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The Research on the Development Trends of New Energy Electric Vehicles in China

topic selection: Problem C
team number: apmcm2304124

Abstract

As a kind of vehicle using electric power or hybrid power, new energy vehicles are more energy-efficient than traditional fuel vehicles, and can effectively reduce fuel consumption, thus reducing operating costs, and can also reduce pollutant emissions, reducing the risk of environmental pollution and climate change. With the development of the times, the concept of energy saving and environmental protection has led to a quiet shift in people's consumption of automobiles, and they have begun to pay more and more attention to the use of new energy vehicles. China's new energy vehicle industry system is becoming more and more perfect, product technology innovation continues to upgrade, while financial support has weakened in recent years.

The article analyzes the development of new energy electric vehicles in China, explores the trends and discovers the patterns, which will provide decision-making references and support for relevant parties and promote the sustainable development of new energy electric vehicles. In terms of research methodology, public data are collected and analyzed by using data software such as SPSS and Python language programming.

Question 1: Construct a multiple linear regression model using stepwise regression analysis to model and analyze the influencing factors and influencing paths of the development of new energy electric vehicles in China from the perspectives of production and sales. Indicators such as variance inflation factor (VIF) and tolerance are examined to analyze whether there is multicollinearity, and indicators such as correlation coefficient and significance are examined to diagnose the model effect. Subsequently, a gray correlation model was also developed to explore the factors affecting market penetration.

Question 2: The ARIMA time series model was applied to forecast the future development trends of the new energy electric vehicle industry in China for the next 10 years, based on the sales, production, and number of charging stations for new energy vehicles. This process involved change point detection, stationary tests, and differencing techniques, and the model parameters (p, d, q) were determined through the analysis of ACF and PACF. The industry's development score was calculated by combining historical and forecasted data.

Dezhao Su Lifan Zhang | Yang Ji

Question 3: Establish a mathematical model to describe the relationship between traditional energy vehicles and new energy electric vehicles in the market. Firstly, the correlation between the two is confirmed by the Person test, and then the VAR vector autoregression model is established, and Granger causality test and impulse analysis are interspersed and applied to analyze the data, and it is found that new energy automobile sales have a significant effect on the change of fuel automobile sales, and traditional energy automobile sales do not have a significant effect on the change of fuel automobile sales.

Question 4: There are limited policies that really meet the requirements of the question "targeted to resist the development of new energy electric vehicles in China", and the impact of the EU's countervailing investigation is examined through the case study method. The impact of the EU's countervailing investigation was examined through a case study and analyzed through the double-difference (DID) method, and it was found that the policy's effect has been quite limited so far, but the government and enterprises still can't let down their guard, and it is still necessary to ease trade friction through effective means.

Question 5: By analyzing the national car ownership rate and the quantity of new energy vehicles, the per capita car ownership rate per one million people is proportionally calculated. This is further used to assess carbon emissions, reflecting the impact of electrification on the ecological environment. Additionally, by predicting future sales volumes, we can infer the changing impact of new energy vehicles on the ecosystem.

Question 6: This open letter advocates for New Energy Vehicles (NEVs), emphasizing their global impact and ecological benefits. It recognizes the surge in NEV sales but highlights the accompanying rise in carbon emissions. Urging the electrification of conventional vehicles, the letter emphasizes the potential to reduce emissions, enhance urban air quality, and encourages individuals to choose NEVs or electrified transportation for a collective move towards sustainability.

1 Restatement

As a type of new energy vehicle, new energy electric vehicles have achieved rapid development in recent years due to their properties of low pollution, low energy consumption, and ability to regulate peak electricity consumption. Since 2011, the Chinese government has actively promoted the development of new energy electric vehicles and formulated a series of preferential policies. Using mathematical modeling to analyze the following problems.

Question 1: Analyze the main factors that affect the development of new energy electric vehicles in China, establish a mathematical model, and describe Analyze the main factors that affect the development of new energy electric vehicles in China, establish a mathematical model, and describe the impact of these factors on the development of new energy electric vehicles in China.

Question 2: Collect industry development data on China's new energy electric vehicles, establish a mathematical model to describe and predict the development of China's new energy electric vehicles in the next 10 years. Establish a mathematical model to describe and predict the development of China's new energy electric vehicles in the next 10 years.

Question 3: Collect data and establish a mathematical model to analyze the impact of new energy electric vehicles on the global traditional energy vehicle industry. vehicle industry.!

Question 4: Some countries have formulated a series of policies targeted to resist the development of new energy electric vehicles in China. Establish a mathematical model to analyze the effects of these policies on the development of new energy electric vehicles in China. Establish a mathematical model to analyze the effects of these policies on the development of new energy electric vehicles in China.

Question 5: Analyze the impact of the electrification of new energy electric vehicles (including electric buses) in cities on the ecological environment. Assuming that there is an urban population of 1 million, provide the calculation results of the model.

Question 6: Based on the conclusion of question 5, write an open letter to the citizens to publicize the benefits of new energy electric vehicles and the contributions of the electric vehicle industry in various countries around the world.

2 Analysis

For Question 1, multivariate linear regression was used for modeling. Indicators such as industry scale, industry synergy, financial subsidies, public infrastructure construction, and R&D investment were collated from market, government, and technology as explanatory variables, and two explanatory variables, new energy electric vehicle production and new energy electric vehicle production, were set to reveal the path of the indicators' influence on the development of new energy electric vehicles in China more clearly. The data from 2016-2021 were run in SPSS 27 for analysis, and the method chosen was stepwise regression analysis in multiple regression analysis, through the examination of indicators such as variance inflation factor (VIF) and tolerance to analyze whether there is multicollinearity, and the examination of indicators such as correlation coefficients and significance to diagnose the effect of the model. Subsequently, a gray correlation model was also established to explore the factors affecting the market penetration rate.

For question 2, The ARIMA time series model was employed to model the future development trends of the new energy electric vehicle industry in China. Three representative data points, namely sales, production, and the number of charging stations for new energy vehicles, were used as development indicators for modeling and analysis. This process involved change point detection, stationary tests, and differencing techniques to ensure the suitability of the data for time series analysis.

Subsequently, the key parameters (p, d, q) for the ARIMA model were determined through the analysis of ACF and PACF plots, as well as the order of differencing. The ARIMA model was then applied to the time series data, which had undergone change point detection, to forecast the industry's development trends for the next 10 years. Visualizations were used to compare the model's prediction results with historical data, demonstrating the forecasting performance. Finally, by combining historical and forecasted data and assigning appropriate weights, the industry's development score for the past 20 years was calculated.

For Question 3, Based on the relevant data collected, a mathematical model is established to describe the relationship between traditional energy vehicles and new energy electric vehicles in the market. Firstly, the correlation between the two is confirmed by the Person test, and then a VAR vector autoregression model is established, and the data are interspersed with the application of Granger causality test and impulse analysis methods to assess the potential impacts that exist between the new energy electric vehicles and the traditional energy automobile industry.

For question 4,Based on the policy information collected, it is found that there are limited policies that really meet the requirements of the question about "targeted to resist the development of new energy electric vehicles in China", and through the method of case studies The impact of the EU countervailing investigation is examined, analyzed through the double-difference (DID) method, and recommendations are made.

For question 5, to assess the impact of electrification on the ecological environment, we convert the fuel consumption of conventional vehicles and the electricity consumption of electric vehicles into carbon emissions. Based on the national vehicle ownership and the number of new energy vehicles, we calculate the per capita vehicle ownership per one million people and further analyze its carbon emissions. We then predict the sales volume of new energy vehicles to forecast the changing impact of new energy vehicles on the ecosystem in the future.

For question 6, This is an open letter to the citizens, promoting the benefits of New Energy Vehicles (NEVs) and highlighting the contributions of the electric vehicle industry worldwide. The letter underscores the importance of NEVs in improving the ecological environment and the global electric vehicle sector. Despite the rapid growth in NEV sales, the accompanying carbon emissions have also increased. The letter points out that electrifying traditional gasoline vehicles will significantly reduce carbon emissions, improve urban air quality, and calls on people to consider purchasing NEVs or electrified transportation tools, collectively moving towards a sustainable future.

Modeling and solving

3 Question 1

3.1 Question 2 solution approach

Dezhao Su Lifan Zhang | Yang Ji

The question asks to analyze the main factors affecting the development of new energy electric vehicles in China, and to build a mathematical model to show the impact of these factors on the development of new energy electric vehicles in China.

The first is to quantitatively assess the influencing factors, the second is to calculate the specific impacts of these factors on the development of new energy electric vehicles in China, and the third is to evaluate the effectiveness of the model.

First of all, it is necessary to select appropriate indicators to assess the influencing factors. On the basis of analyzing relevant literature, research reports and news, and combining the characteristics of the new energy electric vehicle industry and available public data, we sort out the indicator system as an explanatory variable.

Table1.1 Indicator System for Explanatory Variables of New Energy Electric Vehicles

latent variable		observed variable
market factor	Alternative commodities	Fuel prices, average prices of fuel and new energy vehicles
	industrial scale	Number of enterprises in related industries
	industrial collaboration	Number of installed power batteries, new energy vehicle leasing market size, etc.
Government factors	financial subsidy	Size of subsidy
	Public infrastructure development	Number of public charging piles, vehicle-to-pile ratio
	Other incentives	Scale of purchase tax exemption, etc.
technical factor	Important technological developments	Power battery production, etc.
	R&D investment	R&D funding
	R&D Results	Number of utility model and invention patents

As for the explanatory variables, in order to more comprehensively examine the impact on the development of new energy electric vehicles in China, the supply and demand sides of the market economy are examined, and the new energy electric vehicle production and sales data are selected as the explanatory variables in order to dig deeper into the impact path of the explanatory variables.

3.2 Data collection and validation

Next, relevant data were collected through authoritative channels such as the Ministry of Industry and Information Technology (MIIT), the National Bureau of Statistics (NBS), Enterprise Search, China Association of Automobile Manufacturers (CAAM), and statements of A-share listed companies. Before using the data for analysis, we conducted data validation and comparison. This included comparisons with other authoritative data sources to confirm the consistency of the resulting data

Dezhao Su Lifan Zhang Yang Ji

with other independent sources. By cross-validating the data, we further enhance the credibility of the data.

Subsequently, the correlation between the variables in the dataset was examined based on the calculation of Spearman's correlation coefficient, a non-parametric correlation coefficient used to measure the monotonic relationship between two variables, which can take any value between -1 and 1, where -1 indicates a perfect negative correlation, 0 indicates no linear correlation, and 1 indicates a perfect positive correlation.

The analysis found the variables collected to be correlated variables of the explanatory variables. The analysis found better correlation between the explanatory variables and the explained variables in the collected data, but the problem of multicollinearity needs to be taken care of during the regression analysis.

