatial distribution characteristics of the samples, this paper first conducts a global Moran's I test for spatial autocorrelation on the number of new energy vehicles in each province in 2017.

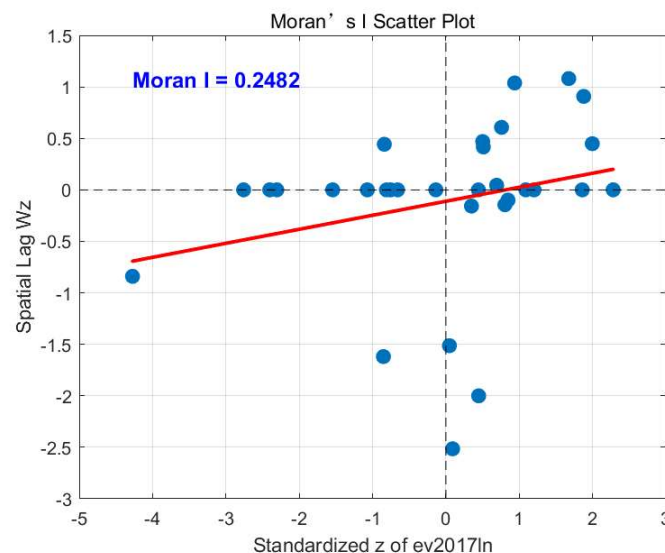


Figure 2. Moran Scatter Plot of New Energy Vehicle Registrations by Province in 2017

The test results show that the Moran's I index is 0.2482. Since this value is greater than 0, it indicates that there is positive spatial clustering in the number of new energy vehicles across China's provinces. The Monte Carlo simulation yielded a pseudo-p-value of 0.001 and a z-value of 4.9496, which is far higher than the critical value of 2.58 corresponding to the 1% significance level, confirming that the spatial clustering pattern in the development of new energy vehicles at the provincial level is highly statistically significant. According to the classical Gauss-Markov assumption, when spatial autocorrelation exists in the sample, the traditional OLS model no longer satisfies the assumption of independent observations. If we only use the traditional OLS model to do empirical analysis, the estimated coefficients are likely to bring systematic bias, so that the reliability of statistical inference will be discounted. Therefore, in order to obtain more robust and more reliable estimation results, it is necessary to use spatial econometric models that clearly take into account spatial dependence.

3.3. Benchmark Regression Analysis

Table 2 lists the estimation results of the spatial Durbin model. In general, the coefficients of the model run out are roughly consistent with the theoretical expectations we have proposed above, indicating that the level of social and economic development of a region, coupled with the existence of spatial dependence, does have a very important role in shaping the distribution of new energy vehicle ownership in each province.

The regression coefficient of the core explanatory variable charging infrastructure(*chg*), is 0.554, which is significantly positive at the level of 1 %. This shows that the more perfect the charging facilities are, the more obvious the promotion effect on the growth of new energy vehicle ownership is. Once the number of public charging stations increases, the car will be more convenient to use, and the mileage anxiety can also be effectively alleviated, thus stimulating everyone's willingness to buy a car and driving the entire market.

Table 2. Benchmark Regression Results

Variables	SDM
chg_{2017}	0.554*(0.100)
inc_{2017}	2.550*(0.936)
gdp_{2017}	-1.407(0.700)
pop_{2017}	0.334(0.154)
urb_{2017}	-0.368(0.715)
Constant term_cons	-6.801(4.946)
ρ	0.427*(0.125)
Control Variables	YES

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively; the numbers in parentheses are standard errors; the same applies below.

Among the control variables, the per capita disposable income(*inc*) and permanent resident population (*pop*) show a significant positive impact. It can be seen that the higher the income level and the larger the population size, the more favorable the promotion of new energy vehicles. The coefficient of regional economic development level (*gdp*) is negative and statistically significant, and the coefficient for urbanization level (*urb*) is also negative, but it does not pass the significance test. Their specific effects are analyzed in detail later when the effect is decomposed.

