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Can Government Environmental Willingness Promote Total Factor Carbon Efficiency?− Evidence from China's Provincial Level

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Abstract: *This study takes the panel data of 30 provinces and cities in China from 2010 to 2019 as the research object. Python software is used to analyze the text of local government work reports, and counts the frequency of words related to environmental protection and their proportion in the full text in order to measure government environmental willingness. EBM-global Malmquist model is employed to measure total factor carbon efficiency; the entropy method is used to calculate the quality index of economic development. The research results show that: (1) Government environmental willingness doesn't promote total factor carbon efficiency, but inhibit total factor carbon efficiency. If the variable is replaced, the results are still valid. (2) The mediating effect results show that there is a channel of "enhancing government environmental willingness-reducing quality of economic development-reducing total factor carbon efficiency". (3) The moderating effect results show that the Gini coefficient strengthens the inhibitory effect of government environmental willingness on total factor carbon efficiency, that is, with the expansion of income gap, the inhibitory effect of government environmental willingness on total factor carbon efficiency will increase. (4) The machine learning method can improve the goodness of fit to the regression, and the importance map of variables shows that the most important thing for improving the total factor carbon efficiency is to optimize the industrial structure.*

Keywords: *Government Environmental Willingness, Total Factor Carbon Efficiency, Text Analysis, Mediating Effect, Moderating Effect*

1. Introduction

Global warming is a common environmental problem faced by human beings, which is closely related to the sustainable development of China's economy. The issue of carbon emissions affected by global warming has received increasing attention. The global emission reduction mechanism led by Kyoto Protocol has been formed. As a big country of CO2 emissions, China's carbon emission reduction has become a hot topic in the global academic circles. In response to climate change, China promises to strive to achieve a carbon peak in 2030 and a carbon neutralization in 2060. Under the condition of market economy, rational enterprises, as the main body of wealth creation, do not naturally have a strong willingness to protect ecological environment, therefore, the construction of ecological civilization needs the active intervention of the government [1]. Some words about environmental protection have been increasingly mentioned in government work reports in recent years and the government's willingness to protect the environment has gradually increased accordingly [2].

Current researches on carbon emission efficiency and total factor carbon efficiency are mainly divided into evaluation research, influencing factors research and policy research. Firstly, in terms of evaluation research, the characteristics of carbon emission efficiency in different regions of China are different: Sheng Liu et al. [3] found that China's urban carbon emission efficiency has improved, but there are also some regional differences. Feng Dong et al. [4] found that the carbon emission efficiency of southeast coastal areas is better than that of northwest China. Li Jian [5] found that the overall level of carbon emission efficiency in China's three major economic circles is low. Secondly, in terms of

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influencing factors, it can be divided into the following three levels: primarily, at the regional level, Jingdong Zhong [6] found that the capital bias increased by technological change is helpful to greatly improve China's total factor carbon efficiency; secondly, at the provincial level, Yuning Gao et al. [7] found that innovation capability, energy and employment structure had a significant positive impact on total factor carbon efficiency; thirdly, at the enterprise level, Hualei Ju and Zihong Chen [8] found that labor factor quality and profitability have a positive impact on low-carbon total factor productivity of China's aviation logistics listed companies, while listing time and operating capacity have a negative correlation with low-carbon total factor productivity. Finally, in policy research, Zhijie Jia et al. [1] found that carbon pilot policy can promote total factor carbon efficiency; Xiufan Zhang and Decheng Fan [9] found that carbon emission trading market can indirectly have a positive impact on carbon emission reduction efficiency through the dual mediating effect of low-carbon technology innovation and industrial structure adjustment.

At the beginning of the United Nations Conference on Human Environment in 1972, China formally embarked on the road of ecological environment protection and governance. Due to the weak awareness of the people at the initial stage, only a small number of command-control policies have been introduced. With the passage of the process, environmental protection has risen to the basic national policy and written into the government work report, and then expanded to the provinces and cities to implement enterprise information disclosure and to establish and implement ecological red line management and control, and to form a large environmental protection pattern. The keyword of environmental protection has gradually appeared in the relevant reports of the government, but the academic circles have less research on environmental protection related vocabulary. Xu Yanqing and Zhou Zhiren [10] found that China's policy texts' attention to the quality of environmental information peaked in 2016, and the number of laws and texts released also formed a "focus period" in 2016; Zhang Leibao and Wang Yijia [2] studied the impact of tax burden and government planning on enterprises' environmental protection willingness, and found that enterprises with lighter tax burden have stronger environmental protection willingness.