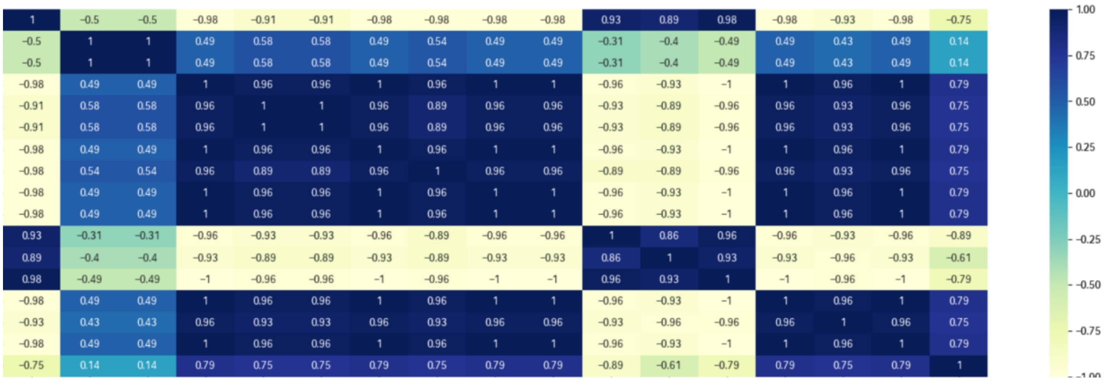


Figure 1.1 Heatmap of the Correlation Distribution between Explanatory and Dependent Variables

3.3 Establishment of a model for factors influencing the development of new energy electric vehicles in China

The following proceeds to calculate the impact of these factors on the development of new energy electric vehicles in China for modeling. In multiple linear regression, the goal is to find the best-fitting line or equation that represents the relationship between the independent variables and the dependent variable. The equation takes the form of:

$$Y = \beta 0 + \beta 1X1 \cdot + \cdot \beta 2X2 \cdot + \cdot \ldots \cdot + \cdot \beta nXn + \varepsilon$$

Where:

Y is the dependent variable

X1, X2, ..., Xn are the independent variables

β0, β1, β2, ..., βn are the coefficients which represent the impact of each independent variable on the dependent variable

ε is the error term or residual, representing the variability in the dependent variable that is not explained by the independent variables

Dezhao Su Lifan Zhang Yang Ji

The multiple linear regression analysis estimates the values of the coefficients (β0, β1, β2, ..., βn) through a process called ordinary least squares. It aims to minimize the sum of squared differences between the observed values of the dependent variable and the predicted values based on the independent variables.

In order to control potential confounders, reveal the interactions between variables, and improve the explanatory power and predictive ability of the model, modeling was performed using stepwise regression analysis, a method that can help to identify the independent variables that have the greatest impact on the predicted results, leading to a more concise and explanatory model.

According to the forward stepwise regression idea, starting from a null model, the independent variables that have a greater impact on the dependent variable are gradually added until a certain predefined target (e.g., significance level) is reached or no further increase in predictive power can be achieved.

The results after running in SPSS 27 are as follows:

Dezhao Su Lifan Zhang Yang Ji

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	56697.390	3	18899.130	42.461	.023[b]
	Residual	890.183	2	445.092		
	Total	57587.573	5			

a. Dependent Variable: S

b. Predictors: (Constant), n, u, t

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	-1097.732	166.249		-6.603	.022		
	u	3.457	1.171	.294	2.952	.098	.782	1.279
	t	.082	.014	1.102	5.943	.027	.225	4.451
	n	20.942	12.989	.293	1.612	.248	.234	4.269

a. Dependent Variable: S

Collinearity Diagnostics[a]

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions			
				(Constant)	u	t	n
1	1	3.891	1.000	.00	.00	.00	.00
	2	.104	6.120	.00	.00	.01	.15
	3	.004	32.426	.11	.98	.12	.09
	4	.002	47.567	.89	.02	.87	.75

a. Dependent Variable: S

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	28.260	344.266	144.933	106.4870	6
Residual	-13.9055	22.4399	.0000	13.3430	6
Std. Predicted Value	-1.096	1.872	.000	1.000	6
Std. Residual	-.659	1.064	.000	.632	6

a. Dependent Variable: S

Dezhao Su Lifan Zhang Yang Ji

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	62980.052	3	20993.351	176.187	.006[b]
	Residual	238.308	2	119.154		
	Total	63218.360	5			

a. Dependent Variable: P

b. Predictors: (Constant), e, a, v

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	-48.015	43.133		-1.113	.381		
	a	22.330	19.845	.080	1.125	.377	.371	2.698
	v	5.267	4.217	.172	1.249	.338	.100	10.050
	e	1.488	.208	.895	7.158	.019	.121	8.286

a. Dependent Variable: P

Collinearity Diagnostics[a]

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions			
				(Constant)	a	v	e
1	1	3.534	1.000	.00	.00	.00	.00
	2	.439	2.836	.00	.02	.01	.02
	3	.020	13.303	.01	.02	.66	.95
	4	.006	23.753	.98	.96	.32	.02

a. Dependent Variable: P

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	59.634	368.013	149.600	112.2319	6
Residual	-7.9335	9.1981	.0000	6.9037	6
Std. Predicted Value	-.802	1.946	.000	1.000	6
Std. Residual	-.727	.843	.000	.632	6

a. Dependent Variable: P

Model formula:

New energy vehicle sales (S) = -1097.732 + 20.942* Infrastructure development in the previous year + 0.082* Average number of patents over two years + 3.457* Average price index of fuel commodities

New Energy Vehicle Production (P) = -48.015 + 22.33*New Energy Vehicle Subsidy Scale + 5.267*Industry Scale + 1.488*Power Battery Production

Interpreting the model formula, it is found that the factors of government subsidies, industry scale, and core technology development affect the new energy EV market by influencing production, while the factors of alternative commodities, infrastructure, and technological advancement work through sales. At the same time, there may be a certain lag in the impact of infrastructure development and technological progress factors on production, sales and the market.

3.4 Evaluation of the model and the conclusions drawn

In terms of model evaluation, for the regression analysis of yield, the analysis of the results of the F-test can be obtained, the significance P-value is 0.006**, which presents significance at the level and rejects the original hypothesis that the regression coefficient is 0, so the model basically meets the requirements. For variable covariance performance, it is also still acceptable.

For the regression analysis of sales volume, the analysis of the results of F-test can be obtained, the significance of the P-value is 0.023**, the level of significance, rejecting the original hypothesis that the regression coefficient is 0, so the model basically meets the requirements. For variable covariance performance, VIF is all less than 10, so the model has no multicollinearity problem.

However, due to the booming development of new energy vehicles and the small amount of data, it is difficult to avoid the overfitting problem of the model, and there is still a certain error in the test on the data of 2022.

In addition, a brief exploration of the factors influencing the market penetration of new energy vehicles in China was done using a gray correlation model.
Gray correlation modeling is a method used to analyze the correlation between factors and is particularly suitable for situations where the data sample is limited, incomplete or uncertain. It helps us to determine the extent to which individual factors affect the target variable and to assess the correlation between them, and is particularly suitable for small samples, nonlinearities, or high levels of uncertainty.

The approximate solution steps are as follows: perform dimensionless processing (homogenization and initialization) for the data; solve for the grey correlation coefficient value between the parent series (comparison series) and the characteristic series; solve for the grey correlation value; rank the grey correlation value and draw the conclusion as follows:

Table1.2 Ranking of Grey Correlation Degree between Comparative Sequence and Feature Sequence

Relevance results		
evaluation unit	relatedness	rankings
Power Battery Production	0.883	1

Relevance results		
evaluation unit	relatedness	rankings
New Energy Vehicle Production	0.881	2
New Energy Vehicle Sales	0.878	3
Infrastructure development	0.725	4
Scale of new energy vehicle subsidies	0.714	5
R&D investment	0.711	6

The correlation value is between 0 and 1, the larger the value is, the stronger the correlation between it and the "reference value", which means the higher its evaluation. As can be seen from the above table: for the six evaluation items, the power battery production has the highest evaluation (correlation: 0.883), followed by new energy vehicle production (correlation: 0.881), which basically involves all aspects of the pre-set indicator system, and has a certain reference value.

4 Question 2

4.1 Question 2 solution approach

In Problem 2, we are required to collect industry development data for new energy electric vehicles and model the future development status of these vehicles over the next ten years. For Problem 1, we have collected industry development data for new energy vehicles. Due to the limited amount of data available, we consider using the ARIMA time series forecasting model to predict three representative indicators. After forecasting, we will assign weights to the three indicators and evaluate them accordingly. By combining this with the data from the past decade, we will describe the future development status.

4.2 Development of data forecasting model establishment

4.2.1 Data analysis

Table2.1 Sales, production, and number of charging stations for new energy vehicles

Year	Sales of new energy vehicles (10,000 units)	Production of new energy vehicles (10,000 units)	Number of charging stations (10,000 units)
2010	0.49	0.72	data loss

2011	0.82	0.84	data loss
2012	1.28	1.26	data loss
2013	1.76	1.75	2
2014	7.48	7.85	2.8
2015	33.11	34.05	6.7
2016	50.7	51.7	16
2017	77.7	79.4	21.3
2018	125.6	127.1	77.7
2019	120.6	124.2	121.9
2020	136.7	136.6	132.2
2021	352.1	354.5	261.7
2022	688.7	705.8	520

Due to the limited amount of raw data, it is not suitable to use machine learning algorithms such as random forest, gradient boosting machine, or convolutional neural network that require a large amount of data. Moreover, the data is organized on an annual basis, without any seasonal trends. Therefore, we choose to use the ARIMA model, which ensures the stationarity of the time series through differencing, and then use the AR and MA models to predict the results.

4.2.2 Establishment of the ARIMA model

The ARIMA model, which stands for "AutoRegressive Integrated Moving Average model," is a widely-used statistical model for analyzing and forecasting time series data.

Dezhao Su Lifan Zhang Yang Ji

The ARIMA model combines the characteristics of autoregressive (AR) models, differencing (I) processes, and moving average (MA) models. Its basic idea is to view the data sequence formed by the object being predicted over time as a random sequence and approximate it with a certain mathematical model. After identification, this model can be used to predict future values based on past and current values of the time series.

The ARIMA model has three parameters: the autoregressive order (p), the differencing order (d), and the moving average order (q), often denoted as ARIMA(p,d,q). The observed values of the research data, denoted as z_t, are defined such that:

$$z_t = \lambda_1 z_{t-1} + \lambda_2 z_{t-2} + \lambda_3 z_{t-3} + \lambda_p z_{t-p}$$

Here, λ_t represents the regression parameter, where i=1,2,...,p indicates the number of lagged variables; v_t represents the white noise process. Therefore, the linear observed values z_t form a pth-order autoregressive model denoted as AR(p).

The white noise v_t can be represented using the lag operator as

$$v_t = \Lambda(L) z_t = \left(1 - \lambda_1 L - \lambda_2 L^2 - \cdots - \lambda_p L^p\right) z_t$$

Translate 'autoregressive operator variant' to

$$\Lambda(L) = (1 - G_1^{-1} L)(1 - G_2^{-1} L) \cdots (1 - G_P^{-1} L)$$

G_1^{-1}, G_2^{-1}, G_3^{-1} are the eigenvalues of the autoregressive characteristic equation. When the characteristic equation satisfies A(L)=0, the AR model is stationary at order p.

