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Research on the Influencing Factors of Carbon Emissions in Anhui Province based on LMDI Model and STIRPAT Model

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Abstract

Based on the improved model of Kaya identity and LMDI decomposition method, this paper conducts decomposition analysis on the influencing factors of carbon emissions in Anhui Province from 2008 to 2020. Based on the results of LMDI decomposition method, this paper uses STIRPAT model to conduct regression analysis to study the internal driving factors of carbon emissions in Anhui Province, and provides targeted carbon emission reduction suggestions. The results show that economic development contributes the most to the positive pull of carbon emissions, and energy intensity contributes the most to the inhibition of carbon emissions. Optimizing the energy structure, improving the energy utilization rate, optimizing the industrial structure, developing the economy with high quality, and improving residents' awareness of low-carbon life can all inhibit CO2 emissions.

Keywords

Kaya Identity; LMDI; STIRPAT; Anhui Province; Carbon Emissions.

1. Introduction

As a major energy province in the central region, Anhui's economy has maintained a high growth rate of 9.8% on average since 2008, which corresponds to the growing energy demand and carbon emissions year by year.Influenced by its regional energy endowment, technology, policies, etc., Anhui Province still has some difficulties in carbon emission reduction tasks.The "Fourteenth Five Year Plan" is a critical period for China to achieve carbon peak in 2035.As the capital of the first echelon of China's carbon emissions, it is of great practical significance for China to analyze the influencing factors of carbon emissions in Anhui Province and give reasonable emission reduction suggestions.

2. Literature Review

Many scholars have used different methods to decompose and analyze carbon emission factors, and given suggestions and solutions from different perspectives. Kaya proposed the Kaya identity in a report at an IPCC seminar in 1989, which is the first time that some scholars have decomposed the factors affecting carbon emissions [1]. In 1971, Ehrlich and Holdren proposed the IPAT model to consider population, wealth and technology as factors affecting the environment [2]. Then Dietz and Rosa proposed the STIRPAT model that allows the decomposition of population, wealth and technology on the basis of the IPAT model, which can flexibly incorporate different factors to analyze environmental impact factors. This model is more flexible and widely used [3]. In 1998, Sun improved the residual problem of the Laplace exponential decomposition method [4]. In 1998, Ang proposed the Logarithmic Mean weight Division Index, which was used to decompose multiple factors [5]. The residual error was zero, thus solving the residual error problem.This method has been widely used in the

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decomposition analysis of factors affecting energy and carbon emissions since it was proposed. Huang and Wang conducted regression analysis on the influencing factors of energy consumption and carbon emissions in Chongqing through STIRPAT model and ridge regression method [6]. The results show that the population has the largest impact on energy consumption and carbon emissions in Chongqing. Yu and Daconducted a decomposition analysis on the influencing factors of carbon emissions in China's transportation industry from 2005 to 2011 through LMDI model [7]. The results show that the main driving factor for the growth of carbon emissions in the industry is the increase of per capita GDP, and the decline of transportation energy intensity and transportation intensity has an inhibitory effect on carbon emissions. Fu and Ma analyzed the factors affecting China's carbon emissions from 2000 to 2012 based on the LMDI model [8]. The results show that the level of economic output, energy structure and population scale have a positive impact on carbon emissions, while energy intensity and industrial structure have a negative impact on carbon emissions.

At present, there are few studies on the decomposition analysis of the influencing factors of carbon emissions in Anhui Province. Li conducted a decomposition analysis of the influencing factors of carbon emissions in the transportation industry in Anhui Province from 2004 to 2016 based on the LMDI model [9]. The results show that the industrial structure effect inhibits the carbon emissions in the transportation industry. The economic output effect, carbon emission intensity effect, energy intensity effect and population scale effect have promoted the increase of carbon emissions from the transportation industry in Anhui Province. Wang and Zhao conducted an empirical study on the influencing factors of carbon emissions of residents' living energy in Anhui Province, Hefei City and Maanshan City from 2005 to 2016 based on the STIRPAT model. The results show that population scale and urbanization rate had a more significant inhibition on carbon emissions of high-density cities than medium-scaled cities. In medium-scaled cities, energy intensity had a slightly more significant inhibition on carbon emissions of living energy consumption than in large cities [10]. Jiang decomposed and analyzed the influencing factors of carbon emission of logistics industry in Anhui Province based on LMDI model, and gave suggestions on carbon emission reduction of logistics industry in Anhui Province [11].

