

The Analysis of Factors Influencing Carbon Emissions in Sichuan Province

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ABSTRACT

Based on the population, economic development level, urbanization rate, industrial structure, energy intensity, government expenditure, and foreign trade of Sichuan Province from 2000 to 2020, an improved STIRPAT model is constructed. Ridge regression estimation method is employed to analyze the relationship between carbon emissions and various influencing factors. The research findings indicate that there is a positive correlation between economic development level, urbanization rate, industrial structure, government expenditure, and foreign trade, and carbon emissions in Sichuan Province, but the degree of influence varies for each factor. Among them, industrial structure, namely the proportion of secondary industry, has the greatest impact, while energy intensity shows a negative correlation with carbon emissions. Finally, considering the above analysis, measures for emissions reduction such as fostering a clean and low-carbon industrial system and promoting technological innovation in the low-carbon sector are proposed.

KEYWORDS

Sichuan Province; Carbon emissions; Influencing factors; STIRPAT Model; Ridge regression

1. INTRODUCTION

Since the 21st century began, significant changes have occurred in the climate. Climate change is primarily driven by the release of greenhouse gases, with carbon dioxide being the main contributor[[1],[2]]. Global temperatures have started to rise, potentially leading to issues such as rising sea levels, climate anomalies, and the extinction of flora and fauna, severely constraining social and economic development. The international community has been actively responding to the challenges posed by climate change. The Kyoto Protocol stipulated that global efforts to mitigate climate change aimed to reduce greenhouse gas emissions by developed countries by 5.2% compared to 1990 levels during the first commitment period from 2008 to 2012[[3]]. The Glasgow Climate Agreement emphasized the urgent, substantial, and enduring reduction of global greenhouse gas emissions to keep global warming below 1.5 degrees Celsius[[4]]. The long-term goal of the Paris Agreement is to limit the increase in global average temperature to within 2 degrees Celsius of pre-industrial levels, with efforts to limit the increase to 1.5 degrees Celsius[[5]]. The transition from the Kyoto Protocol to the Paris Agreement marks global recognition of the severity of climate change. The entry into force of the Paris Agreement heralds a new dawn for global cooperation on climate change[[6]].

China, as the world's largest energy consumer and emitter of carbon, is actively responding to the international call for reducing carbon emissions, firmly establishing the goals of "carbon peaking" by 2030 and "carbon neutrality" by 2060[[7],[8]]. Against the backdrop of this global initiative, Sichuan Province, as a major economic province in western China, inevitably shoulders significant

responsibilities. The province possesses abundant resources and a large population, playing a crucial role as a vital clean energy base and energy transmission hub in China. Meanwhile, the proportion of coal and oil consumption in Sichuan Province has remained at around 60% for many years, imposing immense pressure on its economic and social development as well as environmental conservation due to its high-carbon energy consumption characteristics. Against this backdrop, there is an urgent need to delve into the factors influencing carbon emissions in Sichuan Province. This is not only influential for Sichuan Province itself in achieving carbon emission control and accelerating the establishment of a "clean energy demonstration province", but also significant for addressing the province's low-carbon energy transition and facilitating the comprehensive realization of the national "dual carbon" strategy.