If the observed value z_t satisfies

$$z_t = v_t + \theta_1 v_{t-1} + \theta_2 v_{t-2} + \theta_3 v_{t-3} + \cdots + \theta_q v_{t-q}$$

Where θ_1,θ_2,...,θ_q are the equation parameters and v_{t-q} represents the white noise at time $t-q$. The observed value z_t corresponds to a q-order moving average model, denoted as MA(q).

At this point, the autoregressive equation is transformed into

$$z_t = \Theta(L) v_t = \left(1 + \theta_1 L + \theta_2 L^2 + \cdots + \theta_q L^q\right) v_t$$

$\Theta(L)$is the moving average operator.

The characteristic equation of the moving average operator is

$$\Theta(L) = 1 + \theta_1 L + \theta_2 L^2 + \cdots + \theta_q L^q = 0$$

The variant form of the moving average operator becomes

$$\Theta(L) = (1 - H_1^{-1} L)(1 - H_2^{-1} L) \cdots \left(1 - H_q^{-1} L\right)$$

Where $H_1^{-1}, H_2^{-1}, \dots, H_q^{-1}$ are the eigenvalues of the moving average characteristic equation.

Hence, the research data observation values are

$$z_t = \Theta(L)^{-1} v_t = \left(\frac{k_1}{1 - H_1 L} + \frac{k_2}{1 - H_2 L} + \cdots + \frac{k_q}{1 - H_q L} \right) v_t$$

In the equation, k1, k2, ..., kg are constants.

When the characteristic equation satisfies $\Theta(L) = 0$, the MA model is reversible at order q.

The ARMA model is composed of AR model and MA model, and its expression is

$$z_t = \lambda_1 z_{t-1} + \lambda_2 z_{t-2} + \lambda_3 z_{t-3} + \lambda_p z_{t-p} + v_t + \theta_1 v_{t-1} + \theta_2 v_{t-2} + \cdots + \theta_q v_{t-q}$$

By synthesizing, the transformation of ARMA is obtained as

$$\Theta(L) v_t = \Lambda(L) z_t$$

If the time series does not exhibit stationarity, it is necessary to perform differencing on the non-stationary model, resulting in an ARIMA model.

In this question, the ARIMA model is used to forecast the time series of China's new energy vehicle production, sales, and the number of charging piles.

(1) Original time series and change point detection analysis

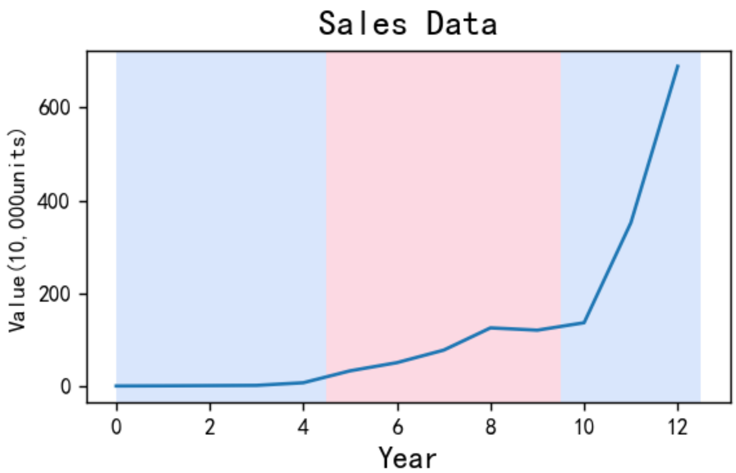


Figure4.1 presents the original time series data of China's new energy vehicle sales (in ten thousand units)

Dezhao Su Lifan Zhang Yang Ji

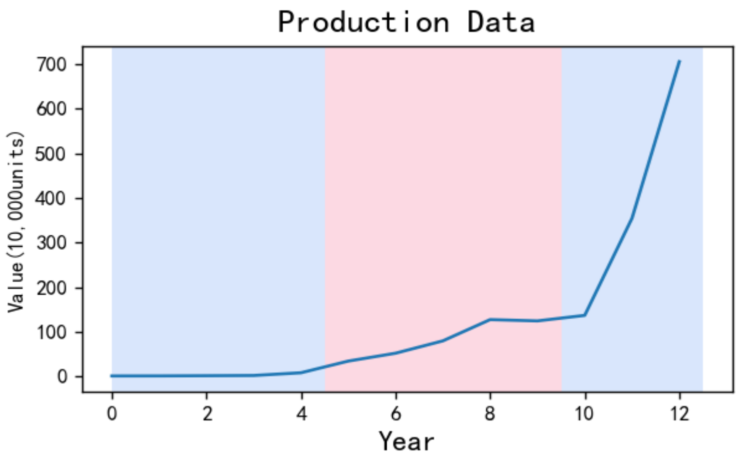


Figure4.2 presents the original time series data of China's new energy vehicle production (in ten thousand units)

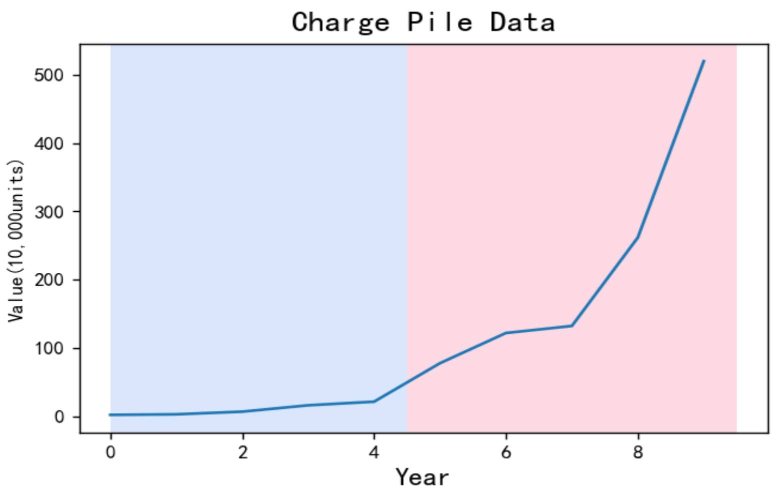


Figure4.3 presents the original time series data of China's new energy charging piles (in ten thousand units)

The first two figures show the line plots of the time series of production and sales from 2010 to 2022. Figure 2.3 represents the line plot of the time series of the number of charging piles from 2013 to 2022. The alternating colors in the figures indicate the detected change points.

Here, the ruptures library in Python is used for detecting breakpoints (change points) in time series. It provides various algorithms such as binary search and dynamic programming for detecting and identifying these points, making it suitable for analyzing structural changes in time series data. In this question, the detection of change points is performed using the cost functions of l1 norm (also known as the Manhattan distance) and l2 norm (also known as the Euclidean distance).

L1 norm, or L1 loss, is the sum of the absolute differences between the actual values and the predicted values. Its mathematical expression is:

$$L1(y,\hat{y}) = \sum_{i=1}^{n} |y_i - \hat{y}_i|$$

Among them, y is a vector of actual values, $\hat{y}$ is a vector of predicted values, and n is the number of samples. The L1 norm is more sensitive to outliers, so it can be used to emphasize outliers in a model.

The L2 norm, or L2 loss (also known as mean square error), is the sum of squares of the differences between actual values and predicted values. Its mathematical expression is:

$$L2(y,\hat{y}) = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2$$

The L2 norm cost function is very common in machine learning, especially in regression problems. Compared to the L1 norm, the L2 norm has lower sensitivity to outliers because it squares the errors before accumulation, giving greater impact to larger errors in the overall cost.

Both methods have good detection performance for short sequences and can detect change points in time series in the sense of minimizing the mean square error, especially when the changes in data are sudden or nonlinear."

It can be seen that the first change point in each plot is around the fifth point. One question is, based on the analysis of change points, we found that the greatest variation in sales occurred in the most recent years, from 2015 to 2022. A common approach to evaluating time series models is to use the second half of the time series as a test set and the first half as a training set.

However, in this study, due to the relatively short length of the time series and the significant changes primarily concentrated in the second half, if we use the second half as the test set, the model will not capture the information of this overall sequence variation, resulting in significant bias in evaluating the model. Therefore, in this case, we will not consider model evaluation and directly proceed with modeling.

Since the changes before the change points are not significant and are difficult to use for predicting future trends in the sequence, in this case, the author uses the change points as the basis for slicing and takes the data after the first change point as the basis for prediction.

(2) ADF testing to obtain the order of differencing

Differencing Process: In order to make non-stationary time series stationary, the ARIMA model utilizes the differencing method. Differencing refers to the difference between the current and previous observations, eliminating trends and seasonality components in the time series by computing the differences between consecutive observations. The differencing order 'd' plays a role in balancing data stationarity and model accuracy in the ARIMA model. First-order differencing is defined as:

$$\Delta Y_t = Y_{t-1} - Y_{t-1}$$

Higher-order differencing follows the same logic. In the ARIMA model, 'd' represents the number of differencing operations performed.

The differenced data undergoes the ADF (Augmented Dickey-Fuller) test, which is a common statistical test method used to detect unit roots in time series data, thereby determining if the series is stationary. If a unit root exists in the time series, the series is non-stationary; if there is no unit root, the series is stationary.

The ADF test is based on the following regression model:

$$L1(y, \hat{y}) = \sum_{i=1}^{n} |y_i - \hat{y}_i| \Delta Y_t = \alpha + \beta t + \gamma Y_{t-1} + \sum_{i=1}^{p} \varphi_i \Delta Y_{t-i} + \varepsilon_t$$

The core of the test is to examine whether the value of γ equals zero, that is, to determine whetherΔY_{t-i} has a significant impact onΔY_t.

```
p-value-sale: 0.998632
p-value-production: 0.998880
p-value-charge_pile: 1.000000
p-value-sale-diff: 0.621048
p-value-production-diff: 0.566246
p-value-charge_pile-diff: 0.989521
p-value-sale-diff2: 0.446045
p-value-production-diff2: 0.337235
p-value-charge_pile-diff2: 0.368880
```

Figure4.4 The original data for sales, production, and the number of charging piles, along with the test coefficients p for the first-order and second-order differences.

The p-value, often referred to as the p-value, is the probability of observing a test statistic (such as the t-statistic in the ADF test) at least as extreme as the one actually observed, under a given statistical model. It provides a quantifiable measure to assess the credibility of the null hypothesis. A low p-value indicates that the probability of observing the current or more extreme results under the null hypothesis is low, giving us reason to reject the null hypothesis. In the context of the ADF test, this means rejecting the null hypothesis that the time series has a unit root, suggesting that the series is stationary.

In the case of short sequences, the p-value after the second-order difference falls between 0.33 and 0.45, which can be considered small, indicating that the series is stationary under these conditions.

Therefore, we can consider that the differencing order for ARIMA is 2.

