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Industrial Energy Consumption and Carbon Emission Decoupling Study and Driving Factor Analysis: A Case Study of Sichuan Province, China

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ABSTRACT

The carbon emission of industrial energy consumption has an important impact on a region's carbon emission reduction and optimization of carbon emission path. Based on the STIRPAT model and the TAPIO decoupling model, this study analyzes the driving factors and decoupling relationship between carbon emissions from industrial energy consumption and economic growth in Sichuan Province. The research shows that: (1) The industrial carbon emissions in Sichuan Province are increasing first and then decreasing, with an increase of 18.78% from 2005 to 2022, and the carbon emission intensity has decreased from 1.94 tons/10,000 yuan to 0.29 tons/10,000 yuan; (2) The decoupling relationship between industrial carbon emissions and economic growth in Sichuan Province presents three development periods, mainly strong decoupling and weak decoupling. According to the decomposition factors, the decoupling relationship between industrial carbon emissions and economic development is mainly affected by the decoupling coefficient of value creation and emission reduction; (3) The proportion of secondary industry, the number of industrial enterprises, and the total industrial assets are the main carbon promoting factors of industrial carbon emission in Sichuan Province, with elastic coefficients of 0.097, 0.057 and 0.040 respectively; population size is a carbon reduction factor with an elastic coefficient of -0.087. Finally, the study puts forward some suggestions to realize industrial carbon emission reduction.

KEYWORDS

Energy Consumption; Industrial Carbon Emissions; STIRPAT Model; Driving Factor

1. INTRODUCTION

Industry plays an important role in the economic development of the country and in the lives of its people. Industrial production is the main source of carbon emissions in developing countries [1]. Carbon emissions from China's industrial energy consumption are a major source of carbon emissions for society as a whole, and industrial carbon emissions reduction is a key part of the process of realizing the "double carbon" goal. Sichuan Province is a large economic province in the west of China and is also the most complete province in the western region in terms of industrial categories. At present, Sichuan Province is facing the important mission of promoting high-quality economic development, as well as the realistic task of practicing the goal of "dual-carbon" and protecting the ecological environment. Based on the resource endowment of much water, abundant gas, little coal and lack of oil, promoting industrial transformation and upgrading of industrial industry is the way to go. How to achieve industrial carbon emission reduction in Sichuan Province, optimize the carbon emission path, and grasp the decoupling relationship between carbon emission and economic growth are the primary issues to be solved for the sustainable and healthy economic development of the province. Therefore, this paper focuses on the carbon emissions from industrial energy consumption, driving factors, and the relationship between carbon emissions and economic development in Sichuan Province, so as to provide theoretical references for realizing the upgrading of industrial industrial structure.

2. LITERATURE REVIEW

With the in-depth study of carbon emissions from energy consumption, the content and perspective of carbon emissions measurement research have been gradually enriched. Ping Qian et al. introduced the carbon emission pressure indicator on the basis of China's energy carbon emission accounting to study the temporal and spatial distribution characteristics of China's carbon emission pressure, and concluded that there are obvious differences in the carbon emission pressure of different provinces [2]. Sarolta Somosi et al. take Southeast Asian countries as an example and use a panel vector autoregressive model to estimate the carbon emissions of Southeast Asian countries and explore the difficulty of reducing their emissions [3]. Bosah et al. investigated four machine learning algorithms with high predictive accuracy and low data requirements to estimate U.S. CO2 emissions [4]. Measuring carbon emissions from a national perspective and utilizing the measured data to study related issues tends to overlook the impact of development differences between different regions and industries. Scholars have conducted further research on regional and industry development differences. Xuepei Yuan et al. assessed the carbon offset potential of China's forestry sector using historical inventories and future projections, and carefully synthesized the results of studies of carbon sequestration in China's forest ecosystems and carbon stored in harvested wood products [5]. Zhen Yang et al. quantitatively compared the decoupling of carbon emissions from production and consumption in the economic growth of Guangdong Province from 2002 to 2017 from the perspective of inter-provincial implied carbon flows, and further examined its drivers [6]. Using a spatio-temporal decomposition of production, Azam et al. examined the relative environmental performance of eight geographic regions in China over the period 2006-2014 [7]. Hongjiang Liu et al. proposed a methodology to systematically study the factors influencing carbon emissions from energy consumption at the county level and to project future emissions [8]. After a large number of scholars on the national, regional, and industry perspectives of carbon emissions measurement research, and the use of measurement data to empirically analyze the relevant issues, further enriching the carbon emissions research perspectives and content.