Although there has been a lot of research on total factor carbon efficiency, the current research on government environmental willingness is not sufficient, and the relationship between them is not yet clear. Therefore, the innovation of this paper mainly has the following three points: Firstly, this paper is based on the influence of Chinese government's environmental willingness on total factor carbon efficiency. Secondly, the mediating effect and moderating effect are used to study the influence mechanism between government environmental willingness and total factor carbon efficiency. Finally, the machine learning method is used to improve the goodness of fit of regression and draw the importance map of variables. The content of this paper has a certain contribution to the future direction of government work, promoting environmental protection propaganda and practicing of carbon peak and carbon neutralization goal.

2. Theoretical Basis and Research Hypothesis

It is generally believed that government increase environmental protection willingness will bring more environmental investment, that is, the improvement of environmental regulation level. There are two main viewpoints on the impact of environmental regulation on environmental quality: one is that the improvement of environmental regulation can improve the ecological environment, that is "Porter Hypothesis"; another view is that too high environmental regulation will lead to "follow the cost" effect, not conducive to improving the ecological environment. Xiujie Tan et al. [11] found that the implementation of carbon emission regulations during the twelfth Summit had contributed not only to achieving carbon intensity reduction targets, but also to improving total factor carbon efficiency, carbon emission regulations positively enhance the promotion effect of energy price on total factor carbon efficiency and alleviate the negative effect of export; Jin Dianchen et al. [12] found that government investment in environmental protection has a significant effect on the improvement of regional environmental quality; strengthening environmental supervision by the government can alleviate the negative externality of air pollution [13]. However, Ning Zhang and Yongrok Choi [14] found a missing link in the role of the Chinese government in promoting CO2 emissions performance; Xu Yanqing and Zhou Zhirin [10] believe that China's environmental information quality management has formed the prototype of the responsibility system, but the guarantee mechanism still has a long way to go; Li Jian [5] found that the changes of carbon emission efficiency in the three economic circles of China have experienced high value fluctuation, continuous decline and low value fluctuation, and there is insufficient scale efficiency and huge room for improvement of carbon emission efficiency.

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This paper thinks that the improvement of the government's willingness to protect the environment should play a role in improving the ecological environment. However, few literatures measure the government's willingness to protect the environment by counting the word frequency of environmental protection based on the text analysis method, and there is no unified view. Therefore, it is not excluded that the government's willingness to protect the environment in this paper inhibits the total factor carbon efficiency. Therefore, we propose:

H1a: Increased government environmental willingness promotes total factor carbon efficiency.

H1b: Increased government environmental willingness inhibits total factor carbon efficiency.

At present, China's economy is committed to coordinated development according to the overall layout of innovation, coordination, green, open and sharing. As a positive index to measure environmental quality, total factor carbon efficiency has a strong positive correlation with ' green ' in the ' five-in-one '. Therefore, the impact of government environmental willingness on the quality of economic development should be consistent with the impact on total factor carbon efficiency. In order to further reveal the influence process of government environmental willingness on total factor carbon efficiency, this paper constructs a channel based on mediating effect, that is, the enhancement of government environmental willingness can improve the local economic quality, and the improvement of economic quality can promote total factor carbon efficiency. But the possibility of H1b is not ruled out. Therefore, we propose:

H2a: There is a channel of "increasing government environmental willingness -improving the quality of economic development-improving total factor carbon efficiency".

H2b: There is a channel of "enhanced government environmental willingness -reducing quality of economic development-reducing total factor carbon efficiency".

There may be a correlation between income gap and environmental protection. The widening income gap leads to some people entering relative poverty, and people in relative poverty pay less attention to environmental problems. Sun Lu-Xuan et al. [15] found that the total factor carbon efficiency of countries with high income levels rose faster than that of countries with low-income levels, and the income gap would expand the inequality of global carbon productivity. In order to further reveal the influence mechanism of government environmental willingness on total factor carbon efficiency, this paper constructs the influence mechanism based on the moderating effect, that is, the income gap plays a moderating role in the influence process of government environmental willingness on total factor carbon efficiency. Therefore, we propose:

H3a: Shortening the income gap strengthens the role of government environmental willingness in promoting total factor carbon efficiency.

H3b: The widening income gap strengthens the inhibitory effect of government environmental willingness on total factor carbon efficiency.

