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Original Research

Analysis of Influencing Factors of CO_2 Emissions in China's Power Industry and Policy Implications

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Abstract

The Chinese power industry's CO_2 emissions account for the largest proportion of the country's total CO_2 emissions. Therefore, studying the influencing factors of CO_2 emissions in the power industry and developing mitigation policies are of great significance for reducing CO_2 emissions. According to the electricity-related data from 2000 to 2014 in China, this paper employed the improved STIRPAT model to examine the impact factors of economic growth, urbanization level, industrialization level, power consumption efficiency, power generation efficiency, and electric power structure of the CO_2 emissions in China's power industry. Then we adopted the Ridge Regression method to fit the extended STIRPAT model. The results show that power generation efficiency is a decisive factor of CO_2 emissions reduction. Electric power structure and economic growth play important roles in reducing CO_2 emissions. Power consumption efficiency has a large potential to mitigate CO_2 emissions, while urbanization and industrialization levels are less important impact factors. Based on the above conclusions, the Chinese government needs to formulate appropriate policies in terms of power generation, supply, and consumption to reduce the power industry's CO_2 emissions.

Keywords: power industry, CO_2 emissions, STIRPAT models, ridge regression

Introduction

Since the industrial revolution, with the global greenhouse gas emissions surge, the climate has undergone dramatic changes. At the same time, extreme weather phenomena have increased annually and the global warming trend is more and more obvious. The fifth assessment report (2013) of the Intergovernmental Panel on Climate Change (IPCC) pointed out that there is no doubt the climate system is warming. Since 1950, many changes observed by the climate system have been unprecedented over the past few decades or even thousands of years. From 1880 to 2012, the global mean temperature of sea and land surface increased linearly by 0.85ºC [1]. The reason is the excessive production of carbon dioxide, methane, and other greenhouse gases in human production and life, leading to a significant increase in greenhouse gas concentrations in the global atmosphere, which exceeds the capacity of the Earth's own regulation. As a result, global temperatures have risen significantly. Human

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activities will change the environment, which has become an indisputable fact.

With rapid economic development, China has made remarkable achievements. But the extensive economic growth model caused a lot of energy consumption and low efficiency of energy use, resulting in a sharp rise in air pollution emissions – especially carbon dioxide. At present, China has become the world's largest carbon emitter [2]. In 2009, in order to reduce greenhouse gas emissions, the State Council executive conference proposed a restrictive target of "CO_2 emissions per unit of GDP in 2020 that will decline by 40-45% compared to that in 2005" [3].

Electric power is an indispensable high-quality energy for social and economic development. China's electric power consumption accounting for the proportion of total energy consumption increased continuously: the proportion was only 9.53% in 1991 but it has reached 22.56% in 2012. In addition, the CO_2 emissions in China's power industry accounted for 48.79% of total CO_2 emissions [4]. Due to the restriction of the natural resource structure, China's electric power production is dominated by thermal power. Moreover, the thermal power production mainly depends on coal. As we all know, fossil energy combustion is the culprit of large amounts of CO_2 emissions. Therefore, in order to complete China's energy-saving emission reduction targets, we must pay attention to the power industry's CO_2 emissions reduction.

Research on the driving factors of CO_2 emissions at the international level started early and the research results are more abundant. A large number of quantitative models and statistical analysis methods are used in the research methods. Paul and Anne Ehrlich [5] proposed the IPAT equation, which indicated that the combined influences of factors such as population scale, economic development, and technological progress are the main driving factors of CO_2 emissions. Dietz and Rosz [6] constructed the STIRPAT model, which is the random form of the IPAT equation. They tried to introduce more relevant factors and study the impact of human factors on the natural environment. York et al. [7] studied the relationship between CO_2 emissions and population using the STIRPAT model. Ramanathan [8] employed data envelopment analysis (DEA) to analyze the relationship between CO_2 emissions, gross domestic product (GDP), and energy consumption. Dalton et al. [9] adopted a population-environment-technology model (PET model) to conduct an empirical study of CO_2 emissions. The results demonstrated that there was a positive correlation between GDP and CO_2 emissions, and it is also found that population structure was one of the factors affecting CO_2 emissions. Stretesky and Lynch [10] used the fixed effect model to analyze data from 169 countries between 1989 and 2003, and the results indicated a significant relationship between U.S. exports and per capita carbon emissions. Through the IPAT equation, Hubacek et al. [11] found that population growth had no significant effect on China's CO_2 emissions. The growing economy was the main driver of China's CO_2 emissions growth.