Currently, there is a wealth of research on the factors affecting carbon emissions. The main factors affecting carbon emissions are population size [9], climate change [10], energy structure [11], economic development [12], and other factors. Some scholars have also argued that there is a causal relationship between geopolitical and energy security risks and carbon emissions [13]. Gnanba et al. found that in sub-Saharan African countries, urbanization, economic growth, industrial structure, trade, and population all positively affect CO2 outflows, except for energy intensity, which did not pass the significance test [14]. Xin Li et al. used stepwise regression and geographically weighted regression (GWR) to explore the differential impacts of carbon emissions on different tiers of metropolitan areas in terms of socio-economics, transportation services, and road networks [15]. The empirical results of Pinjie Xie et al., who studied the industrial sector as a whole, showed that ownership structure, capital intensity, and energy structure were the main drivers of carbon emission reduction [16]. Currently, the STIRPAT model is most commonly used in the study of carbon emission impact factors. Ebrahim et al. studied the impact of renewable energy (REC) and non-renewable energy consumption (coal, oil, and gas) on CO2 emissions (CO2) in the GCC countries using the STIRPAT model and also compared the impact of various non-renewable energy sources (NREC) sources in order to determine their contribution to the CO2 emission [17]. Peijiong Feng et al. designed the STIRPAT model to analyze the synergistic benefits of the Yangtze River Delta region for the period 2026-2035 from the dimension of synergistic coefficient measurement [18]. Based on the STIRPAT model to measure the carbon emission influencing factors, a large number of scholars have eliminated the multicollinearity problem of each influencing factor by ridge regression analysis. Mingjun Deng et al. calculated the CO2 emissions from the transportation sector in Beijing from 1999 to 2019, constructed the extended STIRPAT model, and used ridge regression to mitigate the effects of multicollinearity among eight indicators, which revealed the degree and direction of the influence of different indicators on CO2 emissions [19]. Misbah et al. study examines the impact of energy use and the Uruguay Round on carbon emissions over the period 1995-2018 using the extended STIRPAT model for Asian countries [20]. However, ridge regression does effectively eliminate the problem of multicollinearity, but it is still more difficult to find a suitable k value when actually judging the bias coefficients, and the method has a certain degree of subjectivity, which is not as objective as methods such as principal component regression. Therefore, Lei Wen et al. used principal component analysis to extract four principal components as input data for the prediction of support vector machine (SVM) to accurately predict the CO2 emission trend of residential domestic energy consumption [21].

The decoupling of carbon emissions and economic growth is a topical issue for developing countries [22]. Currently, domestic scholars' research in this area mainly refers to the mature theories and models from abroad, among which the Tapio decoupling model is the most widely used in the study of carbon emissions and economic growth. On the one hand, Zhe Zhang et al. used a Tapio decoupling model and a logarithmic mean Dee's index (LMDI) decomposition model to assess this decoupling based on panel CO2 emissions and GDP data [23]. Yasmeen used comprehensive data from 1972-2017 and applied the Tapio decoupling methodology to explore the decoupling of environmental degradation, energy use, and economic progress in Pakistan [24]. Xiaopeng Guo et al. used the Tapio decoupling model to analyze the decoupling relationship between the two factors that have the greatest impact on the carbon emissions of China's high-energy-consuming and high-emission industries and carbon emissions [25]. With the in-depth study of the Tapio decoupling model, a single decoupling study can no longer meet the practical application, and some scholars have comprehensively analyzed the decoupling problem in practice by expanding the Tapio decoupling model and utilizing the LYQ analysis framework and other methods. Qinmei Wang et al. utilized the LYQ analytical framework to decompose the causal chain of the decoupling indicators of carbon emissions and economic growth in three provinces in central China from 2001 to 2010 and evaluated the methodology [26]. Qifan Guan used the extended logarithmic mean decomposition index (LMDI) to decompose the influencing factors of carbon emissions, and constructed the Tapio index model to analyze the contribution of each influencing factor [27]. On the other hand, according to the differences in the economic development of different regions and industries, some experts use the Tapio decoupling model and other empirical models to conduct a combined study with the actual objects of the study. Kangkang Tong et al. innovatively combined the Tapio decoupling model with the decision tree analysis, which revealed the common socio-economic characteristics of the provinces with the same decoupling status [28]. Miao Wang et al. proposed a research framework by taking into account the Tapio decoupling model and biased directional distance function based on global meta-frontier DEA, so as to reveal the motive force and resistance that can help decouple construction industry economy from its carbon emissions [29].

In summary, scholars have conducted a large number of studies in the field of carbon emissions from industrial energy consumption. First of all, carbon emissions from energy consumption research country, region, and industry perspective literature is relatively rich, but the literature on the study of important industrial provinces in the west is lacking, especially from the perspective of regionally important industries, exploring the impact of industry on the region, there is a lack of research. Sichuan province is one of the important industrial bases in China, and the total industrial output value has been increasing year by year, which has made an important contribution to the economic development of Sichuan province. The study of carbon emissions in the industrial sector of Sichuan Province is of great significance. Secondly, the analysis of carbon emission influencing factors in this paper is more from the perspective of industrial scale, to avoid the shortcomings of the traditional influencing factors that are not in line with the reality of industrial research, and it adopts the principal component regression analysis to measure the influencing factors from a more objective perspective.

Finally, the construction of the LYQ analysis framework and combined with the STIRPAT extended model comprehensive analysis of the overall decoupling state of industry in Sichuan Province and influencing factors, effectively overcomes the shortcomings of a single decoupling model and research methodology, in order to promote the high-quality development of the regional and industrial economy, and build a new path to reduce emissions and reduce pressures to offer advice. Therefore, based on the STIRPAT extended model, this paper studies and analyzes the driving factors through principal component analysis, and at the same time constructs the LYQ analysis framework to introduce decoupling intermediate variables to decompose the decoupling elasticity index of Sichuan's industry as a whole, so as to accurately analyze the factors affecting economic growth and carbon emissions and put forward corresponding suggestions to ensure the realization of the “double carbon” target in the industrial field and promote sustained and healthy economic growth.

3. RESEARCH METHODS AND DATA SOURCES

3.1. Research methodology

3.1.1. Carbon emission measurement methodology

The IPCC method is currently the most common and widely used carbon accounting method in the international arena, so this paper also adopts this method to measure the industrial energy carbon emissions in Sichuan Province. The basic calculation formula is as follows:

$$C=\sum_{i=1}^{n}[FC_i*CAL_i*CC_i*CO_i*(44/12)] \tag{1}$$

Equation (1): C is the total carbon emission from industrial energy in Sichuan Province; FCi is the energy consumption of category i; CALi is the low-level heating value of energy category i; CCi is the carbon content of energy category i; COi is the carbon oxidation rate of energy category i; and 44/12 is the ratio of carbon dioxide to the molecular mass of elemental carbon.