3. Research design

3.1. Research methods

3.1.1. Super-efficiency EBM model considering undesirable outputs

The traditional DEA model measures the efficiency value based on the radial perspective, and its input-output ratio expands and shrinks, so there is a problem of high efficiency value. In order to solve the drawbacks of the traditional DEA model, Tone [16] proposed a SBM model considering slack variables, which can calculate the slack variables to measure the inefficiencies of input and output indicators. However, the projection point of the evaluated decision-making unit of the SBM model is the farthest point from the evaluated decision-making unit on the frontier, and the result is contrary to the goal that the evaluated person hopes to reach the frontier by the shortest path [17]. Tone and Tsutsui [18] proposed EBM model to solve the shortcomings of traditional DEA model and SBM model. In this paper, the undesirable output and super-efficiency model are written into the EBM model to obtain the super-efficiency EBM model considering the undesirable output (Equation 1).

In the formula, X, Y, B are input, expected output and undesirable output ; x_k, y_k, b_k are the input, expected output and unexpected output of unit k ; m, p, q are the number of inputs, expected outputs and undesirable outputs ; w_i^- , w_r^+ , w_t^- are the relative importance of input, expected output and unexpected output ; s_i^- , s_r^+ , s_t^- are slack variables for inputs, expected outputs, and undesirable

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outputs ; λ is a combination coefficient ; ε is the importance of the non-radial part, and the value ranges from 0 to 1. Take 0 as the radial model and take 1 as the SBM model.

$$min \frac{\theta+\varepsilon^{-}\frac{1}{\sum_{i=1}^{m} w_i^{-}}\sum_{i=1}^{m}\frac{w_i^{-}s_i^{-}}{x_k}}{\varphi-\varepsilon^{+}\left(\frac{1}{\sum_{r=1}^{p} w_r^{+}}\sum_{r=1}^{p}\frac{w_r^{+}s_r^{+}}{y_k}+\frac{1}{\sum_{t=1}^{q} w_t^{-}}\sum_{t=1}^{q}\frac{w_t^{-}s_t^{-}}{b_k}\right)}$$

$$\begin{cases} X\lambda-\theta x_k-s_i^{-}\le 0 \\ Y\lambda-\varphi y_k+s_r^{+}\ge 0 \\ B\lambda-\varphi b_k-s_t^{-}\le 0 \\ \varphi-\varepsilon^{+}\left(\frac{1}{\sum_{r=1}^{p} w_r^{+}}\sum_{r=1}^{p}\frac{w_r^{+}s_r^{+}}{y_k}+\frac{1}{\sum_{t=1}^{q} w_t^{-}}\sum_{t=1}^{q}\frac{w_t^{-}s_t^{-}}{b_k}\right)>0 \\ \lambda, s_i^{-}, s_r^{+}, s_t^{-}\ge 0 \\ i=1,2,\dots,m; r=1,2,\dots,p; t=1,2,\dots,q \end{cases} \tag{1}$$

3.1.2. Malmquist index

Malmquist [19] proposed the Malmqusit index to solve the problem of relative efficiency change. Caves et al. [20] defined the Malmqusit index in period t as:

$$MI^{t}(\mathrm{t}-1,\mathrm{t})=\frac{Score_t(x_t,y_t)}{Score_t(x_{t-1},y_{t-1})} \tag{2}$$

Fare et al. [21] defined the above Malmqusit index as the geometric mean of two Malmquist indices (formula 3).

$$MI(\mathrm{t}-1,\mathrm{t})=\sqrt{MI_{(t-1,t)}^{t-1}\times MI_{(t-1,t)}^{t}}=\sqrt{\frac{Score_{t-1}(x_t,y_t)}{Score_{t-1}(x_{t-1},y_{t-1})}\times\frac{Score_t(x_t,y_t)}{Score_t(x_{t-1},y_{t-1})}} \tag{3}$$

Where $Score_t(x_t,y_t)$ and $Score_{t-1}(x_{t-1},y_{t-1})$ are the technical efficiency values of the decision-making unit in period t and period t-1, respectively, and the ratio is the technical efficiency change (EC) in the two periods (Equation 4).

$$EC(t-1,t)=\frac{Score_t(x_t,y_t)}{Score_{t-1}(x_{t-1},y_{t-1})} \tag{4}$$

3.1.3. Spatial autocorrelation test

Spatial autocorrelation test is to measure and analyze the agglomeration phenomenon in a certain spatial range, and to determine whether the spatial econometric model should be constructed. Global spatial autocorrelation depicts the spatial distribution of economic activities. This paper reveals the spatial correlation of total factor carbon efficiency with global Moran index. The specific measure standard is: the value of Moran index is between -1 and 1, when between -1 and 0, the regional distribution is negatively correlated; when it is between 0 and 1, it indicates a positive correlation; when it tends to 0, it means that there is no spatial correlation.