In the above research on the influencing factors of carbon emissions in Anhui Province, the author's perspective and methods on carbon emissions in Anhui Province are not comprehensive enough. For example, Li and Jiang only analyzed the carbon emission factors of the transportation industry and logistics industry in Anhui Province through LMDI model, which could not fully explain the carbon emission trend and impact effects of the whole Anhui Province. On the basis of previous studies, we conducted a decomposition analysis of the factors affecting the carbon emissions of the three major industries in Anhui Province, which can more comprehensively study the carbon emissions of the whole Anhui Province. In terms of research methods, we paid attention to the internal relationship between LMDI model and STIRPAT model. First, we used LMDI model to decompose the factors affecting carbon emissions, Then, based on the results of LMDI decomposition analysis, the STIRPAT model is used to conduct regression analysis on each influencing factor. The regression equation can not only represent the impact of each influencing factor on carbon emissions, but also make a reasonable prediction of carbon emissions in Anhui Province to a certain extent. The logic is more rigorous and the results are more accurate.

The first part is introduction, which mainly introduces the background and significance of this topic. The second part is literature review, including the research status of domestic and foreign scholars on carbon emission influencing factors through LMDI model and STIPAT model, the inadequacies of research on carbon emission influencing factors in Anhui Province, and the innovation points of this paper. The third part is the research method, which explains the Kaya identity, LMDI model and STIRPAT model used in this paper. The fourth part explains the data

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sources and data processing methods in this paper. The fifth part is the empirical research results, which conducts an empirical study on the carbon emission factors of Anhui Province. The sixth part is summary and suggestions. Based on the empirical research results in the fifth chapter, reasonable suggestions are put forward for carbon emission reduction in Anhui Province.

3. Research Method

3.1. Kaya Identity and its Decomposition Form

Kaya identity:

$$C = \frac{C}{En}\frac{En}{GDP}\frac{GDP}{P\_s}P\_s \tag{1}$$

Where, C represents CO2 emissions, En represents energy consumption, GDP represents gross product (economic output level), and P_ s is the population.

Decomposition of Kaya inequality by energy type and industry type [12]:

$$C = \sum_i \sum_j C_{ij} = \sum_i \sum_j \frac{C_{ij}}{En_{ij}} \cdot \frac{En_{ij}}{En_j} \cdot \frac{En_j}{GDP_j} \cdot \frac{GDP_j}{GDP} \cdot \frac{GDP}{P\_s} \cdot P\_s \tag{2}$$

Where, Cij represents the CO2 emissions generated by class i energy consumed byj industry, Enij represents the consumption of class i energy byj industry, Enj represents the total energy consumption ofj industry, GDPj represents the economic output level ofj industry, GDP represents the total economic output, P_ s is the population scale.

3.2. LMDI Decomposition Method

Model (2) is expressed as follows based on Kaya identity expansion:

$$C = \sum_i \sum_j C_{ij} = \sum_i \sum_j \delta_{ij} \cdot en_{ij} \cdot eg_j \cdot g_j \cdot gp \cdot ps \tag{3}$$

In the above formula, δ_{ij} represents the energy emission coefficient, enij represents the energy industrial structure, egj represents the industrial energy intensity, gj represents the industrial structure, gp represents the per capita output level, and ps represents the population scale.