3.1.2. (2) STIRPAT modeling

The STIRPAT model is a significant improvement on the IPAT model, which, by introducing non-proportional effects and extensibility, allows the model to be more flexible in describing and quantifying more accurately the extent to which each factor affects the environment. The extended model was analyzed through regression analysis to assess the impact of the three independent variables, population (P), affluence (A), and technology (T), on the dependent variable, environmental stress (C), using the following formula:

$$C=a*P^b*A^c*T^d*\mu \tag{2}$$

Equation (2) is logarithmized to obtain:

$$lnC=lna+blnP+clnA+dlnT+lnu \tag{3}$$

In Equation (3): C is the carbon emission; P is the population factor; A is the regional affluence; T is the technology level; b,c,d correspond to the elasticity coefficients of the model variables lnP, lnA, and lnT, respectively, and a,u are the model constant term and error term, respectively.

In this paper, based on the carbon emission characteristics of the industrial sector in Sichuan Province, the demographic, economic, and technological factors in equation (3) are extended, and seven indicators, namely, population size (P), per capita GDP (A), total industrial assets (E), the proportion of secondary industry (M), the number of industrial enterprises (H), the intensity of carbon emission (T), and the rate of urbanization (G), are selected as the explanatory variables to carry out empirical evidence on the energy consumption of the industry in Sichuan Province. The final STIRPAT prediction model is constructed as follows:

$$lnC=lna+blnP+clnA+dlnE+elnM+flnH+glnT+hlnG+lnu \tag{4}$$

3.1.3. TAPIO decoupling modeling

Tapio introduces the concept of elasticity in economics into decoupling theory, establishes a relatively complete decoupling system, and empirically analyzes the degree of decoupling between economic growth and carbon emissions in the European transportation industry [30]. Based on Tapio's research, this paper selects the indicators of GDP and industrial carbon emissions in Sichuan Province to construct a decoupling model of industrial carbon emissions, as shown in equation (5):

$$\delta=(\Delta C/C)/(\Delta Q/Q) \tag{5}$$

Where δ is the elasticity decoupling coefficient between industrial carbon emissions and Sichuan GDP, C and Q are industrial carbon emissions and Sichuan GDP, respectively, and ΔC and ΔQ denote the amount of changes in industrial carbon emissions and Sichuan GDP over a period of time, respectively.

Based on different elasticity indicators, the relationship between carbon emissions from industry and changes in Sichuan's GDP can be categorized into different decoupling states. The ideal state of carbon emission and economic development is a negative growth rate of carbon emission and a positive growth rate of economic development. The optimal strong decoupling state is when $\Delta Q>0$, $\Delta C<0$, $\delta<0$, when the growth rate of industrial carbon emissions is negative and the growth rate of gross product is positive, which is the optimal development state of industry. According to Tapio's research, the decoupling model can be divided into 8 states, as shown in Figure 1

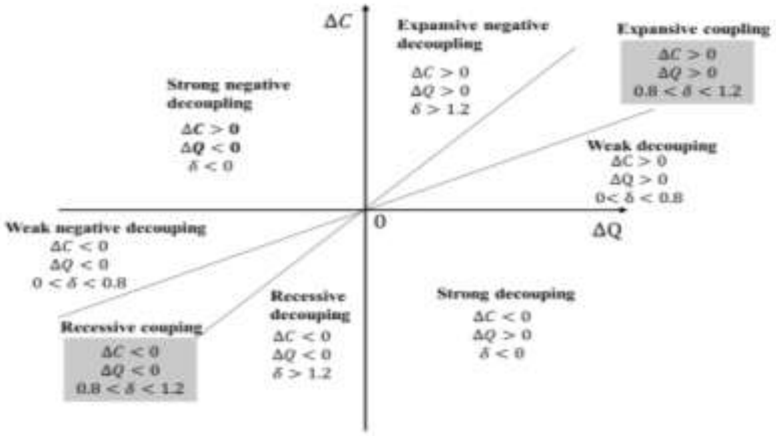

Figure 1 Classification of Tapio decoupling states[错误!未找到引用源。]

Based on the Tapio decoupling model and referring to the method of Qinmei Wang and other scholars to construct the LYQ analytical framework, introduce the intermediate variables of industrial energy consumption and gross output value, and factorize the total decoupling elasticity coefficient [错误!未找到引用源。]. The overall elasticity of decoupling is studied in depth based on different variables of factor decomposition, as shown in equation (6).

$$\delta=\frac{\Delta C/C}{\Delta Q/Q}=\frac{\Delta E/E}{\Delta G/G}\times\frac{\Delta C/C}{\Delta E/E}\times\frac{\Delta G/G}{\Delta Q/Q}=\delta_{EG}\times\delta_{CE}\times\delta_{GQ} \tag{6}$$

Where E is the industrial energy consumption, G is the gross industrial product, ΔE and ΔG denote the relevant amount of change over time, δEG is the energy saving decoupling elasticity coefficient, δCE is the emission reduction decoupling elasticity coefficient, and δGQ the value creation decoupling elasticity coefficient.

3.1.4. Principal Component Analysis

Principal Component Analysis (PCA) method is a commonly used data analysis method to downscale data and extract features from it. It filters out a few composite indicators from multiple indicators through orthogonal transformation, these composite indicators are the principal components, and the selected principal components retain most of the information in the original data. This method effectively simplifies the complexity of the original model data analysis and eliminates the redundancy of the original data. When analyzing the driving factors of carbon emissions, principal component analysis can effectively help researchers to extract the key variables and provide a scientific basis for the formulation of reasonable emission reduction policies.