$$I=\frac{\sum_{i=1}^{n}\sum_{j=1}^{n}w_{ij}(x_i-\bar{x})(x_j-\bar{x})}{[\frac{1}{n}\sum_{i=1}^{n}(x_i-\bar{x})^2]\sum_{i=1}^{n}\sum_{j=1}^{n}w_{ij}} \tag{5}$$

3.1.4. Spatial econometric model setting

This paper uses the spatial lag model to study the influencing factors of total factor carbon efficiency. The model is set as follows: $TFCE_{it}$ is total factor carbon efficiency, $lnEWF_{it}$ is government environmental willingness, X_{it} is the control variable matrix, ρ is the spatial autocorrelation coefficient, W is the spatial weight matrix, ε_{it} is the random interference item.

$$TFCE_{it}=\beta_0+\beta_1 lnEWF_{it}+\beta_2 X_{it}+\rho \mathrm{W}TFCE_{it}+\varepsilon_{it} \tag{6}$$

3.1.5. Mediating effect analysis

In order to reveal whether the quality of economic development plays an intermediary role in the process of government environmental willingness affecting total factor carbon efficiency, this paper takes the quality of economic development as an explanatory variable to study the impact of government environmental willingness on the quality of economic development. HQD_{it} is the quality of economic development. If β_1 is obvious in formula 6 and γ_1 is obvious in formula 7, the mediating variable plays an intermediary role.

$$HQD_{it}=\gamma_0+\gamma_1 lnEWF_{it}+\gamma_2 X_{it}+\rho \mathrm{W}HQD_{it}+\varepsilon_{it} \tag{7}$$

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3.1.6. Moderating effect analysis

In order to further reveal the influence process of government environmental willingness on total factor carbon efficiency, this paper takes income gap as a moderating variable to study whether there is a moderating effect between income gap and government environmental willingness. Based on Cao Qingfeng [22], this paper verifies the moderating effect and studies the performance of income gap at different quantile levels. The model is set as follows, where $GINI_{it}$ is the income gap, $EWF_{it} \times GINI_{it}$ is the intersection and multiplication of government environmental willingness and income gap, and its variable is the same as above. If θ_3 in formula 8 is obvious, it is considered to have a moderating effect.

$$TFCE_{it} = \theta_0 + \theta_1 EWF_{it} + \theta_2 GINI_{it} + \theta_3 EWF_{it} \times GINI_{it} + \theta_4 X_{it} + \rho W TFCE_{it} + \varepsilon_{it} \quad (8)$$

3.2. Variable description

3.2.1. Dependent variable

The dependent variable refers to total factor carbon efficiency in the paper. Taking capital, labor and energy as input variables, GDP as expected output and carbon emissions as undesirable output, the specific indicators are shown in table 1. In order to avoid the impact of price on the results, GDP reduction index is used to deal with the total GDP at the same price. The data envelopment analysis (DEA) method is used to combine the Epsilon-Based Measure (EBM) model with unexpected output with the global Malmquist model to measure the Malmquist-Luenberger (ML) index of carbon emission efficiency. Since this paper studies the impact of government environmental willingness on productivity, rather than the growth of productivity, it is necessary to transform the Malmquist productivity index. The paper would like to learn from the method of Qiu et al. [23]. The total factor carbon efficiency (TFCE) is obtained by multiplying the measured Malmquist productivity index, because the Malmquist productivity index refers to the change rate of productivity relative to the previous year. The paper assumes that the TFCE in 2010 is 1, and the TFCE in 2011 is the 2010 TFCE multiplied by the 2011 Malmquist productivity index. TFCE in 2012 is TFCE in 2011 multiplied by Malmquist productivity index in 2012. Carbon dioxide is a hot topic in the current academic research, and the total factor carbon efficiency obtained by its combination with the total factor production rate is undoubtedly a topic worthy of study. This index can well measure the economic operation and production status of a region with the introduction of carbon emissions, which is a positive index to measure economic development and low-carbon environmental protection.

Table 1: Measurement index system of total factor carbon efficiency.