LMDI decomposition method includes additive decomposition method and multiplicative decomposition method. The results of the two decomposition methods are consistent. For the purpose of this paper, we consider combining model (3) and additive decomposition method to decompose the carbon emissions of energy consumption in Anhui Province into the following factors:

$$\Delta C_\delta = \sum_{i=1} \sum_{j=1} \left(\frac{C_{ij}^t - C_{ij}^0}{ln^{C_{ij}^t} - ln^{C_{ij}^0}}\right) \cdot ln^{\frac{\delta_{ij}^t}{\delta_{ij}^0}} \tag{4}$$

$$\Delta C_{en} = \sum_{i=1} \sum_{j=1} \left(\frac{C_{ij}^t - C_{ij}^0}{ln^{C_{ij}^t} - ln^{C_{ij}^0}}\right) \cdot ln^{\frac{en_{ij}^t}{en_{ij}^0}} \tag{5}$$

$$\Delta C_{eg} = \sum_{i=1}\sum_{j=1}\left(\frac{C_{ij}^{t}-C_{ij}^{0}}{ln^{C_{ij}^{t}}-ln^{C_{ij}^{0}}}\right)\cdot ln^{\frac{eg_j^t}{eg_j^0}} \tag{6}$$

$$\Delta C_{g} = \sum_{i=1}\sum_{j=1}\left(\frac{C_{ij}^{t}-C_{ij}^{0}}{ln^{C_{ij}^{t}}-ln^{C_{ij}^{0}}}\right)\cdot ln^{\frac{g_j^t}{g_j^0}} \tag{7}$$

$$\Delta C_{gp} = \sum_{i=1}\sum_{j=1}\left(\frac{C_{ij}^{t}-C_{ij}^{0}}{ln^{C_{ij}^{t}}-ln^{C_{ij}^{0}}}\right)\cdot ln^{\frac{gp^t}{gp^0}} \tag{8}$$

$$\Delta C_{ps} = \sum_{i=1}\sum_{j=1}\left(\frac{C_{ij}^{t}-C_{ij}^{0}}{ln^{C_{ij}^{t}}-ln^{C_{ij}^{0}}}\right)\cdot ln^{\frac{ps^t}{ps^0}} \tag{9}$$

In the above formula, ΔC_{δ} is the energy emission effect, which is zero because the energy emission coefficient is fixed; ΔC_{en} is the energy structure effect; ΔC_{eg} is energy intensity effect; ΔC_{g} is the effect of industrial structure; ΔC_{gp} is the effect of economic growth; ΔC_{ps} is population scale effect. The comprehensive effect of carbon emissions can be expressed as:

$$\Delta C = \Delta C_{\delta} + \Delta C_{en} + \Delta C_{eg} + \Delta C_{g} + \Delta C_{gp} + \Delta C_{ps} \tag{10}$$

3.3. STIRPAT Model

The STIRPAT model expression is:

$$I = a \cdot P^{b} \cdot B^{c} \cdot T^{d} \cdot e \tag{11}$$

Where, I is the environmental load; P is the population scale; B is the richness; T is the technical level; a is a constant term; b, c and d are exponential terms, and e are error terms. The STIRPAT model has good scalability. In addition to the independent variables in the random form of the model, other factors that affect the environment can also be introduced into the model to analyze their impact effects. The model also has the characteristics of high reliability of the analysis results, which can be used to test the significance of undetermined coefficients.

4. Data Source and Processing

In this paper, the gross output value of Anhui Province and the added value of the three major industries are from the Anhui Statistical Yearbook, and the prices in all years are normalized to the constant prices in 2008. The total number of permanent residents and population density of Anhui Province at the end of the year are from the National Bureau of Statistics; The physical energy consumption data of various industries and the standard coal conversion coefficient of various energies are respectively from the energy balance table of Anhui Province from 2008 to 2020 in the China Energy Statistical Yearbook and Appendix 4. This paper uses eight types of primary energy consumption to estimate the carbon emissions of energy consumption in Anhui Province. CO2 generated by various energy consumption is estimated by Formula (12):

$$C = \sum_{j=1}\sum_{i=1} f_i E_{ij} \tag{12}$$

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Where, C is the total carbon emission, unit: 10000 tons; fi is the standard coal to carbon dioxide coefficient of class i energy; Eij is the energy consumption of class i in j industry, with unit of 10000 tons of standard coal.The reference data for calculating fi is from IPCC. See Table 1 for the physical quantities and standard coal conversion coefficients of various energies.

