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Analysis of Factors Influencing China's New Energy Vehicle Exports: Empirical Evidence from Ten Destination Markets

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Abstract
As global non-renewable energy reserves gradually decrease, new energy vehicles (NEV) are gaining increasing attention worldwide. The NEV industry in China has significant resource advantages and vast market potential. However, Chinese NEV enterprises have not yet fully met international market demands, which means it is worthwhile to explore how to improve their export competitiveness in the international market. Based on panel data from ten countries between 2019 and 2022, using principal component analysis and gray relational analysis methods on the foundation of the gravity model of trade, the study examines the factors affecting China's NEV exports. The three most important factors, the GDP, carbon emissions, and distance of the target export markets, are extracted from the analysis. In other words, the higher the economic level and carbon emissions of the target export market, the greater the demand for NEVs. Conversely, the closer the distance, the more NEVs are imported from China. It also finds that China's exports to developed countries, particularly those with an advantage of NEV production, are relatively low. In order to have a greater impact on the international market, China still needs to strive to create internationally renowned NEV brands.
Keywords: New Energy Vehicles, Export Influencing Factors, Principal Component Analysis, Grey Relation Analysis

Introduction

Over the past decade, the prominence of climate and environmental issues has made energy conservation and emission reduction a global priority. The negative impact of climate change on China's sustainable development has led to a proactive response, with carbon peaking and neutrality goals serving China's domestic and international economic circulation. Current strategies focus on green transformation and improving ecological quality, with energy conservation and emission reduction being critical to achieving these goals. New Energy Vehicles (NEVs) - including electric and hydrogen-powered vehicles - are at the forefront of this effort, offering low or zero emissions and improved engine efficiency.

China's NEV industry, initiated in the early 21st century, has grown significantly with government support. As of March 2022, production and sales of NEVs are strong and growing, outperforming the overall industry. Since 2013, global NEV sales have surged. This rapid growth, along with expanding export trade, has seen Chinese companies increasingly compete internationally, with half of the top 20 global NEV brands being Chinese since 2019. Identified as a strategic emerging industry, China's NEV industry has experienced significant growth, driven by national policies like the New Energy Vehicle Industry Development Plan (2021-2035). This plan emphasizes NEVs as crucial for China's transition from a major automotive country to an automotive powerhouse and for the sustainable growth of the world economy.

Based on the background mentioned above, the research objectives are as follows:

- To investigate the current situation of China's NEV export market.
- To explore the main factors that affect the competitiveness of China's NEV exports.
- To provide suggestions on how to enhance the competitiveness of Chinese NEVs in the international market.

Despite the industry's growth, challenges remain, including immature core technology, high production costs, market constraints, and difficulty in creating internationally competitive brands. While Chinese NEV exporters, such as BYD and Beijing NEVs, have expanded overseas, they face issues like high costs, infrastructure development, and weak international competitiveness. This paper leverages international competitiveness theories to study NEVs. It first provides a theoretical basis, assessing the current situation of the NEV export trade, noting a market gap that China could potentially fill. It then employs empirical analysis, using data from ten destination markets countries, to construct a trade gravity model, examining factors influencing export trade competitiveness. The study concludes with development suggestions based on the findings.

Literature Review

Status of China's NEV industry

As one of the world's largest automotive markets and manufacturers, China plays a significant role in this trend. However, the export trade of China's NEVs faces several challenges. A key challenge that emerges from the literature is the lack of mature core technology in China's NEV industry (Zhang & Van Biesebroeck, 2018). The development of NEVs in China is still in its early stages, and there is a significant gap in technological innovation and quality control when compared to established markets such as the US and Europe (Wang et al., 2020). High production costs and difficulties in constructing supporting infrastructure are identified as substantial barriers in the literature (Lin & Li, 2021). While domestic infrastructure has seen improvements, the lack of globally compatible charging infrastructure and different regulatory standards pose challenges to the export market. The literature suggests that NEV products currently produced in China do not fully meet the needs of the international market (Zhou et al., 2019). Issues such as the low energy density of power batteries and concerns over vehicle range and reliability have hindered the global acceptance of Chinese NEVs. China's NEV industry has been significantly supported by national policies. However, in the international market, Chinese NEVs face different regulatory environments, which can limit their export potential (Zhang et al., 2019). These include stringent environmental standards, safety regulations, and trade policies. Despite the industry's rapid growth domestically, Chinese NEV brands struggle with international competitiveness (Li & Shi, 2020). High production costs, coupled with the issues mentioned above, contribute to this challenge.

Influencing Factors of Vehicle Export

Most current researches on NEV export factors are qualitative. Since NEVs are a subset of automobiles, their export trade is influenced by similar factors as traditional automobile exports. As such, a summary of traditional automobile export factors is provided for reference. Cai(2022) used 1998-2020 data, with China's automobile industry's comparative advantage as the dependent variable, foreign direct investment as the core variable, and using development levels, labor productivity, and trade openness as control variables, studied the influencing factors of China automobile exports. Liu and Zhang (2020) noted that despite China's automobile industry is successful in export scale, it lacks competitiveness in core technologies, international development models, and strategic positioning. Zhang, Song, & Yan(2019) highlighted issues like an unbalanced export structure, low independent brand image, inadequate management and after-sales services, and technical barriers in China's automobile export trade. Furthermore, Jia (2019) suggested that good international cooperative relations are beneficial to automobile exports, while unilateral trade protectionism hinders local market access. Wang (2019) used Porter's "diamond model" to analyze the factors impacting the export competitiveness of finished vehicle products and identified main issues in China's exports, including overall low quality of finished vehicle products, low brand awareness, insufficient R&D investment, lack of core technology, frequent trade and technical barriers, and an imperfect management and after-sales service system.