In addition, the spatial lag coefficient ρ is significantly positive, which means that the number of new energy vehicles has a significant correlation in space. The development of new energy vehicles in a region will have a certain spillover effect on the surrounding areas, showing strong spatial agglomeration and diffusion characteristics.

3.4. Testing for Spatial Spillover Effects

Table 3 decomposes the estimated spatial spillover effects. First look at the charging infrastructure, its direct effect is 1.2055, significant at the level of 1 %, which tells us that a province to build charging facilities on their own boundaries, the local new energy vehicle ownership has a very obvious role in promoting. The indirect effect is 0.292, which also passed the 5 % significance test, indicating that the neighboring provinces spread the charging network and can produce a positive spillover. There is indeed a clear inter-provincial spatial spillover pattern. Combined with the regression results of SDM in Table 2, the spatial autoregressive coefficient ρ is significantly positive, which further confirms a judgment : in 2017, there was a stable spatial positive correlation between the number of new energy vehicles in each province, and the pattern of regional industrial linkages began to emerge.

Overall, the total effect of charging infrastructure is 1.498, which is highly significant at the 5 % level. Based on these information, it can be seen that charging facilities have a relatively strong positive driving effect on the promotion and popularization of new energy vehicles. Comparing the different effects, the local direct effect obviously accounts for a larger proportion, but the cross-regional spillover does exist. A province builds a charging station locally, which can not only drive the province 's demand for new energy vehicles, but also radiate outward and drive the market growth of surrounding provinces.

The situation on the side of control variables is more complicated. The total effect of regional economic development is -3.62, but not significant, indicating that economic growth itself has

not formed a stable long-term relationship with the penetration rate of new energy vehicles. The total effect of the size of the resident population is 0.008, which is significant at the level of 10 %. The intensity is not large, but the direction is in line with expectations : more people means more market demand, which is a small boost to the development of new energy vehicles. The total effect of urbanization level is 0.148, which is not statistically significant, which may reflect that the impact of urbanization is determined by structural fluctuations to a considerable extent, rather than a simple linear model. The household income level is the most prominent among the control variables, with a total effect of 3.178, which is significant at the level of 5 %. Income growth is obviously a core demand-side driving factor behind the consumption of new energy vehicles. Interestingly, its indirect effect is also significant - the green consumption concept brought about by the increase in income level seems to produce cross-regional demonstration spillovers.

Combining the results of this part of the effect in 2017, a clearer judgment can be drawn : the promotion of new energy vehicles at this stage depends largely on two core local drivers-local charging infrastructure construction and household income level. Charging facilities and household income have shown observable positive inter-provincial spillovers, indicating that the mechanism of regional industrial synergy has been initially formed. However, it should also be noted that the driving force of cross-regional spillovers is still significantly weaker than the direct driving effect of local factors.

Table 3. Results of the Decomposition of Spatial Spillover Effects

Variables	Direct Effects	Indirect Effects	Overall Effect
<i>chg</i> ₂₀₁₇	1.2055*	0.292	1.498
<i>inc</i> ₂₀₁₇	2.4754*	0.703*	3.178
<i>gdp</i> ₂₀₁₇	-2.3272*	-1.29	-3.62
<i>pop</i> ₂₀₁₇	0.121	-0.113	0.008*
<i>urb</i> ₂₀₁₇	0.086	0.062	0.148

3.5. Robustness Test

To test the sensitivity of the empirical results to the choice of spatial weights, this study conducts a robustness analysis by replacing the baseline 0-1 adjacency weights with geographic distance weights. After changing the weights, the sign and significance of the coefficient for the core explanatory variable-charging infrastructure-remain largely consistent with those in the baseline regression, and there are no significant changes in the direct, indirect, or total effects. This indicates that the core research conclusions of this study possess good robustness.

The SDM regression results under the distance weighting show that charging infrastructure, population size, and household income all significantly and positively contribute to the increase in the province's new energy vehicle fleet; the coefficient for regional economic level is significantly negative, while urbanization has no significant effect. This pattern is consistent with the baseline regression. The spatial lag term, with $\rho = 0.392$, was significantly positive at the 5% level, corroborating the Moran's I index and baseline SDM results discussed earlier. Across different specifications of the spatial weight matrix, the development of new energy vehicles consistently demonstrates a positive and stable pattern of spatial dependence.