Although China's research on CO_2 emissions started late, in recent years there has been much fruitful research. Zhao and Long [12] established the Jiangsu CO_2 emissions influencing factors model and utilized LMDI decomposition analysis of population, economy, and science and technology investment on the impact of CO_2 emissions in Jiangsu. According to the LMDI decomposition method, Tan et al. [13] explored the driving factors affecting China's carbon intensity and found that the power industry played an important role in reducing the intensity of CO_2 emissions in China. From the perspective of China's electricity consumption, Zhang [14] conducted a scenario analysis on the carbon emissions intensity of electricity consumption in 2020. The results forecasted that China's carbon emission intensity is expected to decrease by 33-37% compared to 2007. Wang et al. [15] adopted the logarithmic mean weight Divisia decomposition method to construct the decomposition model of the per capita carbon emission factors in the coastal areas of Jiangsu Province. Shen [16] used the vector autoregressive model (VAR model) and the granger causality test to study the long-term and short-term causal and dynamic relationships between China's carbon emissions, economic growth, and energy consumption. By applying the data envelopment analysis (DEA) model, Lin and Fei [17] researched the influences of technologically improving on carbon emission reduction in China's agriculture sector and indicated that the two components play a key role in final carbon emissions performance. Using the panel data model, Xu and Lin [18] and He and Wang [19] suggested that economic growth and increase in population have a positive effect, and that technological improvements help reduce China's CO_2 emissions.

In recent years, the STIRPAT model has been widely applied by more and more researchers. Song et al. [20] constructed the STIRPAT model to study the impact of population scale, population structure, consumption structure, and energy intensity on CO_2 emissions in China. Using the STIRPAT method, Zhu and Zhang [21] studied the relationship between population, urbanization, per capita GDP and CO_2 emissions in Beijing. They proposed the necessary measures for carbon reduction in Beijing and provided a reference for Beijing to achieve high-quality economic development in the future. All of the studies outlined above prove that STIRPAT is an efficient model for examining the impact factors of CO_2 emissions.

Previous studies paid attention to population, economic, and technical levels, and seldom focused on power industry-related indicators. In addition, the STIRPAT model most widely used in studies involves ordinary least squares (OLS) regression, which may lead to unreliable regression coefficients. To the best of our knowledge, there are no reports in the literature that use the STIRPAT model fitted by the ridge regression method to analyze the influencing factors of CO_2 emissions of the whole power industry in China. Compared with other papers, the innovation in and contribution of this paper lies in its examination of the following impact factors: GDP, urbanization level, industrialization level, power consumption efficiency, power generation efficiency, and electric power structure on the power industry's CO_2 emissions in China. These influencing factors can reflect the characteristics of the power industry. For instance, this paper introduced two indicators – power generation efficiency and power consumption efficiency – to study the energy efficiency of the electric power production side and demand side. Furthermore, in order to avoid multiple collinearity, we used the ridge regression method that replaced OLS regression to fit the extended STIRPAT model.

Material and Methods

Estimating CO_2 Emissions of the Power Industry

Since China has not yet announced CO_2 emissions in the power sector, it is necessary to estimate CO_2 emissions. Based on data on various energy consumption in the power industry, and their CO_2 emissions factors from the 2006 IPCC reports [22], we calculate the power industry's CO_2 emissions from 2000 to 2014. Then, the calculation method is as follows:

$$\mathrm{C} = \sum_i E_i \cdot K_i \cdot \varepsilon_i \cdot \eta_i \cdot \frac{44}{12} \tag{1}$$

…where C represents the power industry's CO_2 emissions, i is energy type, E refers to energy consumption, K denotes the average low calorific value, ε is the carbon content of the energy, and η represents to the carbon oxidation factor (which is usually replaced by constant 1).