In summary, many studies explore the current situation, challenges, strategies, and recommendations for China's NEV foreign trade, there's a noticeable lack of empirical analysis and comprehensive examination of the factors affecting this trade. Literatures and empirical studies highlight environmental factors, consumer factors, government policies, and charging and infrastructure equipment as significant influences on NEV market trade.

Current Situation of China’s NEV export

Main Export Market of China's NEV

With the continuous development of China's NEV industry, China's exports of NEVs are also increasing. According to China customs’ data, China exported 310,000 NEVs in 2021, and the number reached 494,000 in 2022. Driven by the strong momentum of demand, China's automobile exports are expected to reach around 3 million units this year, reaching a new high and potentially making China the world's second-largest automobile exporter.

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Table **Error! No text of specified style in document.**-1
2020-2022 Top 22 export countries' volume of NEVs of China

China's NEV Export markets	Export Volume of NEVs in 2020-2022			Total
	2020	2021	2022	total
Total	223697	589967	1002340	1816004
Belgium	16285	106844	181254	304383
Bengal	76903	82625	46942	206470
Britain	13607	56853	99812	170272
India	43862	19046	55515	118423
Thailand	3276	40662	67670	111608
The Philippines	3510	12030	57436	72976
Germany	9452	29031	30473	68956
Slovenia	47	18389	46063	64499
France	2012	21138	33973	57123
Australia	753	17112	33576	51441
Israel	1470	9424	36714	47608
U.S.A	3255	17788	25716	46759
Spain	753	1093	41402	43248
The United Arab Emirates	161	4851	34067	39079
Norway	7515	10734	15772	34021
Netherlands	8582	6359	11109	26050
Hong Kong, China	116	7996	15029	23141
Japan	595	11055	10482	22132
New Zealand	288	4623	14114	19025
Brazil	1959	4281	11400	17640
Jordan	105	1590	8968	10663
Columbia	947	1174	2944	5065

This article presents the trade data of China's top 22 NEV export partners from 2019 to 2021. Over the past three years, developed countries in Europe and America have accounted for almost half of the top 20 countries (regions) in China's NEV exports. Bangladesh, as an emerging market that has transitioned from the least developed countries to developing countries, stands out and ranked first in 2019. Belgium experienced rapid growth after 2020, becoming the top market over the three-year period.

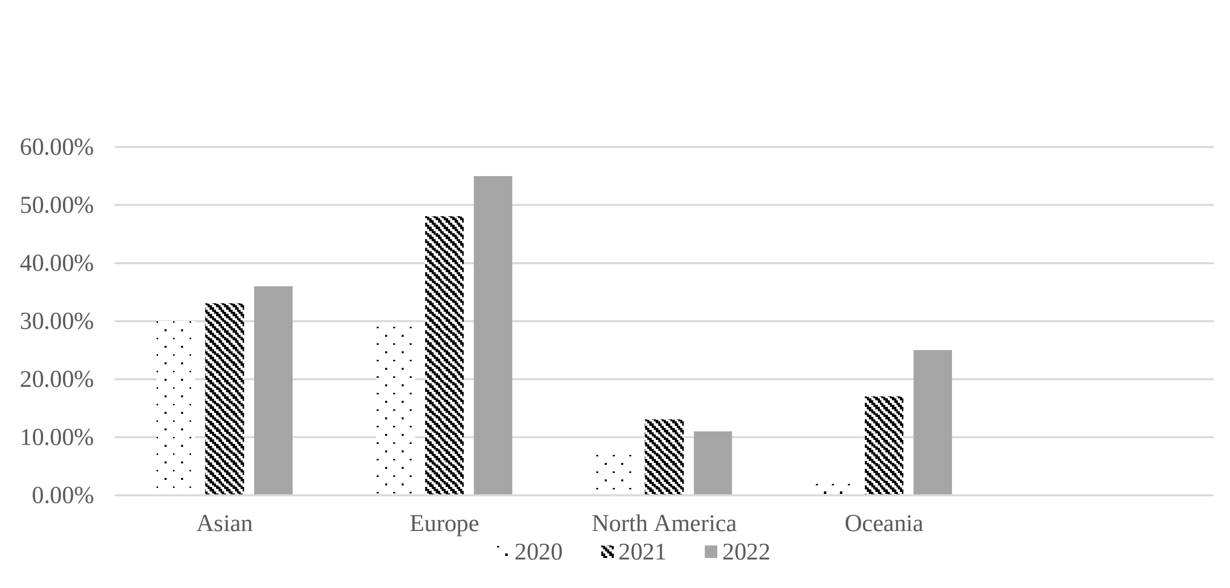

Figure **Error! No text of specified style in document.**-1 Proportion of China’s NEV exports

From a regional perspective, as shown in the figure 3-1, exports to Europe and Asia are relatively large and have experienced rapid growth over the past three years, followed by Oceania, while there is a decrease in North America in 2022. From the total amount over the three years, the overall growth in 2021 is relatively fast.