Moreover, the evidence of spatial agglomeration remains robust and unchanged, indicating that this conclusion is not sensitive to alternative weight matrix settings.

Table 4. SDM Regression Results Under Distance Weighting

Variables	Coefficient
chg_{2017}	0.409*
inc_{2017}	1.921
gdp_{2017}	-1.142*
pop_{2017}	0.593*
urb_{2017}	-0.1
Spatial lag coefficient $\rho(W \cdot ev)$	0.392

The results of the effect decomposition under distance weighting show that the direct, indirect, and total effects of the core explanatory variable-charging infrastructure-are all significantly positive. Both local spillover effects and cross-regional positive spillover effects coexist, consistent with the conclusions of the baseline regression; the sign and significance characteristics of the control variables-such as household income, regional economic level, permanent resident population, and urbanization-also closely align with those of the baseline regression. These results demonstrate that the specification of the spatial weight matrix does not alter the mechanism through which each variable influences the stock of new energy vehicles. The core conclusion of this study-that charging infrastructure exerts positive local pull effects and cross-regional spatial spillover effects-exhibits good robustness.

Table 5. Results of Effect Decomposition Under Distance Weighting

Variables	Direct Effects	Indirect Effects	Overall Effect
chg_{2017}	1.131*	0.232*	1.363
inc_{2017}	2.032	0.681*	2.713
gdp_{2017}	-1.189	-0.733	-2.922
pop_{2017}	0.634*	-0.624	0.01
urb_{2017}	0.287	0.058	0.346

3.6. Further Analysis

To further examine the dynamic evolution of factors influencing the stock of new energy vehicles and their spatial spillover effects, and to verify the trend of strengthening spatial linkages between regions amid the rapid development of the new energy vehicle industry, this paper estimates spatial Durbin models for 2020 and 2023, respectively, and analyzes the evolution patterns of the local effects and spatial spillover effects of each influencing factor based on the results of effect decomposition. The baseline regression results for 2020 and 2023 are presented in **Table 6**, while the spatial effect decomposition results are shown in Table 7 and Table 8, respectively.

From the results of the benchmark regression, the charging infrastructure has shown a strong positive effect in both years-the coefficient in 2020 is 1.054 and 0.796 in 2023. It can be seen that the construction of charging facilities is still a core driving force for the growth of new energy vehicle ownership. The negative pull of regional economic development level has eased

over time, and the coefficient of GDP has narrowed from -0.812 in 2020 to -0.643 in 2023. This change is quite meaningful-after the implementation of support policies such as purchase tax relief, old-for-new subsidies, and new energy license quotas, the car purchase thresholds that existed in developed regions in the past have slowly subsided. Household income shows a significant positive effect in 2020, while the impact of population size and urbanization level is more characterized by stages and transitions.

Looking at the decomposition results of the spatial effect, the direct effect of the charging infrastructure is always significantly positive, and the indirect effect rises from 0.517 to 0.741 . This shows that the more dense the charging network is, the more it not only drives the development of local new energy vehicles, but also has a stronger spillover effect on the surrounding areas. The spatial spillover effect of household income is also continuing to strengthen, reflecting that the demonstration effect of consumption is gradually spreading from the local to the periphery. At the same time, the direct negative effect of economic development level is further weakened, which also confirms that policy support is constantly eliminating the constraints of traditional economic factors on the promotion of new energy vehicles. In addition, the spatial lag coefficient increased from 0.516 to 0.615 , which means that the development of new energy vehicles among provinces has become closer, and the effects of regional synergy and spatial spillover are further enhanced, which provides empirical support for the coordinated development of new energy vehicle industry.