(2) Calculate and plot the autocorrelation and partial autocorrelation graphs

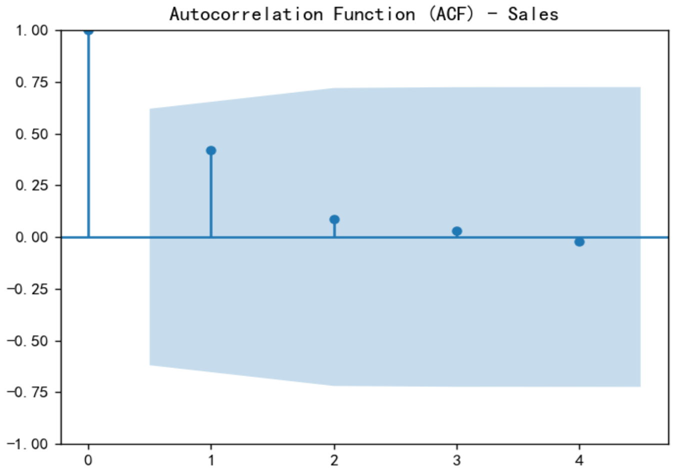


Figure4.5 Autocorrelation Chart (ACF) for New Energy Vehicle Sales.

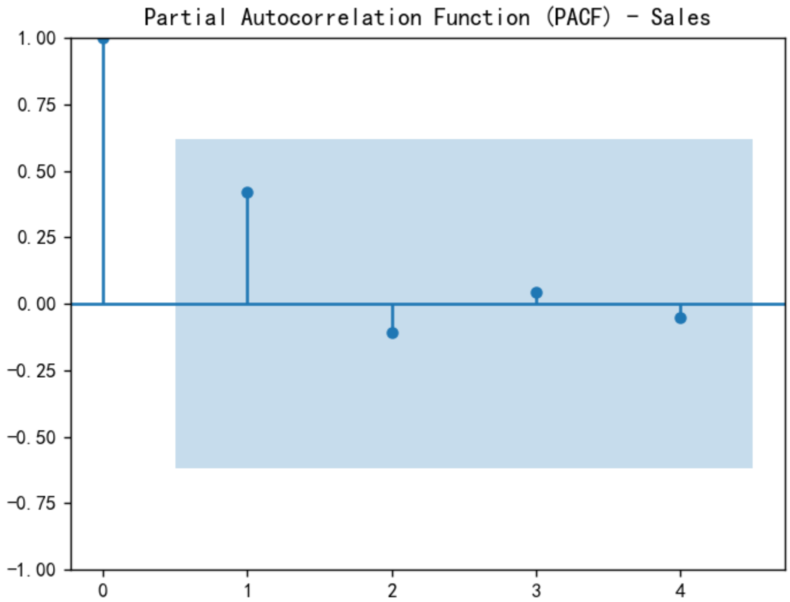


Figure4.6: Partial Autocorrelation (PACF) Chart for New Energy Vehicle Sales

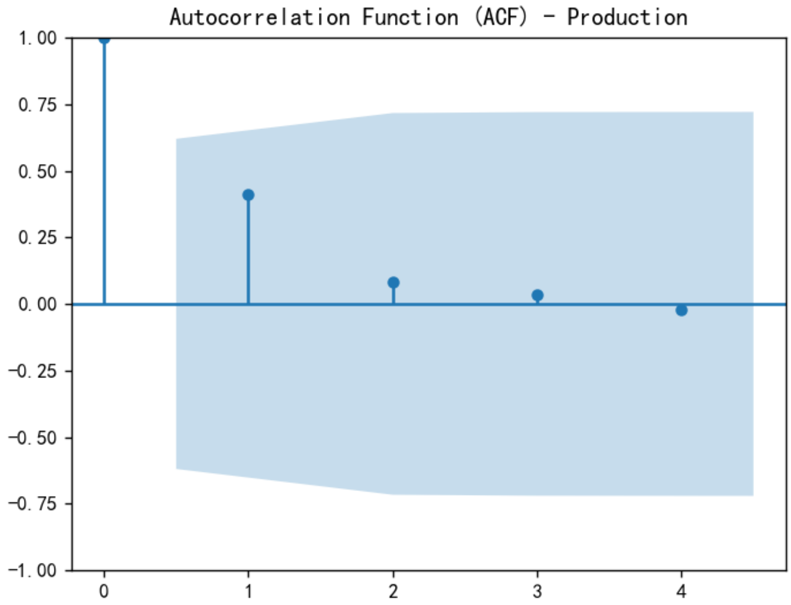


Figure4.7 Autocorrelation (ACF) Chart for New Energy Vehicle Production

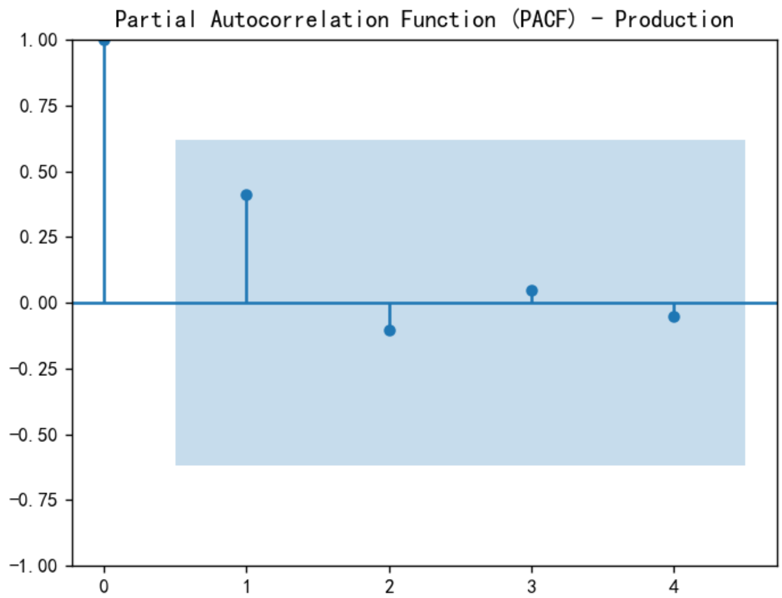


Figure4.8 Partial Autocorrelation (PACF) Chart for New Energy Vehicle Production

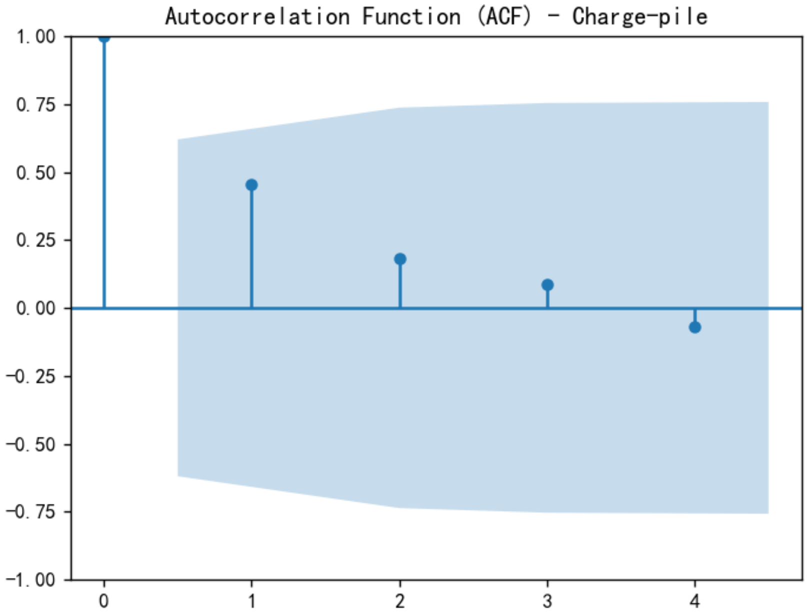


Figure4.9 Autocorrelation (ACF) Chart for the Number of Charging Piles

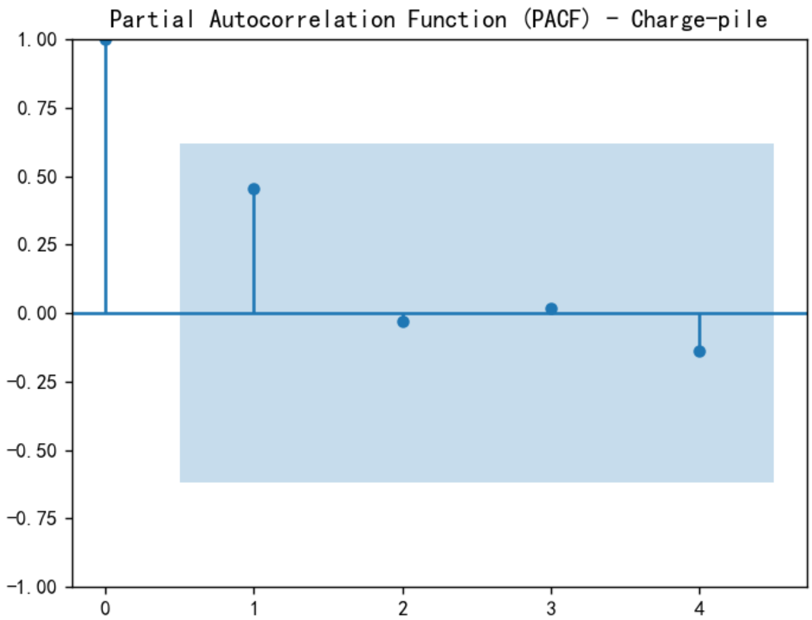


Figure4.10 Partial Autocorrelation (PACF) Chart for the Number of Charging Piles.

Autocorrelation and Partial Autocorrelation are important concepts in time series analysis, used to describe the correlation between values in a time series and their past values.

Autocorrelation refers to the correlation between values of a time series at different time points. It measures the degree of correlation of the same time series at two different points in time. For a time series Y_t (where t represents time), the autocorrelation coefficient ρ_k at lag k can be expressed as:

Dezhao Su Lifan Zhang Yang Ji

$$\rho_k = \frac{\sum_{t-k+1}^{n} \quad (Y_t - \bar{Y})(Y_{t-k} - \bar{Y})}{\sum_{t-1}^{n} \quad (Y_t - \bar{Y})^2}$$

Where $\bar{Y}$ is the mean of the time series, n is the number of observations, and k is the number of lag periods.

The Autocorrelation Function (ACF) is commonly used to detect seasonal or cyclical patterns in a time series, as well as to identify the presence of autoregressive patterns.

Partial autocorrelation refers to the correlation between values of a time series at different time points, after excluding the influence of intermediate (lagged) observations. It measures the direct relationship between a specific lagged value and the current value, given the other lagged values.

The calculation of the Partial Autocorrelation Function (PACF) is relatively complex, involving the exclusion of the influence of each lagged value in the time series on other lagged values. For lag k, the partial autocorrelation ϕkk can be obtained by estimating the autoregressive model of the time series, which includes all terms from lag 1 to lag k. In simple cases, the partial autocorrelation at lag 1 is the same as the autocorrelation. For higher lag values, they can be calculated using the Yule-Walker equations or more advanced statistical software.

For non-seasonal ARIMA models, the ACF and PACF are very useful tools. Therefore, in the ARIMA model used in this case, the PACF can help determine the order p of the autoregressive (AR) part, while the ACF can help determine the order q of the moving average (MA) part.

The reason for not using AIC and BIC to select the best parameters in this case is that although AIC (Akaike Information Criterion) and BIC (Bayesian Information Criterion) are criteria used for statistical model selection and are very useful in choosing the optimal model among multiple models, both require a relatively large amount of data. AIC focuses on assessing the model's fit quality, suitable for model selection especially when the number of parameters in the model varies, but may lead to overfitting in cases of limited data. Meanwhile, BIC is applicable in large sample scenarios and tends to favor simpler models.