Extended STIRPAT Model

The STIRPAT model (Eq. (2)) is usually employed to analyze pollutant emissions factors. It was proposed by Dietz and Rosa [6] in 1997 as a basic:

$$I = aP^b A^c T^d \mathrm{e} \tag{2}$$

The meaning of each variable is shown in Table 1.

Eq. (2) may be converted to logarithmic form:

$$InI = Ina + bInP + cInA + dInT + Ine \tag{3}$$

Table 2. Symbols and meanings of factors.

Variable	Definition
CO_2	CO_2 emissions in China's power industry
POP	Population scale
GDP	Level of economic development
ENE	Energy production input divided by its physical output

In order to study the impacts of the driving forces on CO_2 emissions in China's power industry, Eq. (3) can be rewritten as follows:

$$lnCO_2 = a + blnPOP + clnGDP + dlnENE \tag{4}$$

The definition of each abbreviation is shown in Table 2.

To further our study of the impact factors from power industry CO_2 emissions, the STIRPAT model is expanded by combining urbanization, industrialization, power consumption efficiency, power generation efficiency and electric power structure. But, for a variety of reasons, the factor of population size is excluded.

Firstly, in most of the existing literature about influencing factors of CO_2 emissions, urbanization and industrialization are indispensable indicators. Because China is in a stage of rapid development, there is lots of demand for power energy. Hence, urbanization and industrialization are adopted into the model of the power industry's CO_2 emissions.

Secondly, since 1971 China has fully carried out family planning. The population growth rate slows down, so the influence of demographic changes on the power industry's CO_2 emissions is insignificant.

Thirdly, China is the largest power generation country in the world. Thermal power is the major method of power generation in China, which makes coal the main raw material. Coal will be the major energy of China's power industry for a long time [23]. As we all know, a large number of coal combustion will exacerbate CO_2 emissions [24]. Therefore, electric power structure (EPS) factors (the amount of thermal power generation divided by the total electricity production) are applied to this study.

Finally, the innovation of this paper is that we consider the power efficiency in both the power production and demand sides. The power generation efficiency on the production side and the power consumption efficiency

Table 1. Symbols and meanings of variables.

Variable	Representative	Variable	Representative
a	Intercept term	b	Elasticities of environmental impact with P
P	Size of the population	c	Elasticities of environmental impact with A
A	Country's affluence	d	Elasticities of environmental impact with T
T	Technological progress	e	Random disturbance

on the demand side will both have a crucial impact on the decrease of carbon emissions in the power industry. Therefore, on the production side, we use power generation efficiency (PGE) to represent power generation standard coal consumption, and the unit of PGE is gram per kilowatt hour. On the demand side, we adopt the GDP output value under the unit of power consumption to indicate power consumption efficiency (PCE), and PCE is proxied with total GDP divided by the power consumption (yuan per kilowatt hour).

The extended STIRPAT model can be established as:

$$lnCO_2 = a + \beta_1 lnGDP + \beta_2 lnURB + \beta_3 lnIND + \beta_4 lnPCE + \beta_5 lnPGE + \beta_6 lnEPS \tag{5}$$

…where CO_2 represents CO_2 emissions in China's power industry (10^4 tons), GDP is the economic growth level, URB represents urbanization level (%), IND is the industrialization level (second industry GDP divided by total GDP), PCE represents power consumption efficiency (yuan per kilowatt-hour), PGE represents power generation efficiency (gram per kilowatt hour), and EPS indicates the electric power structure (the amount of thermal power generated divided by total electricity production).

Multicollinearity Test

Multicollinearity refers to the exact correlation or high correlation between the explanatory variables in the linear regression model, which makes the model estimates distorted or difficult to estimate. If there are serious multicollinearities between variables, the coefficients fitted under the ordinary least squares method cannot be reliably guaranteed. In general, we employ the ordinary least squares (OLS) regression and variance inflation factor (VIF) to test whether there is significant multicollinearity between variables. If the value of the variance inflation factor (VIF) is greater than 10, we believe that the variables have multicollinearity problems [25]. The larger the variance inflation factor, the stronger the multicollinearity.