Main Export Vehicle Models of China's NEV

China's NEV exports models are categorized into hybrid and pure electric vehicles based on different energy power, and further divided into passenger cars and buses with more than 10 seats.

Table **Error! No text of specified style in document.**-2
Export volume of different vehicle models

		2020		2021		2022	
Power	Vehicle model	Export volume	Export amount（dollar）	Export volume	Export amount（dollar）	Export volume	Export amount（dollar）
Hybrid electric vehicle	Passenger car (more than 10 seats)	82	8,593,602	400	70,123,904	768	105,047,538
	car			43,170	1,433,551,818		
Battery electric vehicle	Passenger car (more than 10 seats)	2478	622,294,974	2807	648,195,772	6,797	1,114,005,740
	car	193,905	1,578,872,517	499,544	8,595,665,682	944,566	20,088,880,801

This paper selects export commodity vehicles with customs codes 87038000, 87036000, 87024010, 87024020, and 87024030 for data statistics. In terms of energy and power, the export volume and value of pure electric vehicles are significantly higher than those of hybrid vehicles, with the majority being pure electric sedans. The corresponding hybrid passenger cars saw very little exports in 2019 and 2021, indicating that the main exports of hybrid vehicles are passenger cars with more than 10 seats.

Main Competitors of China's NEV Export

This article selects several NEV brands with the largest global sales volume to analyze the export competitiveness of each country. Among them, BYD from China and Tesla from the United States are far ahead. SAIC wuling, Volkswagen, BMW, and Benz follow closely behind. It can be seen that the main competitors for China's NEV exports are the United States, Europe, as well as South Korea in Asia.

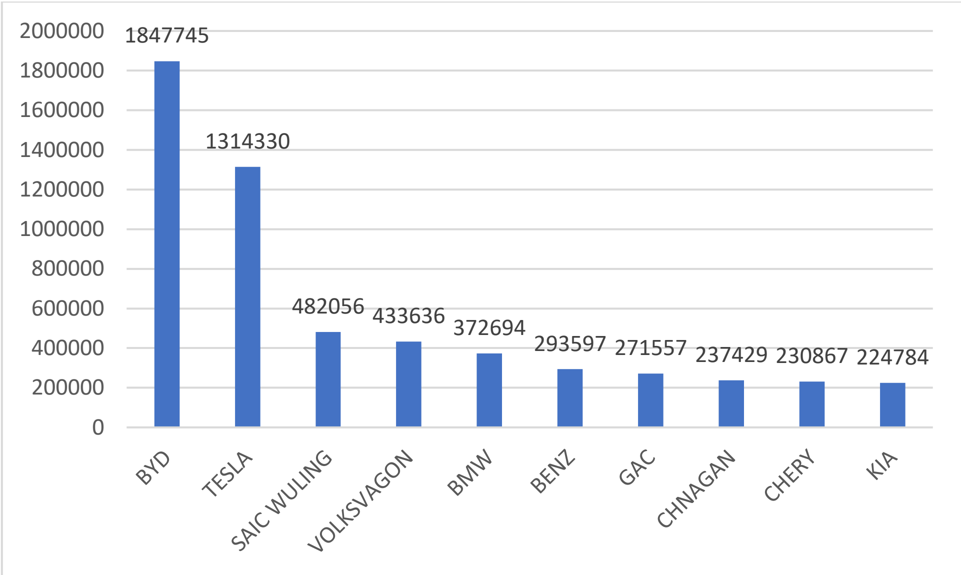

Figure **Error! No text of specified style in document.**-2 Top 10 Global NEV Brand Sales volume in 2022

Empirical Analysis

Selection of Evaluation Methods and Construction of Models

This study employs 11 dimensions as explanatory variables for NEV trade competitiveness. Weights are determined via principal component analysis, minimizing information loss. The grey correlation method is then applied, using NEV export volume as a trade competitiveness proxy, to analyze the influence of the 11 dimensions. The calculation formula is constructed as following

i. Standardized transformation of sample data. Set the sample data matrix as X=(xij)mn, that is, n indicators and m samples. The standardized data matrix is Y=(yij)mn. The standardized transformation formula is:

$y_{ij}=(x_{ij}-\overline{x_j})/s_j$ (i=1，2，…，m; j=1，2，…，n)

Among them,

$x_j=\frac{1}{m}\sum_{i=1}^{m}x_{ij}$, $s_j=\sqrt{\frac{1}{m}\sum_{i=1}^{m}(x_{ij}-\overline{x_j})^2}$

After standardized transformation, the mean and variance of each sample are 0 and 1.

ii. The sample correlation matrix. Set sample correlation matrix R=(r_j)m*n, correlation coefficient

$$r_{ij}=\frac{1}{m-1}\sum_{i=1}^{m}r_{ii}\,y_{ij}$$

And there are rij=rji, rii=1, So R is a symmetric matrix, with all elements on the main diagonal being 1.

iii. Calculate the eigenvalues and corresponding eigenvectors of the correlation matrix R. characteristic equation | $R - \lambda I$ |, solve n eigenvalues. By a system of homogeneous linear equations | R- λ I | L=0, solve for the corresponding eigenvector.

$$L_j = (l_{1j}, l_{2j}, \ldots, l_{nj})^T, \text{(i=1, 2, ..., p)}$$

iv. Extract principal components based on the cumulative contribution rate criterion. Calculate the contribution rate of each principal component.