The basis and method for determining the parameters p and q based on ACF and PACF involve identifying the first lag value that is zero or close to zero. If the bar chart values are close to zero after this point, the preceding number of this point is considered as the order p or q. This point is referred to as the cutoff point.

From the analysis of the six charts, two charts each for sales, production, and charging piles of new energy vehicles, it can be concluded that:

The p-value for the production of new energy vehicles is 2, and q is 3.
The p-value for the sales of new energy vehicles is 2, and q is 3.
The p-value for the number of charging piles is at least 4, and q is 1.

4.2.3 Based on the optimal parameters obtained, use the ARIMA model to make predictions

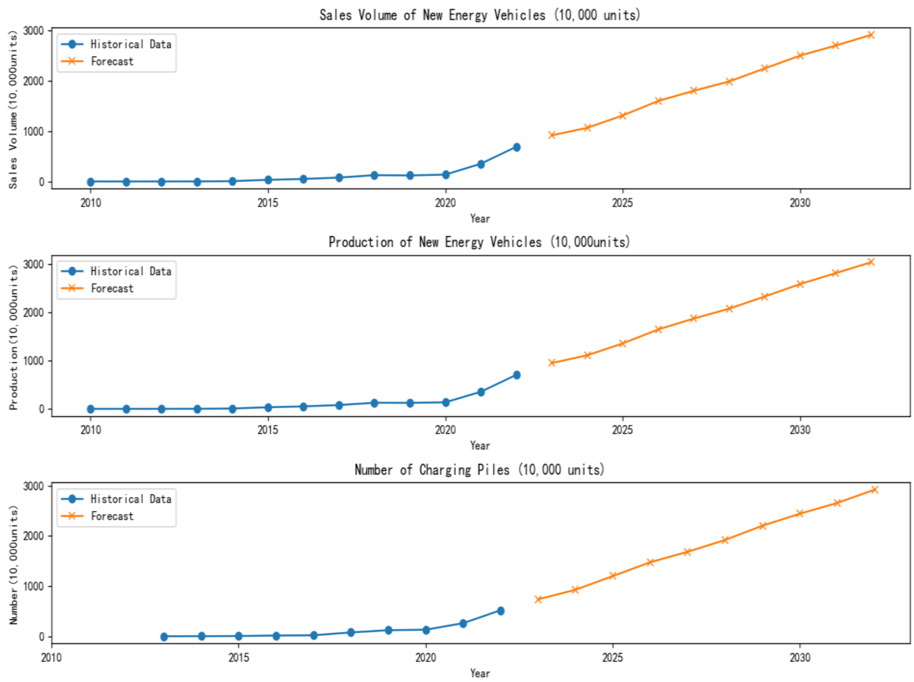


Figure4.11 Development Forecast Curve for the Next Ten Years

This image contains three subplots: the first is sales, the second is production, and the third is the number of charging piles. In the charts, the blue line represents historical data, while the orange line represents forecasted data.

The detailed forecast data are as follows:

Table4.2 Detailed Forecast Data for Development Over the Next Ten Years

Year	Sales of new energy vehicles (10,000 units)	Production of new energy vehicles (10,000 units)	Number of charging stations (10,000 units)
2023	914.7	948.6	736.7
2024	1063.8	1109.7	927.2
2025	1309.1	1355.3	1200.5

2026	1596.1	1644.3	1476.6
2027	1797.2	1869.2	1684
2028	1982.8	2073.8	1920
2029	2240.5	2325.3	2204.7
2030	2495.5	2583.7	2443.2
2031	2693.3	2809.1	2658.2
2032	2905.2	3034.5	2924

4.3 Assessment of Scores for the Next Ten Years and the Recent Decade

Combining the data from 2013-2022 and the forecasted data for the next ten years, and using sales, production, and the number of charging piles as the main basis with respective weights of 0.4, 0.3, and 0.3, the calculation is performed using weighted and standardized methods. The formula for standardization is:

Standardized Value =

(Original Value - Minimum Value) / (Maximum Value - Minimum Value)

Assuming the weights are assigned as ω1, ω2, and ω3, corresponding respectively to sales, production, and the number of charging piles, the development score is calculated as:

The development score for each year = ω1× standardized sales + ω2× standardized production + ω3× standardized number of charging piles

Finally, since some of the calculated scores are negative, add a constant to all of them to ensure they are positive.

The final calculated development score is:

Table4.3 Development Scores of New Energy Vehicles in the Past 10 Years and the Next Ten Years.

Years	Development Scores
2013	0.01

Dezhao Su Lifan Zhang Yang Ji

2014	0.01
2015	0.03
2016	0.04
2017	0.06
2018	0.11
2019	0.13
2020	0.14
2021	0.33
2022	0.64
2023	0.87
2024	1.03
2025	1.29
2026	1.57
2027	1.78
2028	1.98
2029	2.25
2030	2.49
2031	2.7
2032	2.94

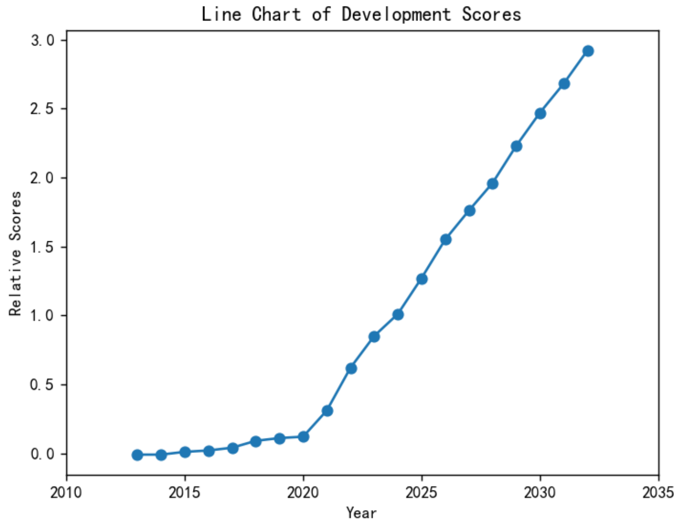


Figure4.12 Line Graph of Development Scores for New Energy Vehicles in the Past Ten Years and the Next Ten Years

In conclusion, it is evident that the future development of China's new energy electric vehicle industry will continue to trend upward and maintain a positive momentum.

5 Question 3

5.1 Data collection

When collecting global data, we face difficulties in data reliability, comparability, access costs and timeliness. To address these challenges, we consider selecting authoritative data sources, using sample surveys or inferential statistics to fill in data gaps, determining an appropriate time span for the study, and incorporating case studies for in-depth understanding. These strategies can help ensure the reliability and usefulness of the research findings.

According to the industry consulting firm Trendforce publicly released data, obtained sales 2013-2022 global new energy electric vehicle sales and global fuel vehicle sales data, and further also obtained global new energy electric vehicle sales growth rate and global fuel vehicle sales growth rate data.

Simple visualization of the data, preliminary findings, overall global new energy electric vehicle sales and growth rate showed growth, while fuel vehicles are declining, and even sales once negative growth.

In the eight years from 2014 to 2022, global sales of new energy electric vehicles increased from 318,000 units to 10.65 million units, an increase of about 33 times. At the same time, the growth rate of new energy electric vehicle sales has increased from 0.41% to 0.61%, with demand continuing to increase and the growth rate gradually stabilizing.

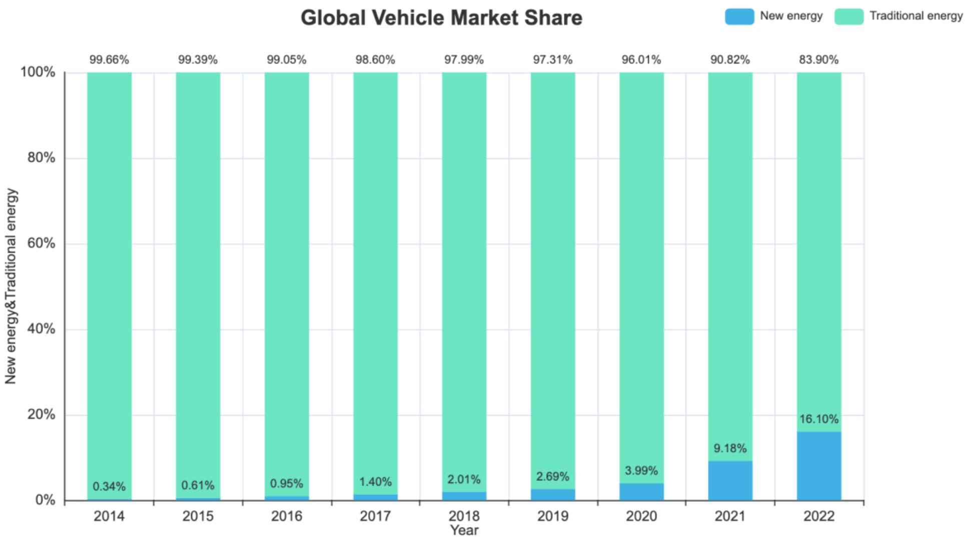


Figure5.1 Global Vehicle Market Share.

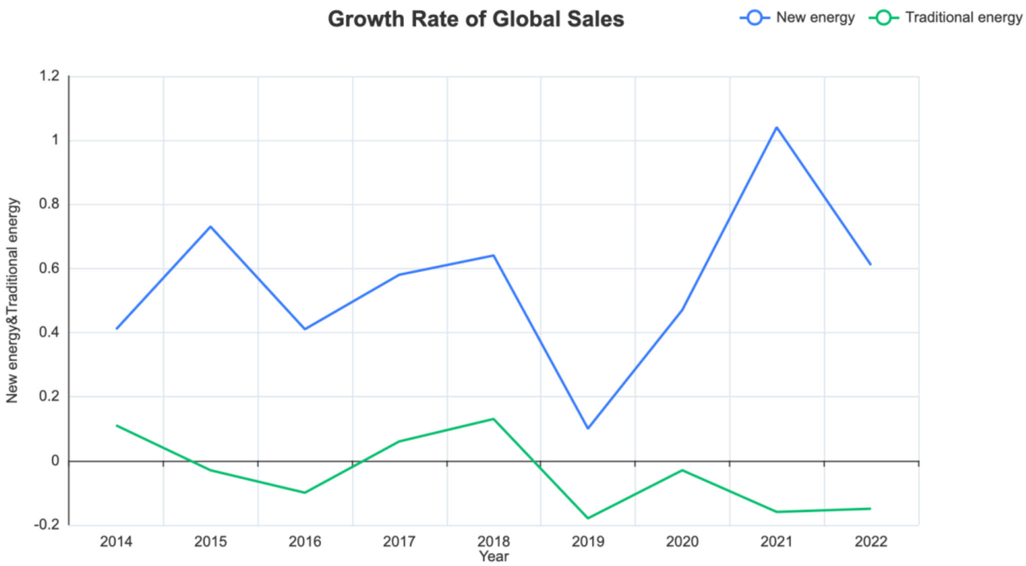


Figure5.2 Growth Rate of Global Sales.