Ridge Regression

According to the studies of Wang et al. [26], we briefly summarize the ridge regression method. The multiple linear regression equation is as follows:

$$Y = X\beta + \varepsilon \tag{6}$$

…where X represents an $n \times p$ matrix of independent variables, β is a $p \times 1$ vector of unknowns, and ε notes an n-dimensional random vector. The least squares estimate of parameter β is $\hat{\beta} = (\acute{X}X)^{-1}\acute{X}Y$. When there is a high degree of collinearity between the independent variables, there are $\acute{X}X \approx 0$. The least squares estimator $\hat{\beta}$ may be extremely unstable, which may result in a lack of reasonable meaning for the parameter estimates. Ridge regression means that a set of positive matrix kI (k>0) (ridge parameters) is added to the $X'X$ matrix, which can eliminate multiple collinearity and maintain general stability. The general form of the ridge regression estimation is as follows:

$$\hat{\beta} = (X'X + kI)^{-1}\acute{X}Y \tag{7}$$

...where k is the ridge parameter. In fact, the ordinary least squares estimate is a special ridge regression estimate. When the ridge parameter k = 0, the ridge regression estimate $\hat{\beta}(0)$ is actually the ordinary least squares estimate. Since ridge parameter k is not uniquely determined, the ridge regression estimation $\hat{\beta}(k)$ obtained by the ridge regression method is an estimated family of the regression parameter β.

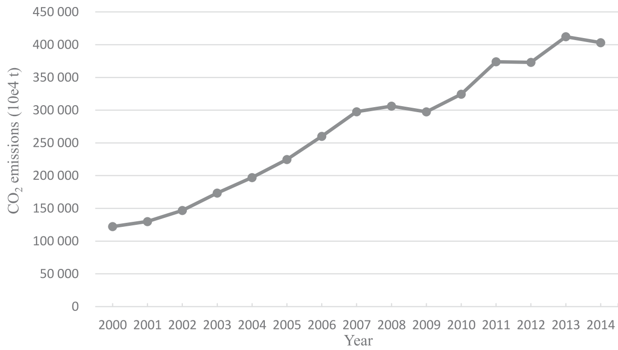

Fig. 1. CO_2 emissions in China's power industry (10e4 tons) from 2000 to 2014.

Data

Data Source

The sample data (2000-14) is obtained from China Statistical Yearbook (2001–15) [27] and China Electric

Table 3. Meanings and units of factors.

Variable	Definition	Units of measurement
CO_2	Total CO_2 emissions in the power industry	10^4 tons
GDP	Per capita GDP	Yuan
URB	Urbanization level	Percent
IND	Industrialization level	Percent
PCE	Power-consuming efficiency on the demand side	Yuan per kWh
PGE	Power generation efficiency on the production side	Gram per kilowatt hour
EPS	Electric power structure	Percent

Table 4. Statistical description of factors.

Variable	Mean	Std. dev.	Min	Max
CO_2	269,531.4	99,508.57	122,296.2	412,298.5
GDP	16,021.96	6,427.102	7,816.298	26,979.31
URB	45.74020	5.984126	36.21975	54.77036
IND	39.90730	1.748807	35.86056	42.21213
PCE	8.801065	1.551674	7.176291	11.43577
PGE	330.6000	23.16648	295.0000	363.0000
EPS	80.65215	2.029716	75.24658	82.97696

Power Yearbook (2001-15) [28]. The per capita GDP is calculated at fixed prices (2000 = 100). All variables are converted to logarithmic form to prevent heteroskedasticity. According to Eq. (1), we can obtain the 2000-14 CO_2 emissions in the power industry, as shown in Fig. 1. Table 3 shows the definition and unit of the variables. Table 4 shows the statistical description of variables.

Data Description

As shown in Fig. 2, these two indicators of GDP per capita and urbanization levels show a synergistic growth

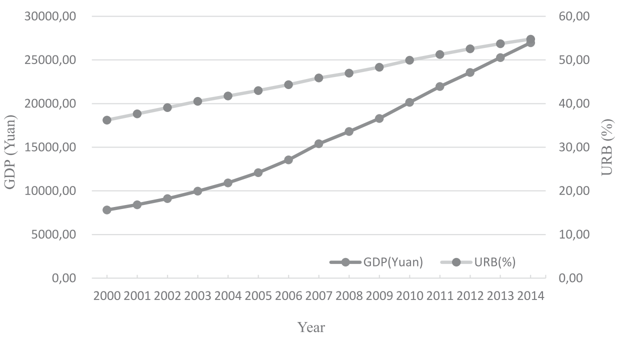

Fig. 2. Changes of GDP and urbanization in China from 2000 to 2014.