Table 6. Benchmark Regression Results

Variables	i=2020 Coefficient	i=2023 Coefficient
chg_i	$1.054^*(0.153)$	$0.796^*(0.089)$
inc_i	$2.300^*(0.701)$	$0.522(0.448)$
gdp_i	$-0.812^*(0.559)$	$-0.643^*(0.358)$
pop_i	$0.129(0.150)$	$0.250(0.117)$
urb_i	$-1.720^*(0.620)$	$0.963(0.456)$
Spatial lag coefficient $\rho(W \cdot ev)$	$0.516(0.441)$	$0.615(0.302)$

Table 7. Results of the Spatial Effects Decomposition for Each Variable in 2020

Variables	Direct Effects	Indirect Effects	Overall Effect
chg_{2020}	1.206^*	0.517	1.723^*
inc_{2020}	2.475^*	1.126^*	3.601
gdp_{2020}	-0.875	0.214	-0.661
pop_{2020}	0.017	-0.085	-0.068
urb_{2020}	-2.497	-0.164	-2.662

Table 8. Results of the Spatial Effects Decomposition for Each Variable in 2023

Variables	Direct Effects	Indirect Effects	Overall Effect
chg_{2023}	0.794^*	0.741	1.535^*
inc_{2023}	0.479	1.362^*	1.841
gdp_{2023}	-0.612^*	-0.415	-1.027
pop_{2023}	0.253	-0.021	0.232
urb_{2023}	0.956	0.114	1.070

4. Conclusion

The empirical findings of this paper demonstrate good robustness. After replacing the baseline 0-1 adjacency weight matrix with a geographic distance weight matrix and rerunning the

regression, the signs and significance levels of the direct, indirect, and total effects of the core variables remained essentially unchanged, and the core characteristics of spatial agglomeration remained the same. This proves that the empirical results obtained in this paper are not biased by the choice of weight matrix, and the econometric conclusions are reliable.

The degree of spatial agglomeration continues to deepen as the market matures. The spatial autoregression coefficients ρ for 2017, 2020, and 2023 were 0.427, 0.516, and 0.615, respectively. These values increased year by year and all passed significance tests, demonstrating that during the gradual maturation of the new energy vehicle market from 2017 to 2023, industrial linkages and consumer demonstration effects among provinces continued to strengthen, and the radiating and driving capacity of provinces with high vehicle ownership toward surrounding regions continued to increase.

There are distinct temporal and dynamic differences in the impact of these variables. Charging infrastructure has consistently been the core driver of NEV adoption, with a stable and significant positive local effect and the intensity of cross-regional spillover increasing year by year; the negative impact of motor vehicle control constraints-represented by economic development and urbanization-has continued to weaken as supportive policies have been implemented; while household income played a prominent role in driving growth in the early stages, spillover value in later stages relied more on cross-regional consumer demonstration effects. The pathways through which different variables exert their influence undergo structural changes as the market matures.

5. Implications

The findings of this study offer practical guidance. During the phase of high-quality development in the new energy industry, improving supporting infrastructure, optimizing support policies, and unlocking the potential for spatial synergy are key measures for fostering green consumption and developing new-quality productive forces. Based on the spatial econometric empirical results from 2017, 2020, and 2023, this study proposes three development recommendations: First, increase investment in charging infrastructure over the long term. Continuously improve the layout of public charging networks, implement preferential charging rates and subsidies for station construction, reduce vehicle operating costs for the public, fully leverage the positive role of charging stations in stabilizing new energy consumption, and continuously amplify the cross-regional spillover effects generated by supporting infrastructure. Second, continue and optimize support policies for the purchase of new energy vehicles[11]. Stably implement favorable policies such as purchase tax exemptions, trade-in subsidies, and preferential new energy license plates; gradually relax restrictions on vehicle purchase quotas and traffic restrictions; continuously mitigate the negative impact of restrictive policies on the development of the new energy vehicle market; and unleash market vitality by leveraging the demonstration effect of these policies. Third, facilitate the flow of production factors to unlock the potential for coordinated development[10]. Simplify supporting systems related to the circulation of new energy vehicles and cross-regional travel; promote the free exchange of vehicle purchasing concepts and industrial support experiences; continuously enhance positive spatial spillover effects across the nation; and drive the steady expansion of the overall new energy vehicle market.

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