3.2. Data sources

The data used in the study are mainly from the Sichuan Statistical Yearbook for the period 2006-2023, and the data on energy low-level heating value, carbon content per unit of calorific value, and carbon oxidation rate are from the China Energy Statistical Yearbook and Guidelines for the Preparation of Provincial Greenhouse Gas Inventories (for Trial Implementation). Population size adopts the number of resident population at the end of the year (10,000 people), GDP per capita adopts the ratio of GDP to population size in Sichuan Province (yuan/person), total industrial assets adopts the total assets of industries above the scale at the end of the year instead of (100 million yuan), the secondary industry share adopts the ratio of output of the secondary industry to the regional GDP (%), the number of industrial enterprises adopts the number of industrial enterprise units above the scale instead of (one), and the carbon emission intensity adopts the ratio of carbon emissions from energy consumption to GDP (tons of standard coal per million yuan), and the urbanization rate adopts the proportion of urban resident population to total population (%).

4. EMPIRICAL RESULTS AND ANALYSIS

4.1. Carbon emissions from industrial energy consumption

Since industrial energy consumption in Sichuan Province is dominated by fossil energy, which are oil, coal and natural gas, this paper takes the sum of carbon emissions from these three types of end-use energy as industrial carbon emissions in Sichuan Province. As shown in Figure 2, the structure of industrial energy consumption in Sichuan Province from 2005 to 2022 is dominated by coal, followed by petroleum, and lastly by natural gas. The share of coal in carbon emissions shows an overall decreasing trend during the 18-year period, from 96.68% in 2005 to 87.7% in 2022, with an average decrease of 0.5%; oil and natural gas carbon emissions show an overall increasing trend, in which the share of oil in carbon emissions rises from 2.37% in 2005 to 9.82% in 2022, and that of natural gas rises from 0.95% in 2005 to 0.95% in 2022. 0.95% in 2005 to 2.48% in 2022. It shows that the structure of industrial carbon emissions in Sichuan Province continues to improve, but the coal resource endowment is too large, and the future road of carbon reduction is still very serious. There is an urgent need to do a good job of energy saving and carbon reduction planning. As shown in Figure 3, from 2005 to 2022, the total industrial carbon emissions in Sichuan Province showed a rising and then falling trend, which the fastest growth rate from 2005 to 2009, from 139.534 million tons to 224.2183 million tons, and then gradually declining, and in 2022, the carbon emissions were 165.7412 million tons. From 2005 to 2022, the industrial carbon emission intensity in Sichuan Province continued to decline, from 1.94 tons/10,000 yuan to 0.29 tons/10,000 yuan, with an average annual decline of 4.72%. It shows that the green and low-carbon development of Sichuan Province has achieved certain results and is moving towards a “dual-carbon” pioneer province.

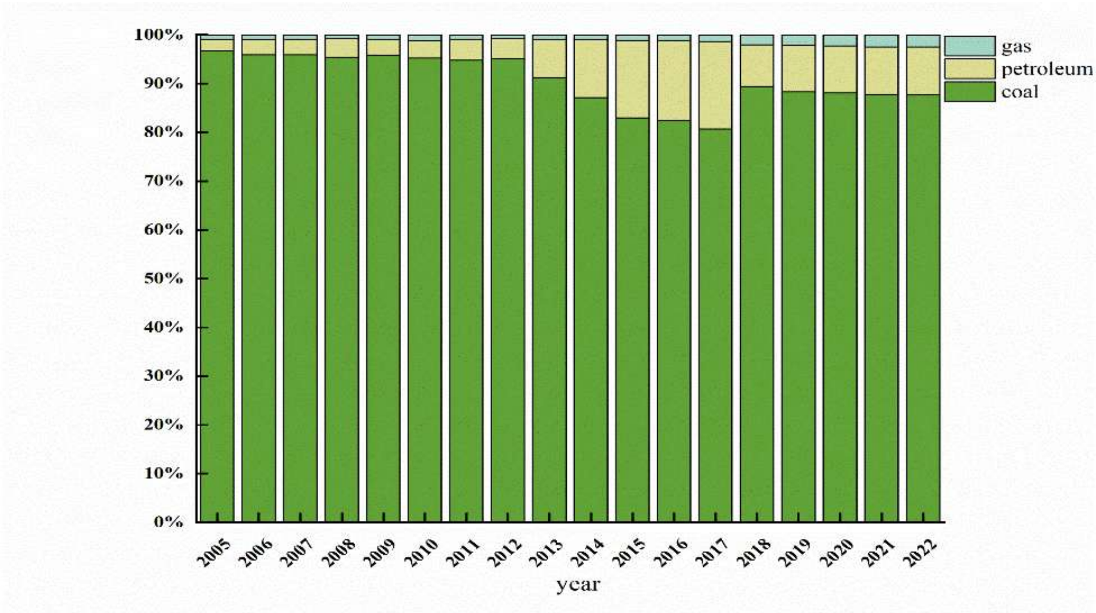

Figure 2 Structure of industrial energy carbon emissions in Sichuan Province, 2005-2022