2. LITERATURE REFERENCES

Against the macro backdrop of "carbon peaking" and "carbon neutrality," factors influencing carbon emissions have become a hot topic of academic research. This issue has been extensively and deeply investigated by numerous scholars both domestically and internationally. GHAZALI A utilized data from 1991 to 2013 and employed an extended STIRPAT model, discovering that per capita GDP, population size, and energy intensity were the primary factors influencing carbon dioxide emissions in these emerging industrialized nations[[9]]. Yang Pingguo employed the Kaya constant model and the LMDI factor decomposition method to conduct a comprehensive analysis of China's carbon emissions from fossil fuel consumption during the period from 2006 to 2018. The study explored the impacts of population, per capita GDP, improvements in energy efficiency, and optimization of energy structure on carbon emissions[[10]]. Yi investigated the relationship between urbanization and carbon emissions, with research indicating that the urbanization process promoted carbon emissions[[11]]. Chontanawat's study, based on the STIRPAT model, demonstrated that from 1971 to 2013, carbon dioxide emissions in the ASEAN region, as well as in specific countries including Indonesia, Malaysia, the Philippines, and Thailand, were primarily driven by several key factors. The research findings clearly indicated that population growth and economic prosperity were the main drivers behind the increase in carbon dioxide emissions in these countries. Additionally, the widespread use of fossil fuels played a significant role in promoting carbon dioxide emissions, while improvements in energy efficiency to some extent mitigated the acceleration of carbon dioxide emissions[[12]]. Wang applied the LMDI (Logarithmic Mean Divisia Index) decomposition method to decompose the factors influencing carbon emissions in China into population, per capita Gross Domestic Product (GDP), energy consumption, and other factors[[13]]. In another study by Gong Li, the STIRPAT model was employed to analyze the carbon dioxide emissions resulting from energy consumption in the Yangtze River Delta region. This study compared these emissions with several factors that might influence them, such as population size, per capita economic level, foreign direct investment, and the extent of technological advancement. The research revealed significant variations in the extent to which these influencing factors either drove or inhibited carbon dioxide emissions. Among these factors, population size had the most pronounced effect, followed closely by per capita GDP[[14]]. In Shi's study, the STIRPAT model was employed to demonstrate that population size was an important factor influencing carbon emissions[[15]]. When Alves employed the STIRPAT model to investigate the factors influencing CO₂ intensity in Portugal from 1996 to 2009, it was found that the energy intensity of the economy sector was a significant factor affecting carbon emission intensity[[16]].

Based on the synthesis of the aforementioned research, explanatory variables selected by scholars both domestically and internationally for factors influencing carbon emissions primarily include per capita GDP, energy consumption structure, population size, energy intensity, and urbanization level in the research area. When exploring these influencing factors, previous researchers have often preferred to analyze them using the STIRPAT model, which enjoys widespread application and recognition in the field of carbon emissions research. However, there have been relatively few

academic studies on the factors influencing carbon emissions in Sichuan Province, and assessments of these factors have not been comprehensive. Therefore, this paper aims to conduct empirical research on the factors influencing carbon emissions in Sichuan Province, building on previous research and using an expanded STIRPAT model combined with specific information about Sichuan Province. By thoroughly analyzing the impact of each factor on carbon emissions, this study seeks to explore effective pathways for Sichuan Province's low-carbon transition and comprehensively promote the implementation of regional actions to achieve the national determined contributions (NDCs), thereby contributing wisdom and strength to the sustainable development of Sichuan Province and the whole country.

3. THEORETICAL FRAMEWORK

3.1. Model Construction and Indicator Selection

In the early 1970s, Ehrlich and Holdren proposed the IPAT model[[17]], with its general form as follows:

$$I = PAT \quad (1)$$

In this model, I represents environmental impact, while P, A, and T respectively denote population, affluence, and technology level. This model is primarily utilized to analyze the extent to which factors such as population, affluence, and technology affect the environment.

The IPAT model, characterized by its simplicity and ease of comprehension, has garnered widespread recognition and application in environmental fields both domestically and internationally. However, its major limitation lies in its assumption of other factors remaining constant while analyzing a problem by altering one factor. However, the biggest limitation of the model is that it can only assume that other factors remain unchanged and analyse the problem by changing one of the factors, which makes the impact of each influencing factor on the environment in the model simply treated as a linear relationship of the same proportion. This is neither in line with the actual situation, nor can it well reflect the degree of change in the impact on the environment when each influencing factor is changed.

In order to address the shortcomings of the IPAT model, York, Dietz, Rosa, and others proposed the STIRPAT model in 1994[[18]], building upon the foundation of the IPAT model. Its basic form is as follows:

$$I = aP^bA^cT^de \quad (2)$$

In this equation, I represents environmental pressure, P denotes population factors, A signifies per capita wealth, and T indicates technological level. a is the coefficient of the model, while b, c, d, and so forth, respectively, represent the indices of population factors, per capita wealth, technological level, and other driving factors. e represents the model error. In the equation, P, A, and T can all be decomposed.

Through the analysis above, it is evident that the IPAT model has a obvious drawback: the linear and proportional changes of influencing factors, which clearly do not align with reality. However, the introduction of exponents in the STIRPAT model can perfectly address this issue. Its greatest advantage lies in its ability to analyze the non-proportional impact of various factors on the environment. Furthermore, due to its flexibility, the STIRPAT model allows for the addition or modification of several influencing factors. Consequently, this model is widely applied in the analysis and research of practical environmental issues.