Table 1. Coefficient of energy converted into standard coal and standard coal converted into CO2 emission coefficient

Energy type	Conversion coefficient of standard coal	Emission coefficient of standard coal conversion CO2
raw coal	0.7143kg-ce/kg	2.6604kg-CO2/kg-ce
Coke	0.9714kg-ce/kg	2.9446 kg-CO2/kg-ce
Crude oil	1.4286kg-ce/kg	2.1141 kg-CO2/kg-ce
Kerosene	1.4714kg-ce/kg	2.051 kg-CO2/kg-ce
Diesel	1.4571kg-ce/kg	2.1247 kg-CO2/kg-ce
Gasoline	1.4714kg-ce/kg	1.988 kg-CO2/kg-ce
Fuel oil	1.4286kg-ce/kg	2.2193 kg-CO2/kg-ce
natural gas	1.33kg-ce/m3	1.6257 kg-CO2/kg-ce

5. Empirical Research Results

5.1. Decomposition Results of Total Effects of CO2 Emissions in Anhui Province

The carbon emissions generated by energy consumption in Anhui Province from 2008 to 2020 are decomposed by Formula (4) - (10), and the effect value of each influencing factor is calculated. See Table 2.

Table 2. Breakdown of Factors Affecting Anhui's Total Carbon Emissions from 2008 to 2020 (Unit: 10000 tons)

Year	Energy structure	Energy intensity	Industrial structure	Economic growth	Population scale	Total effect
2008-2009	-41.92	-1243.21	227.11	1311.77	-6.91	246.84
2009-2010	-32.53	48.70	372.60	1897.13	-336.32	1949.58
2010-2011	-108.39	-696.58	273.56	1628.78	33.89	1131.26
2011-2012	-107.75	-445.14	131.95	1511.13	14.37	1104.56
2012-2013	48.76	-1462.10	131.76	1449.32	25.03	192.77
2013-2014	-84.19	-1006.49	48.33	1321.24	22.90	301.79
2014-2015	12.49	-756.02	-9.50	1274.62	36.55	558.14
2015-2016	-99.54	-1173.08	-34.70	1279.78	58.33	30.78
2016-2017	-71.30	-1563.16	-11.37	1243.14	62.80	-339.89
2017-2018	-114.38	-1605.15	25.06	1141.83	48.15	-504.49
2018-2019	-86.51	-761.73	24.47	1031.16	39.97	247.35
2019-2020	-60.70	690.32	83.78	590.11	33.68	1337.19
Cumulative value	-745.98	-9973.65	1263.07	15679.99	32.44	6255.88

The total contribution of industrial structure effect to carbon emissions can also be further decomposed into the contribution of each industry to industrial structure effect, as shown in Table 3.

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Table 3. Decomposition of contribution of three industries to industrial structure effect from 2008 to 2020 (unit: 10000 tons)

Year	Primary industry	Secondary industry	Third industry	Total contribution
2008-2009	-24.42	271.13	-19.60	227.11
2009-2010	-30.35	461.03	-58.08	372.60
2010-2011	-31.32	333.58	-28.69	273.56
2011-2012	-20.27	159.76	-7.54	131.95
2012-2013	-25.79	161.58	-4.04	131.76
2013-2014	-17.58	50.51	15.41	48.33
2014-2015	-16.82	-45.42	52.74	-9.50
2015-2016	-22.58	-92.04	79.91	-34.70
2016-2017	-17.10	-43.35	49.07	-11.37
2017-2018	-18.43	15.41	28.08	25.06
2018-2019	-14.29	19.85	18.90	24.47
2019-2020	-6.09	136.49	-46.61	83.78
Cumulative value	-245.03	1428.53	79.57	1263.07

The total contribution of energy intensity effect to carbon emissions can also be further decomposed into the contribution of each industry to energy intensity effect, as shown in Table 4.