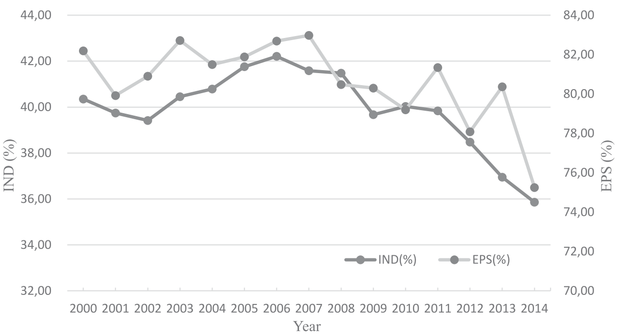

Fig. 3. Changes of industrialization and EPS in China from 2000 to 2014.

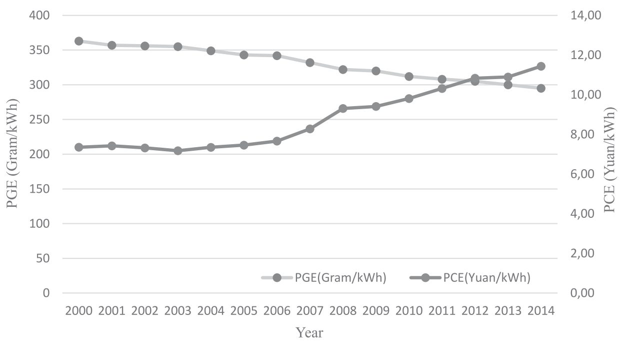

Fig. 4. Changes of PGE and PCE in China from 2000 to 2014.

situation. Fig. 3 shows changes of industrialization levels and electric power structure in China from 2000 to 2014. The electric power structure shows a fluctuating characteristic, but there has been an overall downward trend since 2008, while industrialization levels showed an inverted "U-shaped" form. As we can see from Fig. 4, the power-consuming efficiency on the demand side performed rapid growth. In addition, the power generation efficiency also continuously improved, which was because standard coal consumption has been declining since 2000.

Results and Discussion

Results of Multicollinearity Test

Multicollinearity refers to the existence of a highly linear correlation between explanatory variables in a multivariate regression model. It will lead to the widening of the variance of the least squares parameter estimator and the unreasonable economic meaning of the parameter estimator.

Above all, each variable underwent logarithmic processing in order to avoid the influences of the variable's dimension [29-30]. Furthermore, a correlation test of each variable was carried out by SPSS statistical software. It was evident from Table 5 that there were relatively high correlations among the variables GDP, URB, IND, PCE, PGE, and EPS. Therefore, it can be determined that there were high correlations among the variables.

In the next stage, the ordinary least square (OLS) estimation was carried out for each variable using SPSS. The results are shown in Table 6. It is generally believed that multiple collinearity is determined by OLS regression and variance inflation factor (VIF) value. The VIF threshold is typically 10. If the VIF value is greater than 10, it indicates that there are multiple collinearity problems; otherwise it does not exist. As can be seen from Table 6, the VIF is much higher than 10. Besides, the logarithmic coefficient of per capita GDP and URB are as high as 1,179 and 795, which indicates serious multiple collinearity between variables. Therefore, it cannot be judged according to the results of ordinary least squares

Table 5. Results of correlation test.

	lnGDP	lnURB	lnIND	lnPCE	lnPGE	lnEPS
lnGDP	1	-	-	-	-	-
lnURB	0.998**	1	-	-	-	-
lnIND	-0.542*	-0.529*	1	-	-	-
lnPCE	0.955**	0.938**	-0.682**	1	-	-
lnPGE	-0.990**	-0.983**	0.620*	-0.983**	1	-
lnEPS	-0.587*	-0.575*	0.797**	-0.709**	0.661**	1

Notes: * Correlation is significant at the 0.05 level.
** Correlation is significant at the 0.01 level.

fitting. Only by eliminating the multicollinearity of the independent variables can we obtain robust results.