And according to the cumulative contribution rate criterion, that is, based on the cumulative contribution rate

$$b_j = \lambda_j \left(\sum_{i=1}^{n} \lambda_i \right)^{-1}$$

$$\left(\sum_{i=1}^{k} \lambda_i \right) \left(\sum_{i=1}^{k} \lambda_i \right)^{-1} \geq 80\%$$

Extract k principal components as a criterion.

$$Z_j = \sum_{i=1}^{n} l_{ij} Y_i, \text{(j=1, 2, ..., k)}$$

Data Selection and Source

This paper uses 2019-2021 data from 10 countries, spread across different continents, which are China's main NEV export markets. In 2019, China issued multiple policies supporting NEV development, such as extending the NEV purchase tax exemption till 2022 and encouraging companies to lower NEV prices to match traditional vehicles. Using the trade gravity model and extensive literature, this paper selects relevant variables to create a gravity model for China's NEV exports. Factors influencing NEV trade include environmental conditions, consumer factors, government policies, charging, and infrastructure.

i. Environmental factors: The model includes each country's carbon emissions to examine the impact of environmental pressure on NEV trade.

ii. Consumer factors: The model considers the number of education years in each country as a variable.

iii. Policy factors: This variable is a dummy variable, with a value of 1 for countries with NEV promotion and incentive policies and 0 for those without.

iv. Charging and infrastructure: Two factors reflect this - the electricity consumption rate of each country and the presence of public charging infrastructure, the latter being a dummy variable with a value of 1 for countries with public charging infrastructure and 0 for those without.

v. Automotive market situation: The model examines if importing countries produce NEVs and the impact of domestic production on China's NEV exports. This is a dummy variable, with a value of 1 if the importing country produces NEVs, and 0 otherwise.

In addition, this model includes traditional Gravity model variables: GDP, distance, and population. Distance variables are treated as time-varying variables using the product of geographical distance and international oil prices as interaction terms. The empirical model is as follows:

lnEX = β0 + β1lnYGDP + β1lnDist + β3lnPopj + β 4lnCO2 + β5EA + β6lnEdu + β7Policy + β8Charge+ β9Producerjt +uijt

All data in this article comes as shown in table 4-1.

Table **Error! No text of specified style in document.**-3
Data selection and source

Variable	Description	Source
EX	China's exports of NEVs to other countries	China Customs Statistical Data Query Platform http://43.248.49.97/
Yi	China's (i) GDP	World Bank https://data.worldbank.org.cn/
Yj	GDP of other countries (j)	World Bank https://data.worldbank.org.cn/
Dist	The interaction term between the geographical distance between China (i) and other countries (j) and the annual international oil price product	Geographic distance: CEPII Databases http://www.cepii.fr/ International oil prices: US Energy Information Administration https://www.eia.gov/
Popi	China (i) Population	World Bank https://data.worldbank.org.cn/
Popj	Population of other countries (j)	World Bank https://data.worldbank.org.cn/
CO2	Carbon emission data in $MtCO_2$	Global Carbon Atlas http://www.globalcarbonatlas.org/cn/CO2-emissions
EA	Power on rate%	World Bank (2017-2018), IEA (2019) https://www.iea.org/
Edu	Years of compulsory education in other countries	UNDP http://hdr.undp.org/en/data
Policy	Is there any government promotion incentive policy	Research reports on electric vehicles from various regions/research institutions, policy announcements from various countries, and online news
Charge	Is there a public charging infrastructure available	Research reports on electric vehicles from various regions/research institutions, policy announcements from various countries, and online news
Producer	Is it a country producing NEVs	EV Volumes and other NEV brand analysis data and reports

Basic Data Description

Given that over 99% of NEV trade involves pure electric and plug-in hybrid vehicles, this study focuses on these types. The export data for these vehicles (Chinese customs codes: 887038000, 87036000, 87024010, 87024020, 8704030) are selected as the explanatory variables for trade analysis, ensuring consistent research and statistical standards. Data from the nine countries with the highest Chinese exports from 2019-2021 were collected to ensure data completeness and continuity. The basic statistical data is shown in the table below

Table **Error! No text of specified style in document.**-4
Descriptive Statistics