Table 4. Decomposition of contribution of three industries to energy intensity effect from 2008 to 2020 (unit: 10000 tons)

Year	Primary industry	Secondary industry	Third industry	Total contribution
2008-2009	-2.34	-1106.50	-134.37	-1243.21
2009-2010	-5.36	24.60	29.46	48.70
2010-2011	14.20	-706.63	-4.15	-696.58
2011-2012	-16.52	-728.61	299.98	-445.14
2012-2013	15.44	-1796.00	318.46	-1462.10
2013-2014	-16.69	-915.68	-74.12	-1006.49
2014-2015	-39.64	-577.22	-139.17	-756.02
2015-2016	12.08	-768.87	-416.30	-1173.08
2016-2017	-20.52	-1524.82	-17.82	-1563.16
2017-2018	-22.44	-1432.31	-150.39	-1605.15
2018-2019	-37.60	-549.25	-174.88	-761.73
2019-2020	0.72	890.42	-200.82	690.32
Cumulative value	-118.68	-9190.86	-664.12	-9973.65

It can be seen from Table 2 that from 2008 to 2020, the carbon emissions of energy consumption in Anhui Province increased by 62.5588 million tons. On the whole, the energy structure and energy intensity effect had a restraining effect on carbon emissions, while the industrial structure, economic development and population scale utility had a positive pulling effect on carbon emissions.

Energy structure effect. It can be seen from Table 2 that the energy structure effect is positive only in 2012-2013 and 2014-2015, and negative in other years. The overall impact of energy structure effect on energy consumption and carbon emissions in Anhui Province is negative, which indicates that the optimization of industrial energy structure in Anhui Province has been effective.

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Energy intensity effect. The energy intensity effect reflects the industry's energy utilization efficiency. It can be seen from Table 2 that the energy intensity effect has a negative impact on the carbon emissions of energy consumption in Anhui Province. The energy intensity effect has reduced the carbon emissions by 99.7365 million tons, with a cumulative impact rate of -159.4%, which is the main restraining factor. However, the energy intensity effect has increased the carbon emissions by 6.9032 million tons in 2019-2020.It can be seen from Table 4 that among the three industries, The energy intensity effect of the secondary industry has increased carbon emissions by 8.9042 million tons, which is also the main reason why the growth rate of carbon emissions in 2019-2020 is higher than that in other years. It can be seen that the secondary industry in Anhui Province is the main energy consumption industry. In general, the energy utilization efficiency of Anhui Province has improved, especially in the secondary industry. The energy intensity effect of the secondary industry has reduced carbon emissions by 91.909 million tons.

Industrial structure effect. It can be seen from Table 2 that the effect of industrial structure on carbon emissions is generally positive, but its promotion efficiency on carbon emissions is less than the inhibition efficiency of energy intensity. It can be seen from Figure 1 that the change trend of the proportion of the added value of the secondary industry in GDP is basically consistent with the change trend of the contribution rate of the industrial structure effect to the increase of carbon emissions. Combined with the cumulative contribution of the secondary industry to the industrial structure effect in Table 3, it can be seen that the secondary industry is the main factor of the industrial structure effect.

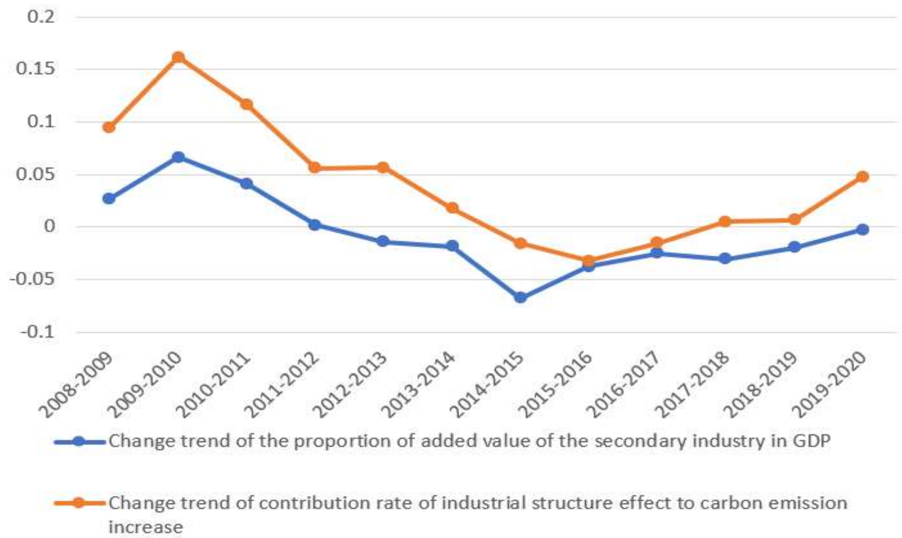

Figure 1. Change trend of the proportion of added value of the secondary industry in GDP and the change trend of the contribution rate of industrial structure effect to the increase of carbon emissions