5.2 Data Analysis and Modeling

To analyze the impact of new energy electric vehicles on the global traditional energy automobile industry with sales data, the correlation between the two was first examined and Pearson correlation analysis was performed.

In terms of correlation, the correlation coefficient between the two is -0.902, which is close to -1, indicating that the global sales of new energy electric vehicles show a strong negative correlation with the global sales of fuel vehicles. In other words, as the sales of new energy electric vehicles increase, the sales of fuel vehicles show a decreasing trend, and vice versa.

In terms of significance, the p-value of the correlation coefficient is 0.001, which is much less than the usual significance level of 0.05, so one can be pretty sure that this negative correlation is significant and not due to random factors.

Overall，Global new energy electric vehicle sales and global fuel vehicle sales show a strong negative correlation, and this correlation is statistically significant.

Table5.1 Correlation Analysis

	New energy_sales	Traditional energy_sales
New energy_sales	1 (0.000***)	-0.902 (0.001***)
Traditional energy_sales	-0.902 (0.001***)	1 (0.000***)
Note: ***, **, * represent the significance levels of 1%, 5%, and 10%, respectively.		

Subsequently, an attempt was made to build a model containing two variables to study the pattern of influence of both.

VAR (Vector Autoregression) vector autoregression model is a multivariate time series analysis method, which is suitable for analyzing the interrelationships among multiple variables and can simultaneously estimate the dynamic linkage effects among variables. Therefore, we can use the VAR model to analyze the relationship between global new energy electric vehicle sales and global fuel vehicle sales.

The VAR(p) model is expressed as:

$$Yt = c + A1Yt\text{-}1 + A2Yt\text{-}2 + ... + Ap*Yt\text{-}p + ut$$

where Yt is a k-dimensional time series vector, ut is a k-dimensional random error vector, c is a constant term, A1 to Ap are k*k-dimensional coefficient matrices, and p is the model order.

Firstly, ADF test was performed, which is a commonly used unit root test to determine whether the time series data has a unit root (non-stationary), and it was found that both sets of variables are stationary data ($p<0.05$),which can be modeled.

Table5.2 ADF test

Variable	t	P	threshold value		
			1%	5%	10%
New energy_sales	-5.48	0.000***	-5.354	-3.646	-2.901
Tranditional energy_sales	-306.553	0.000***	-5.354	-3.646	-2.901
Note: ***, **, * represent the significance levels of 1%, 5%, and 10%, respectively.					

Subsequent **selection of the lag order** is based on the information criterion for vector autoregressive models with lag p order**.**

Table5.3 information criterion of vector autoregressive model

Dezhao Su Lifan Zhang Yang Ji

Lag Order	logL	AIC	SC	HQ	FPE
0	-149.123	24.549	24.609	24.483	45923787855.215
1	-112.976	20.763	20.895	20.48	1097603089.026
2	-88.237	18.883*	18.983*	18.214*	244843973.881*

The above table demonstrates the information criterion of vector autoregressive model with lag order p for selecting the better lag order. It includes logL, FPE, AIC, SC, and HQ, where logL is involved in the calculation of FPE, AIC, SC, and HQ, and ultimately evaluated by the metrics of FPE, AIC, SC, and HQ. It is found that the lag order of 2 has the most * , and the VAR(2) model is established.

Table5.4 parameter estimation table

parameters	estimated quantity	New energy_sales	Tranditional energy_sales
	ratio	0.569	-2.995
New energy_sales(-1)	(statistics) standard deviation	0.098	1.504
	t	5.786	-1.992
	ratio	-0.003	-0.23
Tranditional energy_sales(-1)	(statistics) standard deviation	0.025	0.388
	t	-0.13	-0.592
	ratio	42.743	11149.933
a constant (math.)	(statistics) standard deviation	232.624	3557.612
	t	0.184	3.134

The modeling can be expressed as:

New energy_sales=0.569*New energy_sales(-1)-0.003*Tranditional energy_sales(-1)+42.743 Tranditional energy_sales=-2.995*New energy_sales (-1)-0.23*Tranditional energy_sales(-1)+11149.933

Stability test is carried out and the AR root plot is plotted and it is found that all the points are located within the unit circle, from which it can be judged that the established VAR system is stable and the model can be further impulse response analysis and variance decomposition.

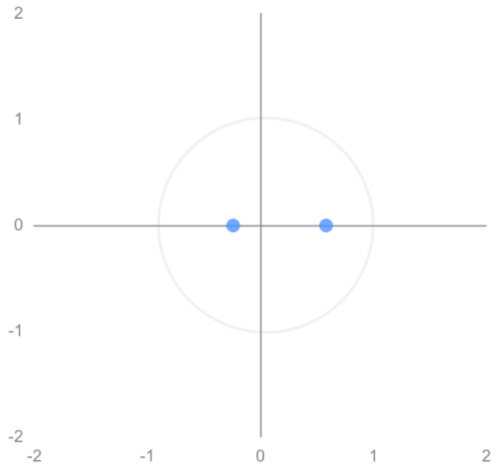


Figure5.3 AR root plot

Before the impulse response analysis, Granger causality test is conducted, which can help us determine the causal factors of new energy electric vehicle sales and fuel vehicle sales, so as to ensure the accuracy of the validation conclusions.

It is based on the Granger causality principle, which determines the causal relationship between two time series by comparing the accuracy of their forecasting models. Although it does not identify the actual mechanism of causality, it can provide a statistical judgment of causality.

The Granger causality principle holds that if the past values of one time series can better predict the future values of another time series, then we can say that the former has a causal influence on the latter. Therefore, the central idea of the Granger test is to compare the prediction errors of forecasting models for two time series. The original hypothesis (null hypothesis) and alternative hypothesis (alternative hypothesis) are proposed:

Hypothesis test 1: To test whether the sales of new energy electric vehicles are a causal factor in the sales of fuel vehicles:

H0: New energy electric vehicle sales are not a causal factor in fuel vehicle sales.

H1: New energy electric vehicle sales are a causal factor in fuel vehicle sales.

Hypothesis test 2: To test whether fuel vehicle sales are a causal factor for new energy electric vehicle sales:

H0: New energy electric vehicle sales are not a causal factor in fuel vehicle sales.

H1: New energy electric vehicle sales are a causal factor in fuel vehicle sales.

Dezhao Su Lifan Zhang Yang Ji

Analyzing the significance of the F-statistic, if it is significant (p<0.1), it indicates the rejection of the original hypothesis (one set of time series is not the cause of the other), i.e., the left-hand side variables can cause changes in the right-hand side variables with Granger causality, and vice versa, no Granger causality exists.

Table5.5 significance analysis of the F-statistic

matched sample		F	P
Tranditional energy_sales	New energy_sales	0.065	0.94
New energy_sales	Tranditional energy_sales	5.236	0.10

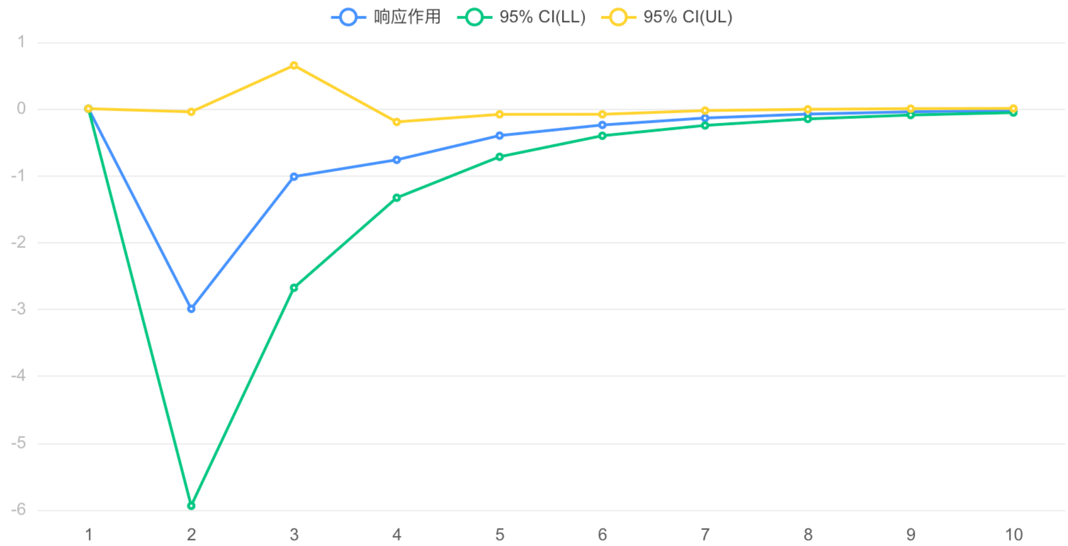
Note: ***, **, * represent the significance levels of 1%, 5%, and 10%, respectively.

For hypothesis test 1, the significance P-value is 0.94, which does not present significance and cannot reject the original hypothesis that fuel vehicle sales are not a causal factor for new energy electric vehicle sales.

With for hypothesis test 2, the significance P-value is 0.10, presenting significance and rejecting the original hypothesis, which considers new energy electric vehicle sales as a causal factor for fuel vehicle sales at 90% confidence level.

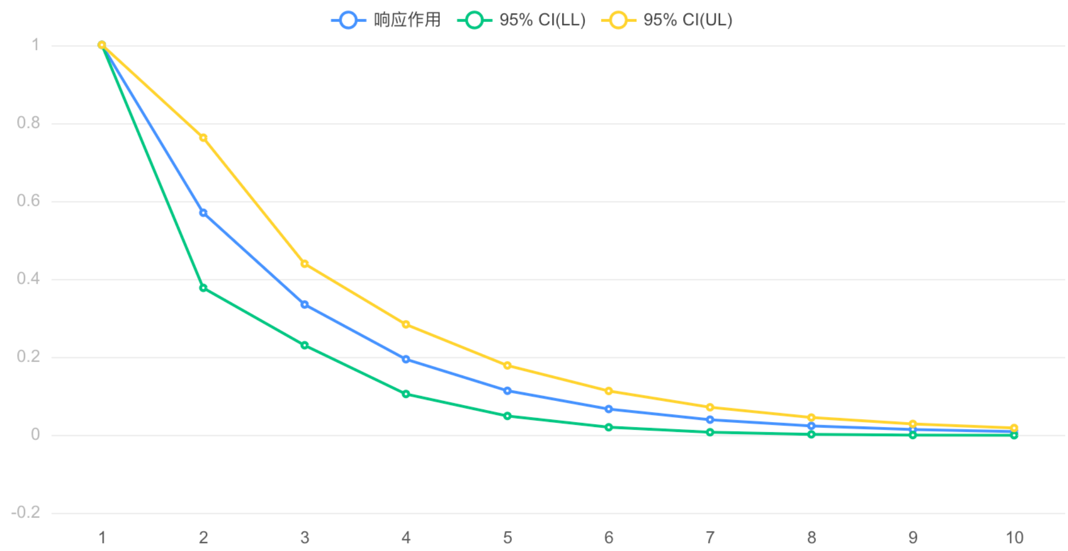
Impulse response analysis is a method used to estimate the dynamic response of a system. It is based on the assumption that sudden shocks (impulses) to one variable will have short and long term effects on other variables. In impulse response analysis, we want to determine how one variable causes changes in other variables.