Results of Ridge Regression Estimation

In order to overcome the influence of multicollinearity problems between variables, ridge regression was employed to estimate the regression model. The relationship between R square and k was deduced, as shown in Fig. 5.

It can be seen from Fig. 5 that when K = 0.02 the prediction error is small, the value of R square tends to be stable, and the model has a high degree of fit. Thus, we chose K = 0.02 to perform ridge regression in this paper. Table 7 shows the results of the ridge regression estimates.

Ridge Regression Estimates

As shown in Table 7, The F-statistic of ridge regression was 58.7882, which passed the significance test at the 5% significance level. In addition, the ridge regression coefficients of all variables passed a 5% significance level test. The VIF test value of each variable is less than 10. R square is 0.978, indicating that the overall model fit very well. Thus, the ridge regression equation can be obtained from Table 7, as shown in the following equation:

$$lnCO_2 = 3.427 + 1.082lnGDP + 0.316lnURB + 0.308lnIND - 0.815lnPCE + 1.410lnPGE + 1.224lnEPS \quad (8)$$

Discussion

Based on the above results, Eq. (8) indicates the direction and contribution of each driving factor to CO_2 emissions. It is apparent that GDP, urbanization level, industrialization level, power generation efficiency, and electric power structure have positive effects on CO_2 emissions. On the contrary, the improvement of power consumption efficiency leads to an adverse impact on CO_2 emissions. Among them, power generation efficiency has the most significant impact on CO_2 in the power industry. The impact of electric power structure, economic growth, power consumption efficiency, urbanization level, and industrialization level are decreased in turn.

Power generation efficiency is the most important factor to effect CO_2 emissions in the power industry. The elastic coefficient of the power generation efficiency is 1.410, which means that every 1% growth in power generation efficiency will lead to a 1.410% increase

Table 6. Results of OLS Regression.

	Unstandardized coefficients	t-Statistic	Sig.	VIF
C	0.367	0.021	0.984	-
lnGDP	1.206	1.627	0.142	1179.165
lnURB	0.124	0.065	0.950	795.050
lnIND	0.845	2.077	0.071	4.094
lnPCE	-0.872	-1.417	0.194	139.688
lnPGE	0.929	-0.368	0.723	392.026
lnEPS	0.949	1.381	0.205	3.808
R square	0.996	-	-	-
F-statistic	350.691	-	-	-
Sig.	0.000	-	-	-

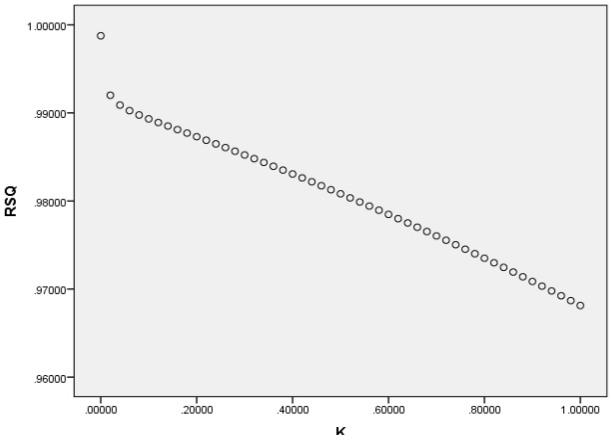

Fig. 5. Relationship variation between R^2 and K.

Table 7. Results of ridge regression.

	Unstandardized coefficients	Standard Errors	t-Statistic	Sig.	VIF
C	3.427	3.509	0.976	0.036	0.832
lnGDP	1.082	0.021	14.820	0.001	0.665
lnURB	0.316	0.093	11.604	0.001	0.408
lnIND	0.308	0.467	2.316	0.049	0.317
lnPCE	-0.815	0.905	3.399	0.009	0.627
lnPGE	1.410	0.105	-13.416	0.001	0.674
lnEPS	1.224	0.832	1.471	0.018	0.419
R square	0.978	-	-	-	-
F-statistic	58.788	-	-	-	-
Sig.	0.0000035	-	-	-	-

in the power industry's CO_2 emissions. In recent years, the increased investment in research on energy-saving technology caused power generation standard coal consumption continuing decline. In 2014, China's power generation average coal consumption is 295 g/kWh and was reduced by 68 g/kWh compared with that in 2000, which already reached the world advanced level. Coal is the main energy resource of China's thermal power generation [31]. Coal combustion will release a lot of carbon dioxide, which is the culprit of CO_2 emissions in China's power industry. Therefore, the improvement of power generation efficiency is conducive to reducing coal consumption and carbon dioxide emissions.