Economic development effect. The economic development effect of all industries has a positive impact on carbon emissions in each time interval. From 2008 to 2020, the economic development effect increased carbon emissions by 156.7999 million tons, which is the leading factor driving the growth of carbon emissions. As shown in Figure 2, in the year of high economic growth rate, the effect of economic development on the increase of carbon emissions will be large. Economic development will inevitably lead to an increase in the demand for energy from the industry. Energy is the basis for development, so economic growth will inevitably lead to an increase in carbon emissions.

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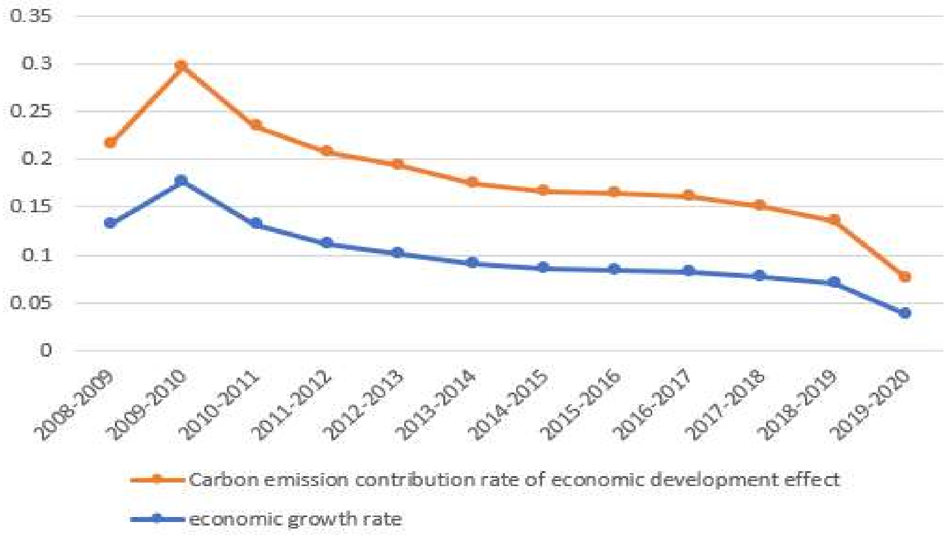

Figure 2. Trend of economic growth rate and contribution rate of economic development effect to carbon emissions

Population scale effect. The population scale effect in Anhui Province has a positive effect on carbon emissions on the whole, but the cumulative contribution rate is only 0.5%, which has a very small impact on carbon emissions. In fact, the population growth in Anhui Province from 2008 to 2020 is not obvious.In 2008-2010, the annual population growth rates of Anhui Province were -0.7% and -2.84%, respectively. In 2009-2010, due to the large negative population growth, the population scale effect reduced the carbon emissions by 3.3632 million tons. Only this year, the inhibition effect was more obvious, and the population scale effect had a stable, small and positive impact on carbon emissions in the remaining time intervals when the population growth rate was positive.People are engaged in social production and labor and daily life consumption. Population growth will drive local economic development and generate more carbon emissions from living consumption, thus to some extent, it will have a positive effect on carbon emissions.