For the aforementioned VAR model, an impulse response plot is drawn.



Shock variable: sales of new energy electric vehicles; shocked variable: sales of fuel vehicles

Dezhao Su Lifan Zhang Yang Ji



Shock variable: sales of new energy electric vehicles; Shocked variable: sales of new energy electric vehicles

Figure5.4 Impulse response plot

As can be seen from the figure, for the shock variable of new energy electric vehicle sales, it firstly produces a positive shock to itself, and then the shock strength gradually decreases steadily and gradually converges to the 0 value.

New energy electric vehicle sales on the impact of fuel car sales, it will first produce a negative inhibition, the first four periods of this negative impact is larger, but from the fifth period onwards, the negative impact has been weakened and stabilized.

In addition, the variance decomposition result table is output with fuel automobile sales as the response variable. Based on the data in the variance decomposition result table, it can be concluded that the sales volume of new energy vehicles has a significant effect on the changes in the sales volume of fuel vehicles, and the sales volume of traditional energy vehicles has no significant effect on the changes in the sales volume of fuel vehicles.

The change of fuel automobile sales is mainly affected by the sales of new energy automobile, and has nothing to do with the sales change of traditional energy automobile sales itself.

Table5.5 change of sales

Order	s	New energy_sales%	Tranditional energy_sales%
1	41.219	100	0
2	47.169	99.823	0.177
3	49.08	99.817	0.183
4	49.7	99.811	0.189
5	49.909	99.81	0.19
6	49.979	99.81	0.19
7	50.003	99.809	0.191
8	50.011	99.809	0.191

Order	s	New energy_sales%	Tranditional energy_sales%
9	50.014	99.809	0.191
10	50.015	99.809	0.191

The global new energy electric vehicle market is growing rapidly, while the fuel vehicle market is facing challenges, and the former is the reason for the latter. Based on the previous analysis, this may be the result of increased awareness of environmental protection, increased demand for energy conservation and emission reduction, and the continuous advancement of new energy technologies and the growth of related industries. In the future, it is expected that the new energy electric vehicle market will continue to grow, while the fuel vehicle market faces competitive pressure, and the impact of new energy on it tends to weaken over time.

This finding may be an important reference for energy policymaking and automobile industry development, suggesting that if the government moves toward reducing the demand for traditional fuel vehicles, it can do so through measures that encourage and support the development of new energy electric vehicles. Meanwhile, according to the market trend, automobile manufacturers can adjust their production and investment strategies to increase the production and technology development of new energy electric vehicles to meet the market demand.

6 Question 4:

6.1 Policies Analysis

Some countries have formulated a series of targeted policies to resist the development of new energy electric vehicles in China. Develop a mathematical model to analyze the impact of these policies on the development of new energy electric vehicles in China.

Finding relevant policies can be found, the policies involved often set up non-technical barriers for China's new energy vehicle exports, which may affect the development of new energy vehicles in China, mainly divided into two categories:

First, green barriers. At present, China's new energy vehicle technical standards are lower than those of the EU and other developed countries. The EU's environmentally friendly standards for new energy vehicles are much higher than the national standards, which will keep a part of the Chinese new energy vehicles with lower standards out of the EU market.

In 2017, the EU formulated the "Fit for 55" climate package, which puts forward clear requirements for the transportation sector. At the same time, the use of its clean energy structure, advanced technology, carbon emissions trade policy to create green barriers to accelerate the development of the local new energy industry chain.

Dezhao Su Lifan Zhang Yang Ji

The second is trade protectionist measures. The global new crown pneumonia epidemic has also brought great damage to the global supply chain and the free multilateral trading system, and the Russian-Ukrainian conflict in February 2022 has intensified the uncertainty of global politics and trade, and the international trade environment has become even more severe, and China's new energy vehicle exports will inevitably encounter more trade frictions after developed countries such as Europe and the United States are paying more and more attention to the market of new energy vehicles.

Not only vehicle exports may face such problems, but also imports of key components of new energy vehicles may be affected, which will affect the overall strategy of China's new energy vehicle exports. For example, the U.S. Inflation Reduction Act specifies a fiscal incentive program for new energy vehicles in the next 10 years, aiming to promote the U.S. to build a complete and independent new energy vehicle industry chain.

However, at the same time, we need to recognize that most of these policies are not targeted, and thus do not qualify as "targeted to resist the development of new energy electric vehicles in China" in the title, which qualifies A typical example of a policy that meets the condition of "targeted to resist the development of new energy electric vehicles in China" in the question is the countervailing investigation carried out by the European Union in the EU against new battery electric vehicles in China.

On September 13, 2023, the President of the European Commission announced at the annual EU State of the Union address that a countervailing investigation would be opened into electric vehicles produced in China. On October 4, the Official Journal of the European Union (OJEU) issued a statement launching a countervailing investigation procedure into imports of electric vehicles produced in China. It is reported that the investigation will be concluded within a maximum of 13 months, the EU may impose a temporary "countervailing duty" on China within nine months.

Data from the passenger association shows that during the five years from 2017 to 2022, China's exports of new energy vehicles increased from from 170,000 to 1.12 million, which has been maintaining a strong growth trend. KPMG report also shows that before 2020, China's new energy vehicle exports to Europe were only about 10,000 units, and in 2022 China's exports to Europe have exceeded 500,000 units.

Now very cost-effective Chinese new energy vehicles are accelerating the expansion of globalization, the EU believes that China's new energy vehicles cost advantage, is due to government subsidies, but in 2023 China's new energy vehicle subsidies have been completely withdrawn, Europe and the United States and other countries may be really worried about, is that its local brands once they can not withstand the strong impact of the Chinese brand, the future of the new energy automobile industry may lose the dominance of the global and the pricing power.

The now-defined policy has been implemented since September, and time-series data on China's exports and total exports of new energy vehicles to the EU were

collected and analyzed using the double-difference (DID) method.

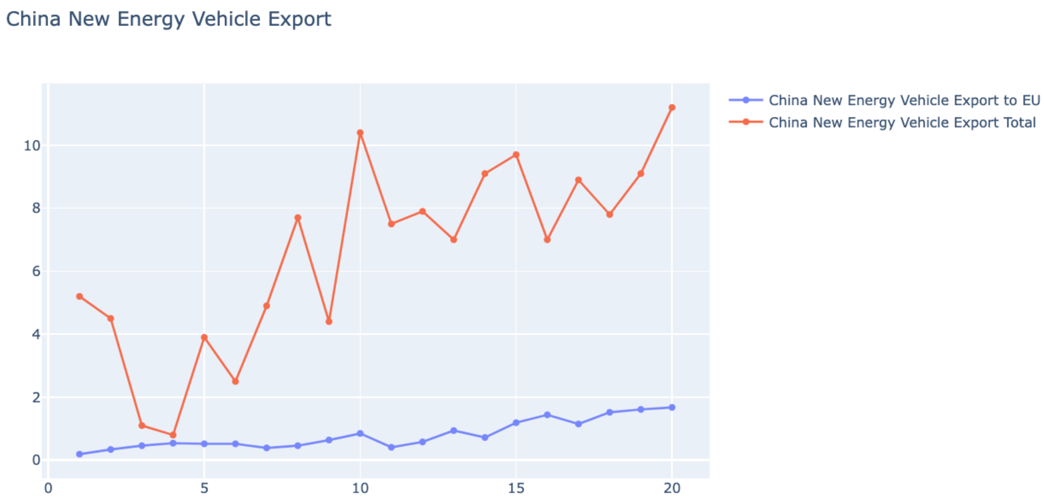


Figure6.1 China New Energy Vehicle Export

6.2 Modeling and Results Analysis

The double difference (DID) method is a statistical model for estimating causal effects. Its main advantage is that it can control for unobserved factors that are fixed in time, thus reducing the bias in the estimates.The DID method is useful for assessing the effects of policy interventions, especially when an experimental design is not feasible. In addition, this approach does not require randomized grouping and is therefore suitable for situations where randomized experiments are not possible.

In general, DID is analyzed as follows:

1. Suppose there are two sample groups, one of which received the policy intervention (experimental group) and the other did not (control group). We want to compare the effect of the policy intervention on the experimental group.
2. Define a time indicator D that represents the difference in time before and after the implementation of the policy:
    1. D = 1, indicating that after policy implementation
    2. D = 0, indicating before policy implementation
3. Define an interaction term that represents the effect of policy intervention and time on the outcome variable:
    1. $DID = \beta_1 + \beta_2 D + \beta_3 T + \beta_4 (D \times T) + \varepsilon$ where β_1 is a constant term, β_2 denotes the impact effect of the policy intervention, β_2 denotes the impact effect of time, β_4 denotes the impact effect of the interaction of the policy intervention and time, and ε is an error term.
4. The parameters of the DID model were estimated using the least squares method and the estimates of β_2 and β_4 and their standard errors were calculated.

Dezhao Su Lifan Zhang | Yang Ji

Hypothesis testing was conducted based on the estimates of β_2 and β_4 and their standard errors. If the estimates of β_2 are significantly not equal to zero and have a positive sign, and the estimates of β_4 are significantly not equal to zero, the hypothesis is rejected, i.e., it is considered that the policy intervention has a significant positive impact effect on the experimental group; otherwise, the hypothesis is accepted, i.e., it is considered that the policy intervention does not have a significant positive impact effect on the experimental group.

Specifically, the effect of the intervention is estimated by comparing the difference in export volumes between the two time periods before and after the intervention. The modeling equation here is:

$$\text{DID effect} = \text{posterior mean} - \text{prior mean}$$

where the DID effect denotes the effect of the intervention, and the late mean and early mean denote the mean export volume after and before the intervention, respectively.

The data were divided by the pre- and post-intervention time periods, including month, volume exported to the EU, and total export volume. The average of the export volumes in the two time periods after and before the policy intervention is calculated, which helps us to understand how the export volumes changed before and after the implementation of the intervention.

Next, the difference between the mean value of the post and the mean value of the pre-intervention period is calculated, which represents the change in export volume after the intervention was implemented relative to the pre-intervention period.
The results show:

Export to EU DID Estimate: 0.9289795555555556
Total Export DID Estimat: 4.0222222222222222221

After the countervailing investigation, China's average monthly exports of new energy vehicles to the EU increased by about 0.93 million units. Meanwhile, China's total average monthly exports of new energy vehicles increased by about 40,200 units.

As the trend of China's new energy vehicle exports to the EU shown in the chart below suggests, despite the EU launching a countervailing investigation into China's new energy electric vehicles, both China's new energy vehicle exports to the EU and total exports have increased significantly in the wake of the investigation. This may be due to the fact that the policy was recently issued and the substantive impact is still quite limited.