Since the STIRPAT model is a multivariate nonlinear model, in practical analysis, in order to reduce heteroscedasticity and facilitate regression analysis using relevant software, it is common practice to

take the natural logarithm of both sides of the model, thereby linearizing it. Taking the natural logarithm of both sides of equation (2), we obtain the equation:

$$\ln I = \ln a + b \ln P + c \ln A + d \ln T + \ln e \quad (3)$$

$\ln I$ represents the dependent variable, while $\ln P$, $\ln A$, and $\ln T$ represent the independent variables, with $\ln a$ being the constant term and $\ln e$ the error term. By performing multiple regression linear fitting on the processed model (Equation 3), we can determine the magnitude of the impact of each factor on the environment. Specifically, when other influencing factors remain constant, 1% change in P , A , or T will result in a corresponding impact on the environment of $b\%$, $c\%$, or $d\%$, respectively.

To conduct a more comprehensive investigation into the influencing factors of carbon emissions in Sichuan Province, and taking into account the province's actual circumstances, this study has augmented the explanatory variables based on the STIRPAT framework. The total population and per capita GDP were widely recognized as consensus factors influencing carbon emissions[[19]]. Since the reform and opening up, significant progress has been made in urbanization development in Sichuan. Therefore, the urbanization rate should be considered one of the factors influencing carbon emissions in Sichuan Province. In the course of economic and social development in Sichuan Province, the secondary industry holds a relatively significant position. The proportion of energy consumption and carbon emissions attributed to the secondary industry is comparatively high. Therefore, the industrial structure also exerts an influence on carbon emissions in Sichuan Province. At the same time, a substantial amount of carbon emissions are implied by foreign trade. In recent years, the Sichuan economy has developed rapidly, with the scale of trade continuously expanding. From 2000 to 2020, the total import and export volume increased from \$2.55 billion to \$147.32 billion. Therefore, foreign trade should also be regarded as one of the primary influencing factors of carbon emissions. In addition, government general budget expenditures also had an impact on carbon emissions[[20]]. Drawing upon the research findings of numerous scholars and considering the economic environmental characteristics of Sichuan Province, this model can be extended to:

$$\ln C = \ln a + \beta_1 \ln P + \beta_2 \ln A + \beta_3 \ln Ur + \beta_4 \ln Is + \beta_5 \ln T + \beta_6 \ln Es + \beta_7 \ln G + \ln e \quad (4)$$

where C denotes carbon emissions; a is the coefficient of the model; P is the population; A is the economic development level; Ur is the urbanization rate; Is is the industrial structure; T is the energy intensity; Es is the foreign trade; G is the government expenditure. e is the error of the model; β_i is the elasticity coefficient of each variable, which means that a 1% change in Influencing factors, will cause the carbon emissions to change to $\beta_i\%$ will cause the carbon emissions of $\beta_i\%$ change.

3.2. Interpretation of Indicators and Data Sources

Environmental pressure is represented by carbon emissions (C). Definitions of population, economic development level, urbanization rate, industrial structure, energy intensity, government expenditure, and foreign trade are provided in Table 1.

According to the benchmark method provided in the Energy section of the "2006 IPCC Guidelines for National Greenhouse Gas Inventories," the formula for calculating carbon emissions generated by energy consumption is:

$$C = \sum_{i=1}^n E_i \times \theta_i \times \delta_i \quad (5)$$

In the formula:

C ——carbon emissions;

i —type of energy;

E_i —different energy consumption;

θ_i —coefficients of discounted standard coal for different energy sources;

δ_i —carbon emission factors for different energy sources;

Table 1. Descriptions of Variables in the Model

Variable	Definition	Unit
Carbon Emissions(C)	Carbon emissions in Sichuan Province	10,000 tons
Population(P)	Year-end resident population	10,000
Economic Development Level(A)	Per capita GDP	RMB yuan
Urbanization Rate(Ur)	Proportion of urban permanent residents to total year-end permanent population	%
Industrial Structure(Is)	Proportion of total energy consumption in GDP	%
Energy Intensity(T)	Proportion of total energy consumption in GDP	tons of CO2 per 10,000 yuan
Government Expenditure(Es)	General budget expenditure	%
Foreign Trade(G)	Proportion of total import and export trade to GDP	%

This study covers the period from 2000 to 2020. The data are collated and calculated from the "Statistical Yearbook of Sichuan Province" and the "China Energy Statistical Yearbook".