Descriptive Statistics					
	N	MIN	MAX	mean	sd
EX	30	156.00	106844.00	16597.5667	24200.86766
Dist	30	68757.20	1385382.31	398412.4294	283165.12365
XGDP	30	14.28	17.73	15.5667	1.56514
YGDP	30	0.50	23.32	4.3334	6.12643
Popi	30	1407745000.00	1412360000.00	1410401666.6667	1980997.36868
Popj	30	1488980.00	1407563842.00	238870261.8333	402994370.68148
CO2	30	90.37	5259.14	1122.8601	1488.13200
Edu	30	8.00	14.00	11.1000	1.95378
Policy	30	1.00	1.00	1.0000	0.00000
Charge	30	1.00	1.00	1.0000	0.00000
Producer	30	0.00	1.00	0.5000	0.50855
EA	30	0.99	1.00	0.9990	0.00305

Descriptive statistics of model variables (after increasing their logarithmic form) are as follows

Table **Error! No text of specified style in document.**-5
Descriptive statistics after optimization

	N	MIN	MAX	mean	sd
lnEX	30	5.05	11.58	8.6042	1.70624
lnDist	30	11.14	14.14	12.6623	0.71719
lnXGDP	30	2.66	2.88	2.7404	0.09768
lnYGDP	30	-0.70	3.15	0.8716	1.05276
lnPopi	30	21.07	21.07	21.0671	0.00141
lnPopj	30	14.21	21.07	18.3516	1.44796
lnCO2	30	4.50	8.57	6.3757	1.11204
lnEdu	30	2.08	2.64	2.3913	0.18186
lnPolicy	30	1.00	1.00	1.0000	0.00000
lnCharge	30	1.00	1.00	1.0000	0.00000
lnProducer	30	0.00	1.00	0.5000	0.50855
lnEA	30	0.99	1.00	0.9990	0.00305

Principal Component Analysis
Applicability test of principal component analysis

During the analysis, the dummy variables Policy, Producer, and Charge facilities created data gaps, and the duration of compulsory education (Edu) remained constant over time, potentially becoming invalid. Consequently, these variables were removed for optimization. Principal component analysis was then performed on the remaining seven variables.

To mitigate potential multicollinearity, SPSS software was used to calculate each primary index via principal component analysis. Prior to this, the KMO test and Bartlett's sphericity test were conducted to verify inter-variable correlation and data suitability for principal component analysis.

Table **Error! No text of specified style in document.**-6
KMO and Bartlett inspection

KMO sampling suitability quantity.		0.598
Bartlett sphericity test	Approximate chi square	126.563
	free degree	21
	significance	0.000

According to the test results of the sample data shown in the table, the KMO value is 0.598 (approximately 0.60), indicating a strong correlation between various variables, meeting the requirements of principal component analysis. The Bartlett sphericity test results showed a significance value of 0.000, which is less than 0.05, indicating that principal component analysis is acceptable.

Principal Component Extraction

Condensed version: Principal component analysis tests how well the principal component explains all variables. The value derived from the common factor variance indicates the representativeness of the principal component's fit to the variable, with higher values indicating better expression. Generally, values over 0.5 are satisfactory. As shown in the table, the explanatory power of the principal components used in this study for the given variables exceeds 0.5. This suggests that the principal components can effectively represent the variable information, indicating successful application of principal component analysis.

Table **Error! No text of specified style in document.**-7
Communalities

	Initial	Extract
lnDist	1.000	0.689
lnXGDP	1.000	0.868
lnYGDP	1.000	0.940
lnPopi	1.000	0.835
lnPopj	1.000	0.876
lnCO2	1.000	0.956
lnEA	1.000	0.893
Extraction method: Principal component analysis.		

Table **Error! No text of specified style in document.**-8
Total variance explanation

Component	Initial Eigenvalue			Extract the sum of squares of the load		
	total	Variance percentage	Accumulated%	total	Variance percentage	Accumulated%
1	2.764	39.480	39.480	2.764	39.480	39.480
2	2.210	31.565	71.045	2.210	31.565	71.045
3	1.084	15.479	86.524	1.084	15.479	86.524
4	0.492	7.027	93.551			
5	0.218	3.119	96.670			
6	0.172	2.460	99.130			
7	0.061	0.870	100.000			
Extraction method: Principal component analysis.						

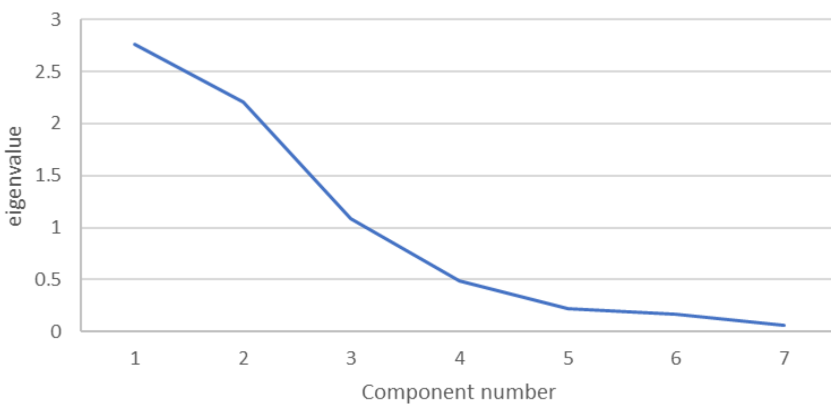

Figure **Error! No text of specified style in document.**-3 Scree Plot

We use principal component analysis to extract common factors for each variable. Table 4.4 shows that the first three components account for 86.524% of the total variance, indicating their substantial impact on the initial variables. The scree plot shows that the eigenvalues of the first three components are greater than 1, with a steep slope, while the remaining four components are relatively flat. Thus, we can use these three new variables to replace the original 12 for principal component analysis.