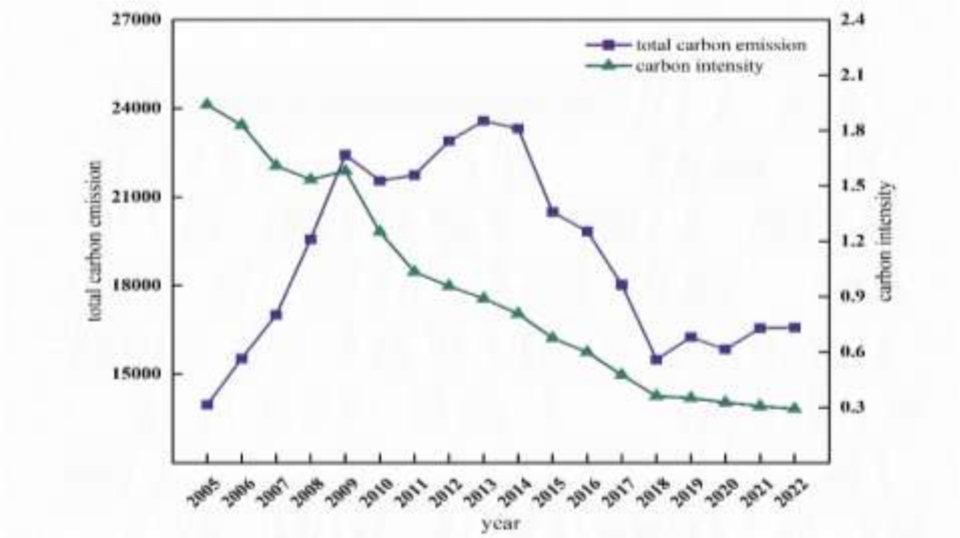

Figure 3 Industrial Energy Carbon Emissions and Carbon Emission Intensity in Sichuan Province, 2005-2022

4.2. Analysis of the results of decoupling industrial energy consumption

The decoupling elasticity coefficients of energy conservation, emission reduction, value creation, industrial carbon emissions, and economic development were calculated , respectively, according to the decoupling model established above and the relevant data of Sichuan Province from 2005 to 2022, and the Tapio decoupling state was paired with the corresponding decoupling elasticity coefficients to obtain Table 1.

In terms of the decoupling state of the decomposition factors, the decoupling state of energy conservation in Sichuan Province in the past 17 years was dominated by strong decoupling and weak decoupling, with only two years in which the decoupling state was expansionary and negative decoupling. This shows that industrial energy consumption and economic growth in general show a positive growth trend. The energy consumption growth rate is lower than the economic growth rate, and at the same time, industrial energy consumption increases at a slower rate, but industrial energy consumption is still increasing. Only in the year of strong decoupling state, industrial energy consumption has declined. From the point of view of the decoupling state of emission reduction, the decoupling state of emission reduction in Sichuan Province in the past 17 years shows seven different decoupling states, which indicates that the growth rate of carbon emission is lower than the growth rate of energy consumption in most of the years, and that the carbon emission calculated based on coal, oil, and natural gas shows a different trend from energy consumption, and energy utilization efficiency still needs to be improved. From the point of view of value creation decoupling state, Sichuan Province in the past 17 years, the value creation decoupling state presents a weak decoupling, and expansive negative decoupling, expansive coupling of the three states, and the proportion of the difference is small, which indicates that the growth of gross domestic product (GDP) of industry from the obvious more than the gross domestic product (GDP) of Sichuan province, to the state of the growth rate of the two is close to the growth rate of the gross domestic product (GDP) of industry to maintain the growth of GDP of Sichuan province, the growth rate of GDP of Sichuan Province is lower. In recent years, the proportion of secondary industry in Sichuan Province has been gradually reduced, and the proportion in 2022 will only be 37.3%, which means that the added value of the industrial GDP will have less impact on the growth rate of the GDP of Sichuan Province compared with the past.

From the comprehensive analysis, the industry as a whole shows 3 decoupling states in 2006-2022: weak decoupling, expansive negative decoupling, and strong decoupling, which correspond to 9, 1, and 7 times, respectively. According to the analysis in Table 1, industrial carbon emissions roughly show three development periods with the following obvious characteristics: 2006-2013 is dominated by weak decoupling, which indicates that the growth of carbon emissions in this period is lower than the economic growth rate, and in 2009 it showed expansive negative decoupling state, and there is a certain recurring risk of economic development; 2014-2018 is dominated by strong decoupling, and the region's economic development is shifting from high-speed growth shifting to high-quality growth, which indicates that economic development in this period maintains growth while industrial carbon emissions decrease; 2019-2022 is dominated by weak decoupling, with economic growth slowing down due to the impact of the new Crown Pneumonia epidemic, high temperatures and droughts, and pulling of the power supply, but industrial carbon emissions are still increasing, and there is a small increase in the proportion of the secondary industry in this period. It shows a strong decoupling state in 2020, which indicates that the economic growth of Sichuan Province in that period still has strong resilience under the influence of many negative factors.

Table 1 Decoupling elasticity and decomposition of industrial carbon emissions in Sichuan Province, 2006-2022

Year	δ_{EG}	Decoupling state	δ_{CE}	Decoupling state	δ_{GQ}	Decoupling state	δ	Decoupling state
2006	-0.15	Strong decouping	-3.11	Strong negative decoupling	1.37	Expansive negative decoupling	0.63	Weak decouping
2007	-0.08	Strong decouping	-4.41	Strong negative decoupling	1.12	Expansive coupling	0.39	Weak decouping
2008	1.41	Expansive negative decoupling	0.41	Weak decouping	1.26	Expansive negative decoupling	0.73	Weak decouping
2009	0.54	Weak decouping	1.86	Expansive negative decoupling	1.28	Expansive negative decoupling	1.30	Expansive negative decoupling
2010	0.37	Weak decouping	-0.42	Strong decouping	1.17	Expansive coupling	-0.18	Strong decouping
2011	0.44	Weak decouping	0.10	Weak decouping	0.91	Expansive coupling	0.04	Weak decouping
2012	0.30	Weak decouping	1.56	Expansive negative decoupling	0.82	Expansive coupling	0.39	Weak decouping
2013	0.39	Weak decouping	0.80	Expansive coupling	0.88	Expansive coupling	0.28	Weak decouping
2014	-1.78	Strong decouping	0.16	Weak negative decouping	0.43	Weak decouping	-0.13	Strong decouping
2015	-9.94	Strong decouping	4.19	Recessive decouping	0.06	Weak decouping	-2.42	Strong decouping
2016	-24.78	Strong decouping	0.25	Weak negative decouping	0.06	Weak decouping	-0.35	Strong decouping
2017	0.01	Weak decouping	-119.41	Strong decouping	0.42	Weak decouping	-0.63	Strong decouping
2018	0.13	Weak decouping	-13.00	Strong decouping	0.61	Weak decouping	-1.06	Strong decouping
2019	0.71	Weak decouping	1.05	Expansive coupling	0.81	Expansive coupling	0.60	Weak decouping
2020	1.24	Expansive negative decoupling	-1.16	Strong decouping	0.39	Weak decouping	-0.56	Strong decouping
2021	0.41	Weak decouping	0.69	Weak decouping	1.39	Expansive negative decoupling	0.40	Weak decouping
2022	-0.66	Strong decouping	-0.02	Strong negative decoupling	1.13	Expansive coupling	0.02	Weak decouping