Optimization of electric power structure has a significant effect on the CO_2 emissions in the power industry. Its elasticity coefficient is 1.224, indicating that CO_2 emissions increase by 1.224% for every one percentage point rise in the electric power structure, which represents the proportion of thermal power generation to total power generation. As we all know, although nuclear power, hydropower, wind power, and many other clean energies accounted for a slight increase in the proportion of power generation in recent years, thermal power generation in China occupies a dominant position (accounting for 75.25% in 2014) owing to resource constraints. The large amount of coal consumption will undoubtedly exacerbate environmental pollution such as CO_2 emissions [32]. Therefore, the low proportion of thermal power is more conducive to reducing carbon emissions.

Economic growth also contributes a prominent, positive impact on CO_2 emissions in the power industry. The elastic coefficient of GDP is 1.082, which implies that a GDP increase of one point will result in CO_2 emissions increasing by 1.082%. At the present stage, export is one of the three driving forces of economic growth in China. China's exports are mostly energy and labor-intensive products such as chemicals, textiles, and household appliances. Production activities of these products consume lots of electrical energy and high-polluting coal [33]. From 2000 to 2014, average annual power consumption was 32.85 billion kWh, which meant that with economic development, electric power consumption was also increasing. Therefore, economic development comes at the cost of large amounts of electric power consumption, which will emit large-scale CO_2 emissions [34].

Power consumption efficiency, namely the value of GDP per unit of kWh, has a significant effect on the decline of CO_2 emissions in the power industry. Power consumption efficiency is negatively correlated with CO_2 emissions with a coefficient of elasticity of -0.815, indicating that a 1% increase in power consumption efficiency results in a reduction of 0.815% in CO_2 emissions. Efficiency was only 7.35 yuan per kWh in 2000 but rose to 11.44 yuan per kWh in 2014. This indicates that over the past decade, with the development of R&D investment in energy-saving, China's electric power consumption efficiency continues to increase. As we all know, the higher the efficiency of electricity use, the more help to save electricity and mitigate CO_2 emissions in the power industry [35]. In the long run, the improvement of power consumption efficiency is one of the main driving forces for reducing power industry CO_2 emissions [36].

The level of urbanization mainly reflects the impact of changes in population structure on CO_2 emissions in the power industry. This effect also has a positive impact. The coefficient of urbanization level is 0.316, indicating that every 1% of the increase in urbanization level will lead to an increase of 0.316% in the power industry's CO_2 emissions. The average annual growth rate of urbanization level is 1.27% from 2000 to 2014. The process of urbanization has promoted the rapid increase in CO_2 emissions from two aspects. On the one hand, the increase in the proportion of urban population directly contributed to the growth of spending power, eventually leading to the rise in urban electric power consumption. On the other hand, urban population growth led to a large amount of urban infrastructure construction, which consumes a great amount of electricity. In fact, production activities consume lots of energy and produce CO_2 emissions [37]. Therefore, the rapid growth of the population will inevitably lead to an increase in total amount of CO_2 emissions in the power industry.

Compared with other factors, the impact of the industrialization level is relatively slight. This factor represents the proportion of secondary industry GDP to total GDP. The elastic coefficient of the industrialization level is 0.308. In recent years, China's economic growth depends mainly on construction and real estate. The growth of the construction industry expands the demand for electric power, leading to a rapid increase in CO_2 emissions of the power industry [38].