4. EMPIRICAL ANALYSIS BASED ON THE EXTENDED STIRPAT MODEL

4.1. Analysis of Ordinary Least Squares Regression Results

After conducting a correlation analysis of carbon emissions and their related explanatory variables, it is found that the correlation between population size and carbon emissions is not significant, as depicted in Table 2. Therefore, it is decided to exclude the factor of population size in subsequent analyses.

Table 2. Correlation Analysis Between Carbon Emissions and Their Influencing Factors in Sichuan Province

	lnC	lnP	lnA	lnUr	lnIs	lnT	lnEs	lnG
lnC	1	0.070	0.865**	0.849**	0.625**	-.703**	.903**	.923**
lnP		1	0.444*	0.507*	-.633**	-.593**	0.122	0.105
lnA			1	0.995**	0.218	-.964**	.879**	.840**
lnUr				1	0.161	-.966**	.854**	.824**
lnIs					1	0.017	.533*	.480*
lnT						1	-.781**	-.699**
lnEs							1	.825**
lnG								1

Note: **:The correlation is significant at the 0.01 level (two-tailed); *:The correlation is significant at the 0.05 level (two-tailed).

Considering the large number of explanatory variables, potential multicollinearity issues may arise. In order to more accurately examine the relationships between variables, this study employs SPSS 26.0 software to diagnose multicollinearity among carbon emissions and its explanatory variables. Ordinary least squares regression analysis is used to analyze the model. Detailed regression results are presented in Table 3.

Table 3. Ordinary Least Squares Regression Results

	Non-Standardized Coefficient	Standard Error	Standardized Coefficient	t	Sig.	Tolerance	VIF
A							
constant(math.)	-1.058	0.771		1.372	0.192		
lnA	0.235	0.332	0.574	0.707	0.491	0.001	1167.274
lnUr	1.500	0.654	1.056	2.294	0.038	0.003	375.273
lnIs	0.829	0.369	0.251	2.245	0.041	0.045	22.100
lnT	0.657	0.258	0.956	2.543	0.023	0.004	250.501
lnEs	0.049	0.110	0.037	0.450	0.659	0.084	11.919
lnG	0.099	0.092	0.089	1.074	0.301	0.082	12.138
F				292.914			
R ²				0.992			
Adjustment R ²				0.989			
Sig.F				0.000			

From the regression results, it can be seen that the adjusted R-squared values are close to 1, indicating that the regression equation can effectively explain the sample data. The high goodness of fit of the regression model verifies the reasonableness of the model settings. The adjusted R-squared value is 0.989, the F-test value is 292.914, and the F-test is highly significant with a p-value of 0.000. The regression equation passes the significance test, indicating a good fit. However, by observing the values of the variance inflation factors (VIF), it is found that all VIF values of the independent variables exceed 10, with the highest reaching 1167.274. This indicates a significant multicollinearity problem among the explanatory variables in the regression equation. Given this, the conventional ordinary least squares method appears inappropriate for unbiased estimation of parameters in the data series involved in this study. To ensure the reliability of the regression results, it is necessary to eliminate the interference of multicollinearity among variables. Therefore, specific methods need to be adopted to reanalyze the model through regression analysis in order to more clearly reveal the inherent relationships between variables.

4.2. Ridge Regression Estimation Results

In light of the multicollinearity issue among variables, the present study has decided to employ ridge regression method for in-depth analysis, aiming to eliminate potential influences. Ridge regression, as an improved method of ordinary least squares, is significantly advantageous in effectively mitigating the common issue of multicollinearity in panel data, thereby more accurately preserving the correlation information between independent and dependent variables. Therefore, the study relies on the STIRPAT model and employs ridge regression method for in-depth analysis. In SPSS software, the fitting process of ridge regression is accomplished using the Ridge Regression macro program.

Based on the construction of the extended STIRPAT model, LnC is set as the dependent variable, while LnA, LnUr, LnIs, LnT, LnEs, and LnG are used as independent variables. This study utilizes SPSS 26.0 software to conduct ridge regression analysis on the aforementioned variables, yielding the K-R² change plot and ridge trace plot, as depicted in Figures 1 and 2. By analyzing these two figures, we can observe that when the K value is set to 0.37, the standardized ridge regression coefficients of each variable exhibit a relatively stable trend. This finding provides important

evidence for our subsequent analysis and discussion. Therefore, the fitting results of the ridge regression with $k=0.37$ are adopted in this paper to determine the ridge regression equation.