In summary, according to the analysis of decomposition factors, the decoupling between industrial carbon emissions and economic growth in Sichuan Province is mainly affected by the value creation and emission reduction decoupling coefficients, and in the future, Sichuan Province needs to take advantage of the abundant water, natural gas, and other resources in the province, and actively develop clean energy, improve energy efficiency, and optimize the structure of energy consumption. From the results of the comprehensive analysis, industrial carbon emissions and economic development are mainly strong decouping and weak decouping, which is related to China's economic growth and the high-quality development stage of the goal, the second period of industrial carbon emissions in Sichuan Province. The decoupling state of the second period of development are strongly decoupled, for the optimal development of the industry. However, due to the influence of internal and external risks, the industrial carbon emissions in recent years mainly show a weak decoupling state, and Sichuan Province needs to improve awareness of risk prevention, strengthen the resilience of economic development, and ensure the smooth operation of economic growth.

4.3. Analysis of drivers of industrial energy consumption

Firstly, the sample data is logarithmized, and then the KMO measure and bartlett test are carried out with the help of SPSS 27.0. As can be seen in Table 2, the value of KMO is 0.833 (>0.6) and the significance (p-value) is 0.000, from which it is judged that the selected sample data is suitable for factor analysis.

As can be seen from Table 3, two principal components are extracted when the eigenvalue is greater than 1, and these two principal components are defined as F1 and F2, respectively, and the cumulative variance contribution rate reaches 97.035% at this time, of which the eigenvalue of F1 is 5.725, the variance contribution rate is 81.785%, and the eigenvalue of F2 is 1.067, the variance contribution rate is 15.250%. And it can be verified that F1 and F2 can reflect the vast majority of the information of the original explanatory variables according to the gravel plot, so it is feasible to analyze the influencing factors of carbon emissions from industrial energy consumption by using these two composite indicators.

The weights of each principal component factor are adjusted according to the variance contribution rate, i.e., $\beta 1=81.785/97.035=84.28\%$, $\beta 2=15.250/97.035=15.72\%$, and the final calculated variance contribution rates of F1 and F2 are 84.28% and 15.72%, respectively. The final formula for calculating the composite score coefficient was obtained as $F=84.28\%*F1+15.72\%*F2$.

Table 2 KMO measures and Bartlett's test

KMO		0.833
Bartlett's test of sphericity	Approximate chi-square	325.970
	Degrees of freedom	21
	Significance (p-value)	0.000***

Notes: * p<0.05; ** p<0.01; *** p<0.001.

Table 3 Total Variance Explained

Ingredient	Initial eigenvalue			Extract the sum of the squares of the loads		
	Total	Percentage of variance	Cumulative %	Total	Percentage of variance	Cumulative %
1	5.725	81.785	81.785	5.725	81.785	81.785
2	1.067	15.250	97.035	1.067	15.250	97.035
3	0.172	2.463	99.498			
4	0.030	0.431	99.928			
5	0.003	0.050	99.978			
6	0.001	0.014	99.992			
7	0.001	0.008	100.000			

Note: The extraction method is principal component analysis.

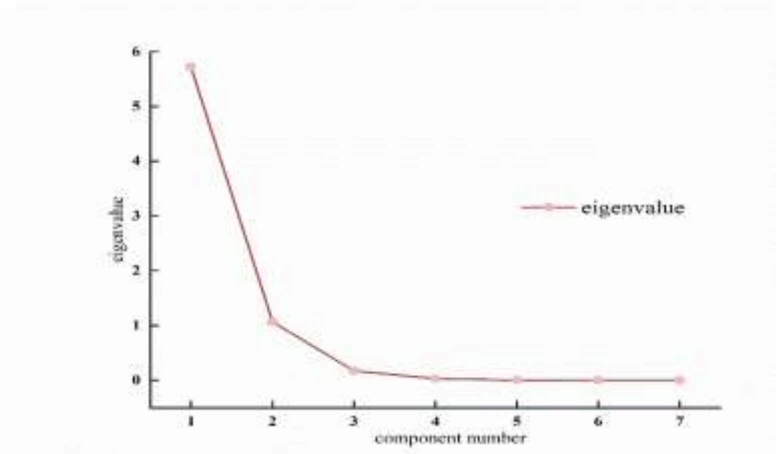

Figure 4 Gravel diagram

Table 4 component matrix reflects the magnitude of the loadings of principal component 1 and principal component 2 on each independent variable, respectively. The larger the loading, the greater the contribution of the principal component corresponding to that variable. It can be seen that population size, GDP per capita, total industrial assets, the number of industrial enterprises, and the urbanization rate have larger loadings in principal component 1, while the proportion of secondary industry and the intensity of carbon emissions have larger loadings in principal component 2.