Conclusions

Based on the extended STIRPAT model, this paper adopted the ridge regression method to analyze the driving factors of CO_2 emissions in China's power industry from 2000 to 2014. The results of empirical analysis showed that power generation efficiency is a decisive factor affecting CO_2 emissions. The electric power structure and economic growth level play significant roles in reducing CO_2 emissions. Power consumption efficiency has great potential to mitigate CO_2 emissions. However, urbanization and industrialization levels have a slight effect on the power industry's CO_2 emissions. In order to effectively control and mitigate the total amount of CO_2 emissions in China's power industry and promote economic harmonious and sustainable development, the central government should take measures from the following several aspects:

First, the most important thing is to improve power generation efficiency and reduce the power generation standard coal consumption. Power plants should increase R&D investment and improve production technology from the three aspects of coal, plant power consumption rate, and boiler equipment. First of all, for coal preparation, thermal power plants should focus on coal quality screening and monitoring to ensure that coal is easily made into powder and fully combusted to release large amounts of heat. Fine pulverized coal not only improves the efficiency of coal use, but also reduces the boiler loss rate. In addition, installing and utilizing online coal quality supervision devices will be beneficial to effectively improving coal burning efficiency. Moreover, power plants should improve power consumption efficiency by improving major energy-use equipment, such as the introduction of a medium-speed pulverizer direct-fired system and cold primary air fan system. Finally, powerplants should replace original boilers with circulating fluidized bed boilers to improve thermal efficiency. The average thermal efficiency of the old boiler units in many power plants is only about 60%. Not only is fuel utilization low, but air pollution also is serious. Some thermal power plants have transformed the old boiler into a circulating fluidized bed boiler, which achieves better energy efficiency along with environmental and economic benefits.

Second, the government should optimize the electric power structure and appropriately reduce the proportion of thermal power generation. As we all know, the power industry's CO_2 emissions is mainly due to coal combustion in thermal power plants. In contrast, hydropower, wind power, photovoltaic, nuclear power, and other clean energy has little impact on the environment. On the one hand, the government should develop hydropower resources and expand the scope of the allocation of hydropower resources. At the same time, wind and solar energy resources should be widely developed. In addition, the government should also vigorously promote the layout of eastern coastal nuclear power. On the other hand, the government should strictly control the planning and construction of thermal power plants and appropriately promote cogeneration and low calorific value coal power generation projects. During the 13th Five-Year Plan, China will cancel and delay thermal power construction projects by more than 150 million kilowatts. By 2020, the national thermal power installed capacity will be expected to control within 1.1 billion kilowatts.

Third, the government should insist on sustainable development and accelerate the transformation of economic growth. The economic development model should be transformed from high energy consumption and low efficiency modes of economic growth to knowledge-intensive and technology-intensive modes of economic growth. Moreover, the government should promote economic and environmental coordination and sustainable development. Only then can enterprises reduce energy consumption and CO_2 emissions while ensuring economic development.

Fourth, power consumption efficiency should be effectively improved through technical, financial, and incentive policies and a smart grid. Major enterprises should learn advanced power technology from developed countries, narrowing the technical differences. The high power-consuming enterprises should also develop energy-saving technologies, update electrical equipment, and improve terminal power efficiency. Moreover, the National Development and Reform Commission should formulate an appropriate electricity price ladder through policy measures to make high-power enterprises save electricity and improve power consumption efficiency. Overall, the government should build a smart grid. The smart grid is a collection of information technology, communications technology, power grid technology, and a series of advanced technology set in a power grid, with reliable, self-healing, economic, compatible, integration, and security features. A smart grid for users and businesses is a win-win choice. Users can freely choose high-quality electricity based on power information. The power grid on the user information collection will help to strengthen power management, reduce power loss, provide users with diversity services, and change the power grid enterprise economic development.

Finally, urbanization and industrialization levels played relatively minor but important positive effects on the power industry's CO_2 emissions, compared with the four main contributing factors (e.g., power generation efficiency, electric power structure, economic growth, and power consumption efficiency). Moreover, the positive effects of urbanization on CO_2 emission growth were stronger than those of industrialization. The rapid growth of living standards and consumption levels of urban residents will put continuously growing demands on the production and supply of electricity and heating power. Therefore, decreased coal use and increased non-fossil energy consumption for power generation will be of great help for CO_2 emissions abatement. In addition, it is crucial to increase environmental awareness of residents and enterprises so that they will take appropriate actions on reducing their carbon footprint in their daily lives and their production activities during the process of urbanization and industrialization. The government should also catch particular attention for the balance between economic benefit and CO_2 emissions mitigation pressure.

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