Rotation Factor Load Matrix

Observing the load matrix, if many components are highly correlated with the original initial variable, it indicates that the original variable should be explained by multiple components together. Conversely, if the components are simultaneously correlated with multiple variables, it indicates that the components cannot represent any of the original initial variables well.

Table **Error! No text of specified style in document.**-9
Component matrix

	Component		
	F1	F2	F3
lnDist	-0.184	0.749	0.307
lnXGDP	-0.028	0.910	-0.198
lnYGDP	0.754	0.169	0.586
lnPopi	-0.026	0.879	-0.246
lnPopj	0.920	0.078	-0.154
lnCO2	0.957	0.052	0.192
lnEA	-0.630	0.100	0.697
Extraction method: Principal component analysis.			
a. Three components were extracted.			

In the above case, the specific meaning represented by the components is uncertain, so a single variable can have a higher load on fewer components through component rotation. This article chooses to use Varimax rotation method for component rotation to better express explanatory factors.

Table **Error! No text of specified style in document.**-10
The rotated component matrix

	Component		
	1	2	3
lnDist	0.104	0.697	0.439
lnXGDP	-0.006	0.930	-0.049
lnYGDP	0.963	0.029	0.108
lnPopi	-0.033	0.908	-0.093
lnPopj	0.707	0.053	-0.611
lnCO2	0.915	-0.031	-0.344
EA	-0.156	0.016	0.932
Extraction method: Principal component analysis.			
a. The rotation has converged after 5 iterations.			

From the rotated factor load matrix, it can be seen that the indicator variables with higher absolute values of coefficients on principal component F1 are lnYGDP (GDP of other countries), lnPopj (population of other countries), and lnCO2 (carbon emissions). The indicator variables with higher absolute values of coefficients on principal component F2 are lnDist (the interaction term between the geographical distance between China (i) and other countries (j) and the annual international oil price product), lnXDGDP (China GDP), and lnPopi (China population). The indicator variables with higher absolute values of coefficients on principal component F3 are lnPopj (population of other countries) and EA (electrification rate%).

Calculating Principal Component Scores

We will calculate the scores of principal components F1, F2, and F3 for 10 sample countries through the score functions of each factor.

Table **Error! No text of specified style in document.**-11
Component score coefficient matrix

	Component		
	1	2	3
lnDist	0.136	0.290	0.311
lnXGDP	-0.049	0.436	-0.101
lnYGDP	0.521	-0.029	0.316
lnPopi	-0.073	0.430	-0.140
lnPopj	0.212	0.041	-0.293
lnCO2	0.388	-0.025	-0.034
EA	0.148	-0.050	0.666
Extraction method: Principal component analysis. Rotation method: Caesar's normalization maximum variance method.			

Table 4-10 shows the covariance matrix of principal component scores. It can be seen that the correlation coefficient between the three rotated principal components is 0, indicating that each principal component is not correlated with each other. The extracted three principal components are representative and in line with practical significance.
Now we use the coefficients of each variable in the component matrix among the three principal components, divided by the square root of the "total" of each principal component in the total variance explanation table, to obtain the component score coefficients of each principal component.

Table **Error! No text of specified style in document.**-12
Component Score Covariance Matrix

Component Score Covariance Matrix			
Component	1	2	3
1	1.000	0.000	0.000
2	0.000	1.000	0.000
3	0.000	0.000	1.000
Extraction method: Principal component analysis. Rotation method: Caesar's normalization maximum variance method.			

The following table shows
Table **Error! No text of specified style in document.**-13
Principal component score coefficient

	F1	F2	F3
lnDist	-0.111	0.504	0.295
lnXGDP	-0.017	0.612	-0.190
lnYGDP	0.453	0.114	0.563
lnPopi	-0.016	0.592	-0.236
lnPopj	0.554	0.052	-0.148
lnCO2	0.576	0.035	0.185
EA	-0.379	0.067	0.670

From Table4-11, we can conclude that the score expressions for each factor are

F1=-0.111lnDist -0.017lnXGDP+ 0.453lnYGDP -0.016lnPopi+ 0.554lnPopj+0.576lnCO2 -0.379EA
F2=0.504lnDist +0.612lnXGDP+ 0.114nYGDP +0.592lnPopi+ 0.052lnPopj+0.035lnCO2+0.067EA
F3=0.295lnDist +0.190lnXGDP+ 0.563lnYGDP +0.236 lnPopi-0.148lnPopj+0.185lnCO2+0.670EA

Comprehensive principal component： F=0.45629F1+0.36481F2+0.1789F3
The comprehensive scores for each country from 2019 to 2021 are seen in table 4-12

Table **Error! No text of specified style in document.**-14
Comprehensive Scores

	2019	**2020**	**2021**
Australia	12.46	12.48	12.69
Brazil	13.25	13.19	13.41
Belgium	10.97	11.48	11.7
Germany	13.14	13.26	13.47
France	12.84	12.83	13.06
U.S.A	14.86	14.87	15.08
Japan	13.34	13.36	13.52
Thailand	12.09	12.09	12.26
India	14.1	14.1	14.35
Britain	12.89	12.88	13.11

It can be seen that the scores of various countries are increasing year by year, with the highest scoring being the United States, Germany, Japan, and Brazil.