5.2. Regression Result Analysis

Based on the results of LMDI model analysis, STIRPAT model is extended. The four factors of energy structure EN, energy intensity EG, economic development GP, industrial structure IND and population scale PS are brought into the model. However, if only the absolute number of population is used to represent the effect of population scale on the analysis of carbon emission influencing factors, there will be some deviation. Zhong believe that the change of population structure and distribution is an important factor affecting carbon emissions [13]. Therefore, this paper takes population scale PS and population density A as population scale factors. EN is the proportion of coal consumption in fossil energy consumption; EG is the energy consumption per GPD; GP is GDP per capita; IND is the proportion of the secondary industry in the GDP of Anhui Province. In order to eliminate heteroscedasticity, both sides take logarithms at the same time, and the final multiple regression model is as follows:

$$ln^{CO} = Cons + \beta_1 ln^{EN} + \beta_2 ln^{EG} + \beta_3 ln^{GP} + \beta_4 ln^{PS} + \beta_5 ln^{IND} + \beta_6 ln^{A} + \mu \tag{13}$$

Where, ln^{CO} is the interpreted variable, Representing the total CO2 emissions of Anhui Province, $Cons$ and μ are constant terms and error terms respectively, which are used to describe the interference of factors other than variables on the model.

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In the calculation of Pearson correlation coefficient of indicators, it is found that there is a high correlation between indicators, so it is not suitable to directly use the least squares estimation method for regression estimation, but use the partial least squares (PLS) [14] for regression estimation. The regression equation obtained by PLS algorithm is:

$$ln^{CO2} = 11.097 + 0.08ln^{EN} + 0.359ln^{EG} + 0.658ln^{GP} - 0.092ln^{PS} + 0.741ln^{IND} - 0.096ln^{A} \quad (14)$$

The goodness of fit of the model is 0.9959, which indicates that the model has a good degree of fit. The regression equation was tested by parameters. Under the 5% confidence level, LNEG, LNGP, LNPS, LNIND and LNA were significant. The selected indicators had good prediction effect on Anhui Province and were of reference value. See Table 5 for the results.

Table 5. Parameter significance test

Variable	Estimate	Std.Error	Df	t value	Pr(>|t|)
LNEN	0.080473	0.057065	9	1.4102	0.1921
LNEG	0.359088	0.121531	9	2.9547	0.0161 **
LNGP	0.657553	0.074890	9	8.7803	1.045e-05 ***
LNPS	-0.091676	0.013254	9	-6.9167	6.937e-05 ***
LNIND	0.541175	0.014052	9	38.5110	2.666e-11 ***
LNA	-0.096129	0.013914	9	-6.9087	6.999e-05 ***

Note: **p<0.05,***p<0.01.

According to Formula (14), for every 1% increase in energy intensity, CO2 emissions will increase by 0.359% on average; For every 1% increase in GDP per capita will increase CO2 emissions by 0.658% on average; For every 1% increase in population scale, CO2 emissions will decrease by 0.092% on average; For every 1% increase in the proportion of the secondary industry in GDP, CO2 emissions will increase by 0.741% on average; For every 1% increase in population density, CO2 emissions will decrease by 0.096% on average.

Except for population scale and population density, other impact coefficients on CO2 are positive, which is obviously in line with economic significance. Although in the LMDI decomposition analysis, the population scale effect has a positive effect on carbon emissions, combined with the population density analysis, if the absolute number of population increases, the number of households will increase accordingly, and the increase in the number of households will reduce the domestic energy consumption, thus reducing the per capita energy consumption. Therefore, in the regression model, the impact of population scale and population density on CO2 emissions is negative.

The significance test results show that the regression coefficient of energy structure on carbon emissions is not significant. In the LMDI decomposition results, although the proportion of coal consumption in fossil energy consumption decreased in 2012-2013 and 2014-2015, it is a positive effect on carbon emissions. Further decomposition of the energy structure found that although the proportion of coal decreased, the consumption proportion of coke with the largest standard coal to CO2 coefficient increased in these two years, almost consumed by the secondary industry. It can be seen that the development of Anhui Province at present mainly depends on the traditional industries that consume a lot of energy and have a high dependence on coal energy, so the energy structure has failed to pass the significance test.

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6. Summary and Suggestions

According to the LMDI decomposition analysis results and the impact of various factors in the STIRPAT model regression results on carbon emissions, optimizing the energy structure, improving energy utilization, optimizing the industrial structure, developing the economy with high quality, and improving residents' awareness of low-carbon life can all curb CO2 emissions.