Table 4 Component matrix

Index	Component	
	Component 1	Component 2
lnP	0.807	-0.563
lnA	0.968	0.222
lnE	0.941	0.316
lnM	-0.765	0.635
lnH	0.836	0.432
lnT	-0.992	0.033
lnG	0.991	0.100

Note: The extraction method is principal component analysis.

Let the standardized values of each variable of population size, GDP per capita, total industrial assets, share of secondary industry, number of industrial enterprises, carbon emission intensity, and urbanization rate be a1, a2, a3, a4, a5, a6, and a7, respectively. As can be seen from Table 5, the score functions of the two principal component factors F1 and F2 are:

$$F1=0.194*a1+0.259*a2+0.307*a3+0.240*a4+0.356*a5-0.123*a6+0.195*a7 \quad (7)$$

$$F2=0.510*a1-0.069*a2-0.144*a3-0.561*a4-0.243*a5-0.126*a6+0.025*a7 \quad (8)$$

Table 5 Matrix of component score coefficients

Index	Component	
	Component 1	Component 2
lnP	-0.194	0.510
lnA	0.259	-0.069
lnE	0.307	-0.144
lnM	0.240	-0.561
lnH	0.356	-0.243
lnT	-0.123	-0.126
lnG	0.195	0.025

Note: The extraction method is principal component analysis.

As can be seen from Table 6, the composite score coefficient from 2005 to 2022 shows a rising trend year by year, indicating that the industrial carbon emissions in Sichuan Province are in continuous growth; in 2022, the score value of Principal Component 1 is the largest, which represents that the industrial carbon emissions are mainly affected by the population size, per capita GDP, total industrial assets, the number of industrial enterprises, and the urbanization rate; the score value of Principal Component 2 is the largest in 2005, but the difference in score values of the years is relatively small. In 2005, Principal Component 2 scored the largest value, but the difference between the scores of each year is small, indicating that industrial carbon emissions are influenced by the proportion of secondary industry and carbon emission intensity.

Table 6 Coefficient values of principal component composite scores of industries in Sichuan Province, 2005-2022

Year	F1		F2		F	
	Score	Ranking	Score	Ranking	Score	Ranking
2005	8.049	18	-1.587	1	6.534	18
2006	8.209	17	-1.669	2	6.656	17
2007	8.430	16	-1.754	3	6.829	16
2008	8.679	15	-1.881	9	7.019	15
2009	8.748	14	-1.921	12	7.070	14
2010	8.929	13	-1.969	16	7.216	13
2011	9.009	12	-1.941	14	7.288	12
2012	9.118	11	-1.963	15	7.376	11
2013	9.221	10	-1.988	18	7.459	10
2014	9.277	9	-1.974	17	7.508	9
2015	9.329	8	-1.939	13	7.557	8
2016	9.370	7	-1.896	10	7.599	7
2017	9.439	6	-1.848	7	7.664	6
2018	9.522	5	-1.814	4	7.740	5
2019	9.586	4	-1.829	6	7.791	4
2020	9.644	3	-1.828	5	7.841	3
2021	9.761	2	-1.879	8	7.931	2
2022	9.838	1	-1.912	11	7.991	1

Regression estimation is done with lnC as the dependent variable and F1 and F2 as independent variables, and the results are shown in Tables 7 and 8. It can be seen that the DW value is 2.208, the R-square is 0.904, the F-value is 70.694, and the corresponding P-value (significance level) is 0.000, which is much less than 5%, indicating that the model fits well. According to the general standard of VIF determination, when $0<VIF\leq5$, there is no complex covariance. The VIF value of the model in this paper is 1, which indicates that there is no multicollinearity problem, i.e., the industrial carbon emissions in Sichuan Province are not explained by the redundancy of the rest of the predictor variables. The obtained regression equations are as follows:

$$\ln C=9.835+0.063*F1-0.146*F2 \tag{9}$$

Substituting equations (7) and (8) into equation (9) gives:

$$\ln C=9.835-0.087\ln P+0.026\ln A+0.040\ln E+0.097\ln M+0.057\ln H+0.011\ln T+0.009\ln G \tag{10}$$

From equation (10), it can be seen that GDP per capita, total industrial assets, the proportion of secondary industry, the number of industrial enterprises, carbon emission intensity, and urbanization rate are the carbon promoting factors, among which the proportion of secondary industry has the largest positive impact on industrial energy carbon emissions in Sichuan Province, with an elasticity coefficient of 0.097; the number of industrial enterprises is next to it, with an elasticity coefficient of 0.057; and then it is the total industrial assets, with an elasticity coefficient of 0.040, and finally GDP per capita, carbon emission intensity and urbanization rate, with elasticity coefficients of 0.026, 0.011 and 0.009, respectively. Population size is a carbon reduction factor with an elasticity coefficient of -0.087.

Table 7 Results of ANONA analysis

Model	Total	Degrees of freedom	Mean square	F	Significance
Regression	0.430	2	0.215	70.964	0.000***
Residual	0.045	15	0.003		
Total	0.475	17			

Notes：The dependent variable is lnC; * p<0.05; ** p<0.01; *** p<0.001.

Table 8 Results of linear regression analysis

	Non-standardized coefficient		Standardized coefficient	t	P	R2	Adjusted R2	DW	VIF
	B	Standard error	Beta						
Constant	9.835	0.013	-	758.157	0.000***				
F1	0.063	0.013	0.379	4.743	0.000***	0.904	0.892	2.208	1
F2	-0.146	0.013	-0.872	-10.928	0.000***				

Notes: The dependent variable is lnC; * p<0.05; ** p<0.01; *** p<0.001.