Calculate Indicator Weights
Use the principal component score coefficients of each indicator we obtain, multiply them by the corresponding principal component variance percentage, sum them, and then divide them by the cumulative percentage to calculate the weight of each indicator.

Table **Error! No text of specified style in document.**-15
Weights of each element

Indicator	**Weight**
lnDist	0.216152
lnXGDP	0.164387
lnYGDP	0.359562
lnPopi	0.145582
lnPopj	0.190595
lnCO2	0.279269
EA	0.054564
	1.41011

Result after normalization are shown in table 4-14:

Table **Error! No text of specified style in document.**-16
Proportion of each element

Indicator	Weight
lnDist	**15.33%**
lnXGDP	11.66%
lnYGDP	**25.50%**
lnPopi	10.32%
lnPopj	13.52%
lnCO2	**19.80%**
EA	3.87%
	100.00%

The variables with the highest impact weight among visible variables are YGDP (GDP of other countries), CO2 (carbon emissions), and Dist (product interaction term). These are also several factors that have a significant impact on China's export volume to this country.

Conclusion of Principal Component Analysis

Through the analysis above, we obtain the weights of the seven variables for the principal component during 2019-2021(table 4-14). It can be seen that the variable with the highest weight is the GDP of other countries (YGDP), accounting for 25%, which is more than 1/4 of all variables. Other countries' GDP represents a country's economic strength. The higher the GDP, the stronger the purchasing power of the country, so the import volume of NEVs from China will be higher.

The second variable is carbon emissions (CO2) and the product of distance (Dist), with weights of 19.8% and 15.33%, respectively, which exceeds the average of the seven variables. In the current social context, protecting the environment and reducing domestic carbon emissions have become a consensus. Purchasing and using NEVs is one of the important ways to reduce carbon emissions. The higher a country's current carbon emissions, the greater its demand for energy saving and emission reduction, and the corresponding demand for NEVs will be higher. For such countries, China should pay attention to them as potential markets.

As we know, the distance between two countries is an important factor that affects international trade. The farther the distance, the higher the transportation cost, and vice versa. This is also true for the export trade of NEVs. Therefore, in the process of China's exports of NEVs, for distant markets (European and American markets, China can: 1) strengthen the construction of transportation methods, such as the extension of the China-Europe Railway Express and the construction of the Belt and Road Initiative; 2) choose to build assembly factories in nearby areas to reduce transportation costs and establish close connections with distant markets.

For the variable of other countries' population (Popj), the weight is 13.52%, slightly lower than the average weight of the seven variables. The population of other countries is an indicator of a country's purchasing willingness. The larger the population, the bigger the market, and the potential demand will be higher. However, due to the special nature of automobile products, most families may replace their cars every 5-10 years, and some people have already purchased traditional gasoline cars and do not have the willingness and ability to switch to NEVs, which is also the reason why the weight of this variable is relatively low.

The variable with the lowest weight among several variables is the electrification rate of a country (EA%). The electrification rate is the basis for a country to use electric cars. However, since the electrification rate of most countries has reached more than 99% currently, only a small number of countries may be around 96%, so the impact of the electrification rate on the export trade of NEVs has been greatly reduced.

Finally, it is worth noting that in the analysis process of this paper, the country that was originally a NEV production country may not completely follow this weight analysis, and the specific analysis is described in detail in section 5.3.2.

In summary, among the factors affecting China's NEV export competitiveness, the YGDP has the greatest impact, followed by CO2 and Dist, and Popj comes in third. China's population and GDP, as representatives of the country's NEV production capacity, also have a certain degree of correlation. The least influential factor is the electrification rate of other countries.

Due to the significant differences between different countries, we will use the grey relational analysis to conduct specific analysis on different countries and various factors in the following sections.

Grey Relational Analysis

Calculate Correlation Coefficient

The purpose of this study is to analyze the correlation between the seven factors that affect the international competitiveness of NEV trade and China's export volume of NEVs to various countries through a grey correlation model and to explore the factors that affect the competitiveness of NEV trade. According to the grey correlation model, this study takes China's NEV trade exports to nine representative countries from 2019 to 2021 as a reference sequence and uses the scores of various factors in Table 4.11 for each country during the same period as a comparative sequence to obtain the correlation coefficients between the seven influencing factors of each country and their competitiveness level.