Optimize the energy structure. It can be seen from Figure 3 that although the proportion of coal energy in the energy consumption structure of Anhui Province has decreased from 2008 to 2020, due to the constraints of resource endowment and other factors, the energy consumption structure of Anhui Province is still dominated by coal energy, At present, the proportion of clean energy such as natural gas in energy consumption is still some distance from the goal that the proportion of non fossil energy consumption will reach more than 15.5% by 2025 and the proportion of non fossil energy power generation will increase to about 18.1% as proposed in the Fourteenth Five Year Plan for Energy Development of Anhui Province. Therefore, Anhui Province should continue to optimize the energy structure and increase the proportion of non fossil energy in energy consumption.

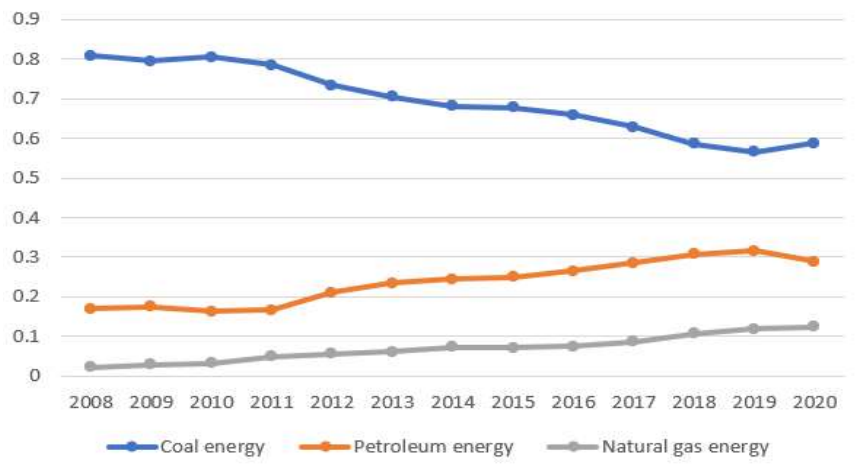

Figure 3. Proportion of energy consumption in Anhui Province

Improve energy utilization. The most fundamental driving force to improve energy utilization is the progress of science and technology. To improve the application of energy in various industries, Anhui Province should increase its investment in scientific research after the 13th and 14th Five Year Plan, set up more energy research institutes, focus on the introduction of talents, accelerate the pace of scientific and technological progress in Anhui Province, and adopt more advanced technologies to transform and upgrade traditional industries. At the same time, the relevant government departments should more strictly supervise the energy consumption intensity of enterprises and put forward higher requirements and standards for resource recycling. It is necessary to implement the corporate responsibility system, urge enterprises to implement the responsibility of waste recycling and disposal, promote the link between production and the ecosystem, and achieve a high resource utilization efficiency level in the production activities of the whole society.

Optimize the industrial structure. At present, Anhui Province belongs to the industrial distribution with a small proportion of the primary industry and a small gap between the proportion of the secondary and tertiary industries. The secondary industry is the most energy dependent industry. Optimizing the industrial structure and increasing the proportion of the tertiary industry can effectively reduce energy consumption. Although the proportion of the tertiary industry has been growing since 2008-2020, there is still a certain gap referring to the

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proportion of the tertiary industry in developed countries, This also means that there is still much room for the development of the tertiary industry. The Anhui provincial government should vigorously encourage the development of the service industry, information industry, catering industry and other tertiary industries.

High quality economic development. To achieve high-quality economic development, Anhui Province should improve the supply side reform, optimize the allocation of production factors, and improve the quality and quantity of economic development; Convert some traditional industries with overcapacity and serious pollution to light and green industries; The government optimizes its business process, creates a transparent, stable and predictable good market operating environment, and provides important support for high-quality economic development.

Improve residents' awareness of low-carbon life. Vigorously promote and publicize the green life concept of "low carbon, environmental protection and health" throughout the province, and build the whole society into a strong energy conservation and environmental protection atmosphere of "low carbon life and environmental protection". At the same time, in the market, increase the supply of green products, solve the problem of insufficient supply of green products, and encourage and guide residents to consume green products.

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