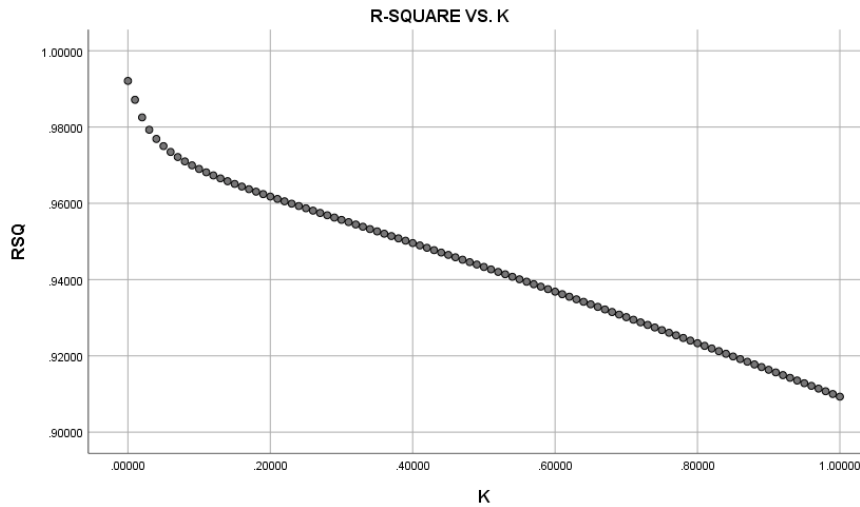


Figure 1. $K-R^2$ Plot

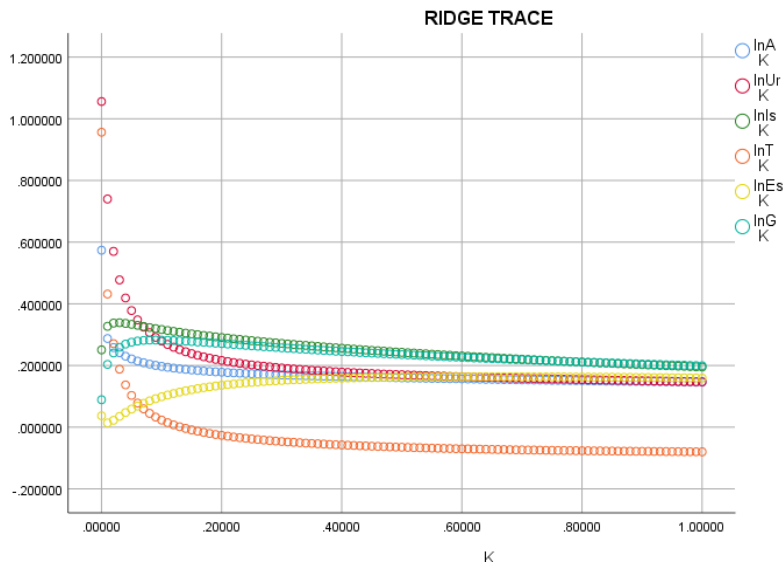


Figure 2. Ridge Trace Plot

The examination of the ridge regression equation with $k=0.37$ is conducted, and the test results are presented in Table 4. From Table 4, it can be observed that the p -values of the t -tests for each independent variable in the ridge regression are all less than 0.05, indicating that all the ridge regression coefficients of the independent variables pass the test at the 5% significance level. The adjusted R -squared value is 0.931, indicating that the explanatory power of the independent variables on the dependent variable exceeds 93.1%, demonstrating strong explanatory power. Additionally, the F -statistic is 45.699, with a corresponding p -value of 0.000, indicating that the regression equation passes the test at the 1% significance level.