Table **Error! No text of specified style in document.**-17
Grey correlation analysis

Country	Dist	XGDP	YGDP	Popi	Popj	CO2	Edu	EA
Australia	0.758065	0.756221	0.75575	0.755917	0.755895	0.75565	0.755902	0.755902
Brazil	0.823083	0.785915	0.695181	0.780236	0.778715	0.760572	0.781198	0.781198
Belgium	0.702298	0.701562	0.701433	0.701435	0.716373	0.701255	0.70143	0.70143
Germany	0.6824	0.667232	0.678474	0.664715	0.664656	0.661603	0.664624	0.664624
France	0.783245	0.766008	0.762091	0.763309	0.763338	0.757532	0.763175	0.763175
U.S.A	0.704018	0.69893	0.698063	0.698068	0.698172	0.6967	0.698032	0.698032
Japan	0.778059	0.777752	0.775088	0.775872	0.775642	0.773624	0.775775	0.775775
Thailand	0.7614	0.762865	0.767926	0.762598	0.762607	0.765473	0.762734	0.762734
India	0.66585	0.761656	0.789286	0.79046	0.787473	0.801563	0.791287	0.791287
Britain	0.701261	0.689815	0.686952	0.687912	0.687964	0.684999	0.687836	0.687836

Conclusion of Correlation Analysis

According to the table, the correlation coefficients between different countries and various factors are different. As can be seen from the table, Brazil and India have the highest correlation coefficients in factors such as distance (Dist), China's GDP (XGDP), and other countries' GDP (YGDP), thus having the greatest impact on China's NEV exports. In contrast, Germany has the lowest correlation coefficients across all factors. In addition, each country's carbon emissions (CO2) and electrification rate (EA) have a similar impact on all countries, with correlation coefficients close to 0.76.

i. Based on the correlation between distance (Dist) and NEV export trade competitiveness, Brazil in South America has the highest correlation, followed by France in Europe, while the correlation for Asian countries like India is lower. This confirms that the distance variable is inversely proportional to export trade, with trade barriers, including transportation, time, communication costs, and market changes, being greater the closer the distance. Therefore, for Brazil, which is far from China, the distance factor has the greatest impact.

ii. Based on the correlation between other countries' GDP (YGDP), other countries' population (Popj), and export trade competitiveness, Asian countries like India, Japan, and Thailand have higher correlations. India's population has the highest correlation with NEV export trade competitiveness, confirming the conclusion drawn from our principal component analysis: the larger the target market's economy and purchasing willingness, the greater China's export trade volume to it. However, countries with high GDP, such as the United States, Germany, and the United Kingdom, have lower correlations, and the specific reasons will be discussed later.

iii. Carbon emission (CO2) are another important variable for importing NEVs, with India having the closest correlation. This also confirms the conclusion in 4.2.6: countries with high carbon emissions have a stronger demand for energy conservation and emission reduction, and thus have a relatively higher purchasing demand for NEVs. Choosing a market with high carbon emissions can benefit the competitiveness of China's NEVs.

iv. China's population (Popi), especially the labor force, represents China's NEV manufacturing capacity and is an important correlated variable for exporting NEVs. The electrification rate (EA) of each country is positively correlated with China's NEV exports. India and Brazil have a strong correlation with EA, and most other Asian and Oceanian countries also show strong correlations. Electrification is the most basic prerequisite for using NEVs; the higher the electrification rate in other countries, the more advantageous the effective export demand for China's NEVs will be.

v. We found in our analysis that some countries, such as the United States, Germany, and the United Kingdom, have lower correlations across all factors. The main reason why China exports relatively fewer NEVs to these countries is that they have strong domestic NEV industries and relatively mature markets and sales channels. In addition, consumers in these countries have higher requirements for the quality, performance, and technology of cars and are more receptive to NEVs. These countries also have relatively higher levels of NEV brands and technology. Furthermore, their governments provide corresponding policies and financial support for the NEV industry, promoting the development and growth of domestic NEV industries.

Conclusion and Recommendations

Research Conclusion and Contributions

In summary, extensive literature review and empirical analysis have proven that various factors significantly influence China's exports of NEVs. These factors include the economic conditions of the importing country, the distance between the two countries, the population size of the importing country, environmental and emission reduction pressure, and whether the importing country is a NEV manufacturer. Furthermore, the research reveals that Europe, Asia, and North America are the primary markets for China's NEV exports, closely followed by Latin America. However, in developed markets such as Europe and the United States, where NEVs are already manufactured, China's exports of NEVs remain relatively low.

The research makes several important contributions. Firstly, it identifies distinct influencing factors for China's NEV exports compared to traditional trade products due to the unique attributes of NEVs. This insight enables a deeper exploration of global markets for Chinese NEV manufacturers. Secondly, the study highlights that China's NEV brands still have a certain gap compared to top global brands like Tesla and Mercedes-Benz. Therefore, China needs to continue its efforts to create NEV brands with distinctive Chinese characteristics.

Recommendations

The findings suggest the need for adopting varying market strategies based on different regions. Well-developed markets such as Asia, North America, and Europe should be maintained and strengthened. On the other hand, unexplored markets should be assessed by considering local economic and social development, government policies, and energy conservation needs. This assessment will help identify potential demand and seize opportunities effectively. Moreover, export strategies should take into account regional consumer factors. This includes implementing suitable product strategies, price positioning, and marketing strategies tailored to each specific region. While China's NEV industry receives robust government support, it still needs to enhance its technological prowess and international competitiveness. Prioritizing technological innovation, intellectual property protection, digital transformation, and product quality aligned with market needs are crucial steps in this regard.

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