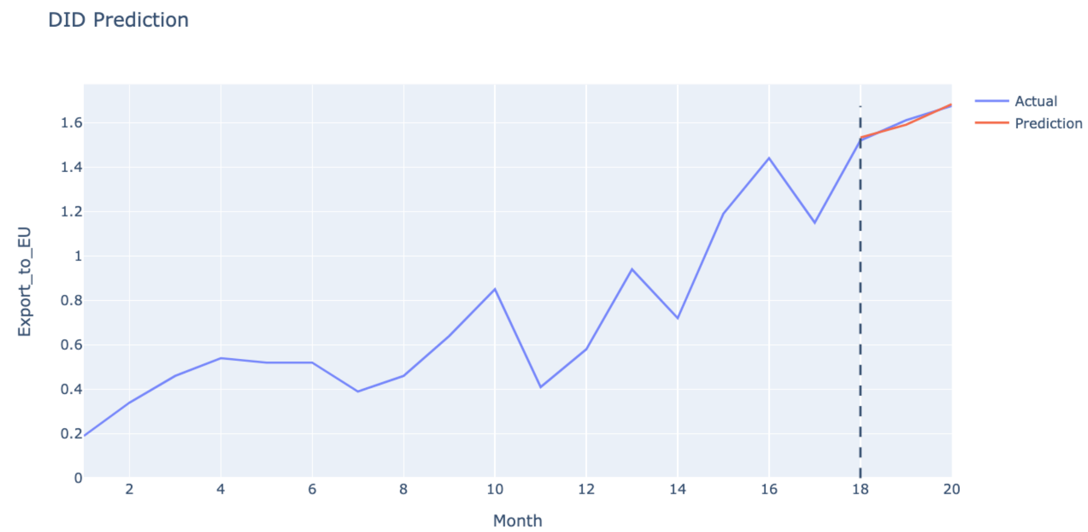


Figure6.2 DID Prediction

However, this is not enough for the Chinese Government and the enterprises concerned to relax their vigilance. After all, once the investigation is further carried out, regardless of whether the conclusion of the countervailing investigation is established or not, it may have a far-reaching impact on the global supply chain of the export enterprises involved in the case.

For the enterprises involved in the case in which the conclusion of the investigation is established, the impact of additional tariffs brought about by the countervailing investigation will last for a minimum of five years, and the EU importers, out of consideration of tariff costs, may choose to give up cooperating with them, so that the enterprises are forced to withdraw from the original market; for the For the enterprises involved in the investigation conclusion is not established, or currently not within the scope of the investigation of the relevant enterprises, should also save for a rainy day, it is necessary to consider through scientific and reasonable planning, reconstruction of the global supply chain, to avoid future similar investigations triggered by the adverse consequences.

Overall, in the face of various risks and challenges in international trade, cooperation and communication are the key to solving problems. Governments can also provide enterprises with the necessary assistance and protection through policy support and guidance, and work together to meet the challenges that may arise. By working together, governments and enterprises can better adapt to and circumvent potential adverse impacts, ensuring the stable and healthy development of economic activities.

Dezhao Su Lifan Zhang Yang Ji

7 Question 5

To analyze the impact of urban electrification of new energy electric vehicles on the ecological environment, it is possible to do so by analyzing the nationwide vehicle ownership of various types. Calculate the car ownership of 1 million people based on the population proportion. Then, calculate the carbon emissions of traditional fuel vehicles and new energy vehicles. Finally, electrify the traditional fuel vehicles and calculate the carbon emissions to determine the emission reduction effect of electrifying new energy electric vehicles.

7.1 Ownership Rate Analysis

The latest data released by the Chinese Ministry of Public Security shows that as of the end of November 2022, the total number of motor vehicles in the country reached 415 million, with the number of automobiles reaching 318 million. This indicates that the vehicle ownership rate in China is about 0.227.

In 2030 and 2035, China's vehicle ownership rates are estimated to be 0.257 and 0.286, respectively, based on the "Energy Saving and New Energy Vehicle Technology Roadmap 2.0." Using these ownership rates and considering the growth in sales of new energy vehicles, we can predict the carbon emissions of new energy vehicles and traditional fuel vehicles for the years 2030 and 2035.

7.2 Carbon Emissions Calculation for Gasoline Vehicles

The carbon emissions per kilometer driven for gasoline vehicles are determined by both the gasoline carbon emissions factor and the fuel consumption per hundred kilometers. The gasoline carbon emissions factor is calculated using the methodology outlined in the "IPCC 2006 National Greenhouse Gas Inventory Guidelines."

$$c_{PV} = \frac{f_Q \lambda_Q^{PV}}{100}$$

$$f_Q = N_{CVQ} C_Q O_Q \times \frac{44}{12} \rho$$

In the formula, f_Q represents the gasoline carbon emissions factor, which is the amount of carbon dioxide emissions produced per unit volume of gasoline. λ_Q^{PV} represents the car's fuel consumption per hundred kilometers, taken as $8.82L/100km$. N_{CVQ} is the car's default net calorific value, taken as $44.3 \times 10^{12} J/10^9 g$. C_Q is the carbon content per unit heat value of gasoline, taken as $18.9kg/GJ$. O_Q is the default oxidation factor for gasoline, taken as 1. The ratio 44/12 represents the molecular weight ratio of carbon dioxide to carbon. ρ represents the density of gasoline, taken as $0.725kg/L$.

7.3 Carbon Emissions Calculation for BEV.

BEV (Battery Electric Vehicles) use electricity as their power source and do not produce carbon dioxide emissions during use. However, there are indirect emissions generated during electricity generation, as well as power losses during transmission and charging processes. The specific calculation method is as follows:

$$c_{BEV} = \frac{f_D \lambda_D^{BEV}}{\eta_1 \eta_2}$$

f_D is the electricity carbon emissions factor, based on publicly available information from the Ministry of Ecology and Environment of the People's Republic of China, this value is taken as $0.5703t\, CO2/MWh$. η_1 and η_2 represent the electricity grid supply efficiency and charging efficiency, with values of 94.4% and 91%. λ_D^{BEV} represents the electric energy consumption per kilometer for the vehicle. Four different types of BEV are obtained using the k-means clustering algorithm, with values of $0.1194kWh/km$, $0.1425kWh/km$, $0.1635kWh/km$, and $0.1818kWh/km$. The average energy consumption per kilometer for BEV can be calculated by weighting these values based on their respective market shares.

7.4 Calculation Result for 1 Million Urban Population

Scenario 1: Normal Growth Rate in New Energy Vehicle Sales, with a 40% increase in 2030 and a 50% increase in 2035.

Scenario 2: High Growth Rate in New Energy Vehicle Sales, with a 50% increase in 2030 and a 70% increase in 2035.

The following chart shows the carbon emissions for both scenarios, with normalization based on the initial values.

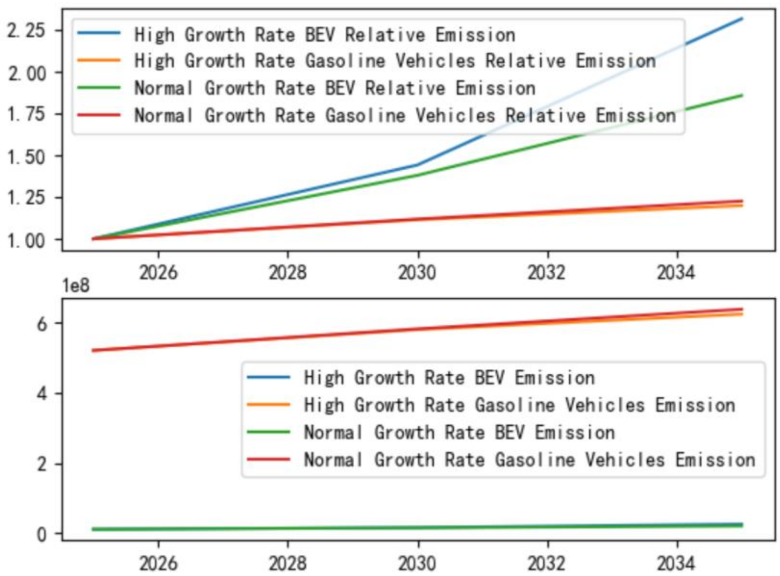


Figure7 Comparison of different scenarios

The following chart illustrates the differences in carbon emissions between gasoline vehiclesand Battery Electric Vehicles, as well as the carbon emissions after complete electrification .

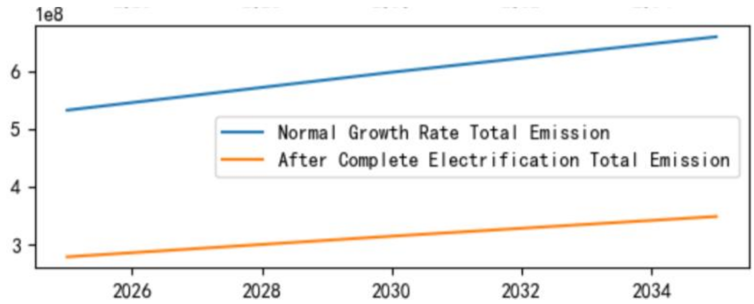


Figure7.1 Comparison of Electrification

7.5 Analysis of the Results

It can be observed that with the increasing sales and market share of new energy vehicles, the carbon emissions associated with NEV are continuously growing, and their growth rate is accelerating. In contrast, the growth rate of traditional gasoline vehicles is slowing down, and their total carbon emissions are decreasing, which is environmentally friendly.

If all traditional gasoline vehicles are fully electrified, there is a significant reduction in carbon dioxide emissions, indicating that the electrification of urban NEVs has a very positive impact on the ecological environment.

8 Question 6

Dear Fellow Citizens,

I write to share vital insights about New Energy Vehicles (NEVs) and their profound contributions to our ecological environment and the global electric vehicle industry. In recent years, we've witnessed a remarkable surge in NEV sales and market share. However, it's crucial to note that the associated carbon emissions have been steadily rising, with an accelerating growth rate. In stark contrast, traditional gasoline vehicles have seen a slowdown in their growth rate, resulting in declining total carbon emissions—a promising environmental trend.

What's truly inspiring, though, is the potential impact of electrifying all traditional gasoline vehicles. This monumental shift promises a significant reduction in carbon dioxide emissions, highlighting the positive ecological influence of urban NEV electrification. But why is this the case? Allow me to elucidate.

First and foremost, NEVs represent a clean energy alternative, powered by batteries rather than the combustion of fossil fuels that give rise to harmful exhaust emissions. This inherent quality means that NEVs operate without emitting noxious gases, subsequently reducing air pollution and enhancing urban air quality—ultimately benefiting our collective health.

Secondly, electric vehicles excel in energy efficiency due to their ability to harness

Dezhao Su Lifan Zhang Yang Ji

electricity more effectively, resulting in reduced energy consumption. This not only alleviates the strain on our finite natural resources but also significantly contributes to the reduction of greenhouse gas emissions, presenting a constructive approach to combating climate change.

Lastly, it's heartening to see that nations worldwide have recognized the pivotal role of the electric vehicle industry. Many countries are increasing their investments to drive the development and widespread adoption of electric vehicle technology. This endeavor not only fosters employment opportunities but also provides a sustainable transportation solution for the future.

In light of these insights, I encourage you to contemplate the purchase of NEVs or the electrification of your existing means of transportation. Such actions will undoubtedly contribute to the improvement of our environment, the reduction of carbon emissions, and a substantial step towards a sustainable future. Let us unite in our efforts to build a cleaner and healthier world for generations to come.

We appreciate your attention and support.

Sincerely,
Yours.