Table 4. Ridge Regression Analysis Results

	Non-Standardized Coefficient	Standard Error	Standardized Coefficient	t	Sig.
A constant(math.)	4.098	0.517	0.000	7.932	0.000
lnA	0.068	0.007	0.166	9.646	0.000

lnUr	0.259	0.030	0.182	8.703	0.000
lnIs	0.861	0.131	0.260	6.580	0.000
lnT	-0.038	0.017	-0.055	-2.173	0.047
lnEs	0.210	0.048	0.157	4.412	0.001
lnG	0.276	0.047	0.249	5.941	0.000
F			45.699		
R ²			0.951		
Adjustment R ²			0.931		
Sig.F			0.000		

By substituting the regression coefficients of the model in Table 4 into Equation (3), the standardized ridge regression equation is:

$$\ln C = 0.166 \ln A + 0.182 \ln U_r + 0.260 \ln I_s - 0.055 \ln T + 0.157 \ln E_s + 0.249 \ln G$$

The non-standardized ridge regression equation is:

$$\ln C = 4.098 + 0.068 \ln A + 0.259 \ln U_r + 0.861 \ln I_s - 0.038 \ln T + 0.210 \ln E_s + 0.276 \ln G$$

Generally, the non-standardized regression model is used as the prediction model. To demonstrate the validity of this prediction model, the actual values of the six factors in Sichuan Province from 2000 to 2020 were substituted into the equation to obtain the fitted values during the study period. Comparing these fitted values with the actual values, as shown in Table 5, it was found that the errors were within a reasonable range, proving that the prediction accuracy of this equation is high.

Table 5. Comparison between actual carbon emissions and predicted carbon emissions

Year	Actual Carbon Emission (10,000 tons)	Predicted Carbon Emission (10,000 tons)	Error (10,000 tons)	Error Rate (%)
2000	12976.13	14500.55	-1524.43	-11.75%
2001	12998.18	15753.91	-2755.73	-21.20%
2002	14933.19	17537.57	-2604.38	-17.44%
2003	18904.58	18617.69	286.89	1.52%
2004	21674.17	19714.37	1959.80	9.04%
2005	22951.07	21372.15	1578.92	6.88%
2006	25334.62	24146.06	1188.56	4.69%
2007	28385.43	25388.83	2996.60	10.56%
2008	29793.08	30124.01	-330.92	-1.11%
2009	33523.58	31986.25	1537.32	4.59%
2010	34551.86	34356.36	195.50	0.57%
2011	34858.73	35503.89	-645.15	-1.85%
2012	36298.63	36608.93	-310.30	-0.85%
2013	37279.69	37262.97	16.72	0.04%
2014	38602.21	36745.45	1856.76	4.81%
2015	33061.23	33125.34	-64.11	-0.19%
2016	32509.91	31037.95	1471.96	4.53%
2017	31921.65	31699.18	222.47	0.70%
2018	31129.39	32688.21	-1558.82	-5.01%
2019	33418.36	33334.74	83.63	0.25%
2020	33853.76	34345.74	-491.98	-1.45%

4.3. Interpretation of Indicators and Data Sources

The magnitude of the absolute values of the coefficients in the standardized ridge regression equation can measure the relative importance of the corresponding explanatory factors in influencing the changes in carbon emissions. Meanwhile, the magnitude of the coefficients in the non-standardized ridge regression equation reflects the elasticity of the various influencing factors on carbon emissions. That is, the percentage change in carbon emissions resulting from a 1% change in any of the six factors: economic development level, urbanization rate, industrial structure, energy intensity, government expenditure, and foreign trade. This effect can be either positive or negative.

Through the non-standardized ridge regression equation, it can be determined that the main influencing factors and their elasticity coefficients of carbon emissions in Sichuan Province from 2000 to 2020 are as follows: the elasticity coefficients of economic development level, urbanization rate, industrial structure, energy intensity, government expenditure, and foreign trade are 0.068, 0.259, 0.861, -0.038, 0.210, and 0.276, respectively. Specifically, as the economic development level increases, carbon emissions will correspondingly increase by 0.068%. Similarly, an increase in the urbanization rate will also lead to an increase in carbon emissions, with each 1% increase in the urbanization rate resulting in a 0.259% increase in carbon emissions. Furthermore, adjustments in industrial structure also significantly affect carbon emissions, especially with a 1% increase in the proportion of the secondary industry, carbon emissions will significantly increase by 0.861%. However, an increase in energy intensity helps to reduce carbon emissions, with a 1% increase in energy intensity resulting in a decrease of 0.038% in carbon emissions. An increase in government expenditure and expansion of foreign trade also have a positive impact on carbon emissions, each increasing by 1%, leading to a rise in carbon emissions by 0.210% and 0.276%, respectively.