5. DISCUSSION

5.1. Conclusion

This paper investigates the decoupling elasticity of industrial carbon emissions and economic development in Sichuan Province from 2006 to 2022 and studies the decoupling status of the decomposition coefficients according to the LYQ analysis framework. Secondly, based on the STIRPAT model to construct its extended form, through the idea of dimensionality reduction in principal component analysis, two comprehensive variables are selected from seven driving factors, and the values of the corresponding score coefficients are calculated and analyzed by multivariate linear regression analysis, and the following conclusions are drawn.

The overall carbon emissions from industrial consumption in Sichuan Province will first rise and then fall, and from 2005 to 2022, industrial energy consumption will be dominated by coal, oil, and natural gas, with energy consumption showing a downward trend. Industrial carbon emissions in Sichuan Province are on the rise, and the realization a "carbon peak" in the industrial sector is still facing certain pressure. From the composition of energy consumption, coal is the main source of energy consumption, natural gas consumption needs to be improved, increasing the proportion of non-fossil energy consumption, and improving the efficiency of energy utilization are still the focus of the future to promote the industrial sector to reduce emissions and reduce pressure.

Carbon emissions from industrial energy consumption and economic development in Sichuan Province from 2006 to 2022 are mainly in strong decoupling and weak decoupling states and generally show three development periods with obvious characteristics. According to the decomposition factors, value creation decoupling elasticity and emission reduction decoupling elasticity have a greater impact, emission reduction decoupling state presents 7 different decoupling states, and value creation decoupling state presents 3 decoupling states. Value creation capacity is the main resistance to the strong decoupling of industrial carbon emissions and economic growth in Sichuan Province, and the change is not large, always a positive coefficient, and negatively affects the overall decoupling elasticity of the industry, which is also one of the largest negative factors affecting the overall strong decoupling. From the trend of the change in the elasticity coefficient of emission reduction, the influence factor on the state of decoupling industrial carbon emissions and economic growth is larger than the elasticity coefficient of energy saving, which is closest to the change in the elasticity coefficient of the decoupling of the overall industry and plays a positive role in promoting the strong decoupling of the overall industry.

Among the carbon emission driving factors of industrial energy consumption in Sichuan Province, the proportion of the secondary industry, the number of industrial enterprises, and the total industrial assets are the main carbon promoting factors, with elasticity coefficients of 0.097, 0.057, and 0.040, respectively, and the proportion of the secondary industry has the largest influence factor. The industrial energy consumption in Sichuan Province is mainly influenced by the above factors, i.e., industrial scale. The positive influence of the elasticity of GDP per capita, carbon emission intensity, and urbanization rate is smaller, with coefficients of 0.026, 0.011, and 0.009, respectively. Unlike the common carbon emission influencing factors, the influence of GDP per capita, carbon emission intensity, and urbanization rate is not obvious. Therefore, promoting industrial structure upgrading, de-industrializing industrial structure, and improving energy use efficiency in key industrial sectors are the keys to achieving carbon emission reduction in the industrial sector. Population size is a carbon reduction factor, with an elasticity coefficient of -0.087. Population size is an inhibiting factor for the following reasons: first, the growth rate is different, the average growth rate of population size in the past 2 years is 0.02%, while the average year-on-year growth rate of industrial carbon emissions is 2.32%, which is much higher than the growth level of population size, so the impact of the increase of emissions brought about by the slow growth of the population size is limited to a certain degree and does not affect the increase of industrial carbon emissions; second, changes in lifestyles and consumption attitudes, the increase in population size in the course of urbanization and modernization has also changed people's living habits and consumption concepts. More people are choosing low-carbon, environmentally friendly lifestyles, thereby reducing individual and household carbon emissions.

5.2. Suggestion

Create a new green and low-carbon industrial model characterized by low energy consumption, low pollution, and low emissions. To build the "three lows" industrial model, the government can introduce relevant policies and measures to support its development. First of all, the research, development and application of energy-saving and emission reduction technology enterprises to give tax incentives and subsidies, in order to promote their development in the direction of clean production. Secondly, establish a perfect environmental protection supervision system, strengthen pollution control in industrial enterprises, and severely punish those who violate the regulations on sewage discharge to ensure the quality of the environment. Finally, increase investment in research and development of low-carbon science and technology, support scientific research institutions and enterprises to carry out scientific and technological research, strengthen international cooperation, and learn from the successful experience and advanced technology of other countries.

Strengthening economic resilience and enhancing the level of resilience of economic development. First, stabilize market expectations and strengthen macroeconomic control. The government has been able to maintain the stable and healthy development of the economy through the precise application of policies and the rationalization of monetary and fiscal policies. At the same time, by continuously improving policy tools and instruments, it provides market participants with clear expectations, enhances market confidence, and promotes long-term stable economic growth. Secondly, it will strengthen synergistic development within Sichuan Province, optimize the allocation of resources, promote balanced regional economic development, be able to respond positively to external risks and challenges, and improve the economy's intrinsic driving force, thereby promoting high-quality economic development.

Formulate a reasonable scale of development that harmonizes industrial development with environmental protection and steadily promotes energy conservation and emission reduction. First, strengthening policy guidance, clarifying the green direction of industrial development, and prompting enterprises to increase investment in environmental protection by establishing strict standards for environmental protection and pollutant emissions. Second, strengthen the construction of ecological civilization and promote green development. In the process of economic development, attention should be paid to protecting the ecological environment, promoting green and low-carbon development, and realizing a win-win situation for economic development and environmental protection. Finally, promote industrial upgrading, enhance innovation capacity, increase investment in scientific research and technological research and development, promote the vigorous development of emerging industries, eliminate backward production capacity, promote the transformation of old and new kinetic energy, and realize high-quality economic development.

CONFLICTS OF INTEREST

The authors declare that they have no conflict of interest.

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