From the absolute values of the coefficients in the standardized ridge regression equation, it can be observed that the influencing factors of carbon emissions in Sichuan Province from 2000 to 2020, ranked in descending order of their impact (measured by the absolute values of the coefficients in the respective variables' standardized regression), are as follows: industrial structure (26%), foreign trade (24.9%), urbanization rate (18.2%), economic development level (16.6%), government expenditure (15.7%), and energy intensity (-5.5%). Notably, the impact of energy intensity on carbon emissions is negative, indicating that carbon emissions decrease with an increase in energy intensity, and conversely, carbon emissions increase with a decrease in energy intensity.

5. SUGGESTIONS

(1) The positive driving effect of the secondary industry proportion in the industrial structure on carbon emissions is most significant. Sichuan Province should pay special attention to key industries with high carbon emissions in the secondary industry, such as petroleum and natural gas industries, which are concentrated areas of carbon emissions. These industries should be encouraged to participate in carbon trading markets and issue guidelines for low-carbon transformation technologies to enhance energy utilization efficiency and production efficiency. Guided by the "5+1" modern industrial system, efforts should be accelerated to transform traditional manufacturing industries into green and low-carbon ones, cultivate advanced industries such as new materials and energy conservation and environmental protection, strengthen the green and low-carbon service industry, and develop green energy-carrying industries. At the same time, promoting the innovative application of new technologies in the energy sector, developing new economies, nurturing new drivers, strengthening support for industrial development strategies, and promoting green and sustainable development of the Sichuan economy.

(2) External trade has a strong positive impact on carbon emissions. It can be inferred that although external trade drives the economic development of Sichuan Province, it also brings pressure on resources, the environment, and carbon emissions. Therefore, Sichuan Province should actively seek

measures to control carbon emissions generated during external trade. In terms of trade, enterprises should be encouraged to produce and export low-carbon products, promote the low-carbon transformation of enterprises, and the government can provide financial and tax incentives to support the adoption of clean production technologies and green manufacturing processes by enterprises, improve the efficiency and environmental friendliness of products, while promoting and advocating the advantages of low-carbon products to enhance their competitiveness in trade. In terms of logistics, Sichuan Province can reduce carbon emissions in the logistics process by improving logistics and transportation networks, encouraging the use of low-carbon transportation tools, promoting multimodal transport and container transportation, reducing packaging waste, and selecting environmentally friendly packaging materials, thereby promoting the realization of the "dual carbon" goal.

(3) A thorough analysis of the model reveals that energy intensity has a certain inhibitory effect on reducing carbon emissions. Therefore, to more effectively implement low-carbon development strategies, it is necessary for Sichuan Province to further increase investment in energy-saving and emission-reduction technologies. This includes but is not limited to accelerating the pace of technological upgrading and actively introducing advanced energy-saving and emission-reduction technologies from both domestic and international sources. Through this approach, not only can production efficiency be improved, but energy losses in production, conversion, and consumption processes can also be reduced, thereby maximizing the goal of reducing carbon emissions. Additionally, Sichuan Province can explore and promote improvements in production processes to reduce resource waste and lower carbon emissions. This may involve adopting more environmentally friendly production methods, promoting the concept of a circular economy, and encouraging enterprises to adopt cleaner and more sustainable production practices. Through these efforts, a better balance between economic growth and environmental sustainability can be achieved, realizing controlled reductions in carbon emissions and laying a solid foundation for the sustainable development of Sichuan Province.

(4) In addressing urbanization rates, economic development levels, and government expenditures, the focus should be directed towards the following areas: Firstly, concerning urbanization rates, urban layout planning should be conducted rationally, and public transportation systems should be optimized to reduce commuting distances and time, thereby lowering carbon emissions. Secondly, regarding economic development levels, emphasis should be placed on promoting green development, increasing support for low-carbon technologies and industries, and fostering the coordinated development of the economy and environmental protection. Lastly, regarding government expenditures, efforts should be made to strengthen energy management and energy-saving measures, optimize resource allocation, enhance the effectiveness of environmental investment, and ensure a win-win situation for economic development and environmental protection.

CONFLICTS OF INTEREST

The authors declare that they have no conflict of interest.

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