Category	First grade indexes	Second grade indexes	Unit
input	capital	stock of capital	billion yuan
	labour	number of employed persons in urban units	million people
	energy source	total energy consumption	ten thousand tons of standard coal
expected output	economic output	total GDP	billion yuan
undesirable output	pollution emission	carbon emissions	10000-ton

The calculation of carbon emissions takes the method of He Yongda et al. [24] as a reference, calculate and add carbon emissions by energy categories, including coal, coke, crude oil, gasoline, kerosene, diesel, fuel oil, liquefied petroleum gas and natural gas, a total of nine energy categories, see formula 9-10. Among them, E_i is the consumption of type I energy (10000 tons), NCV_i is the average low calorific value of the corresponding energy (kJ/kg), CEF_i is the energy carbon emission factor (kg/TJ). It is equal to the product of energy carbon content (CC_i) and carbon oxidation factor (COF_i) multiplied by the molecular ratio of carbon dioxide to carbon (44/12). The low calorific value of each energy is taken from the schedule of China Energy Statistical Yearbook, and the carbon emission factor is referred to the IPCC national greenhouse gas emission inventory (2006) standard.

$$CO_2 = \sum_{i=1}^{9} E_i \times NCV_i \times CEF_i \quad (9)$$

$$CEF_i = CC_i \times COF_i \times (44/12) \quad (10)$$

This paper uses MaxDEA Ultra 8 software to calculate the total factor carbon efficiency. The data sample interval is 2009-2019, and the Malmquist index results will be less than one period, and the result interval is 2010-2019. The change trend of total factor carbon efficiency in China from 2010 to 2019 is shown in Figure 1. The national average, the eastern average, the central average and the western average

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show a downward trend. This paper uses ArcGIS 10.3 software to draw the distribution pattern of China's total factor carbon efficiency in 2019 (Figure 2). From the figure, it can be seen that China's provincial total factor carbon efficiency has obvious spatial agglomeration characteristics. The provinces with high efficiency value are concentrated in southern China, while the provinces with low efficiency value are concentrated in northern China.

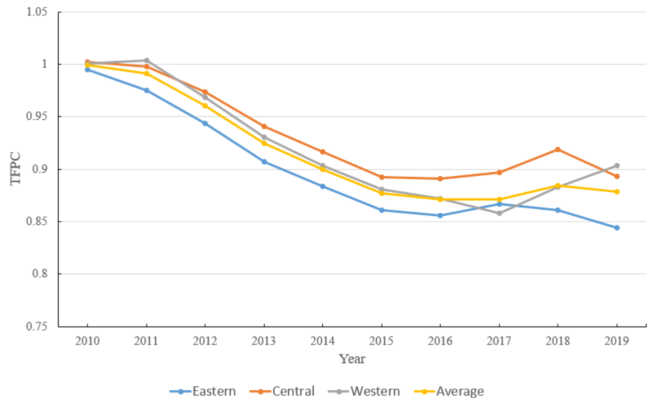

Figure 1: Trend of total factor carbon efficiency in China from 2010 to 2019.

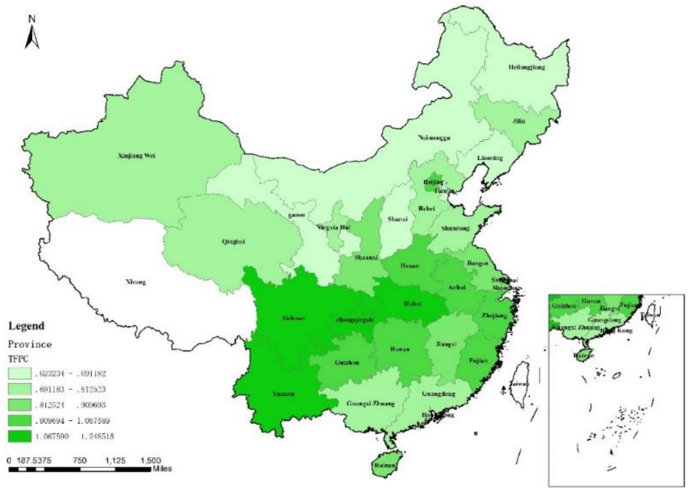

Figure 2: Distribution pattern of total factor carbon efficiency in China in 2019.

3.2.2. Core variable

The core variable of this paper is government environmental willingness. The paper collects government work reports of 30 provinces and cities from 2010 to 2019. Referring to Peng Qi and Yu Chunqiang [25], we imported government work reports into txt text files and converted text coding into Python-supported utf-8 Chinese format. After the Python environment is configured, the processed text is imported into Python, and the jieba-0.39 version module is called to segment the clusters in the natural segment. On this basis, referring to the ' Environmental Protection Dictionary ' edited by Zhu Hongfa [26], 35 environmental protection high-frequency words were selected as the environmental protection dictionary*. The word frequency statistics code refers to the code of Fang Ziling and Kuang Fangjun [27]. Python software is used to count the number of relevant environmental word frequency and the total number of word frequency in the full text. What's more, the paper uses the number of environmental word frequency to measure government environmental willingness, and use the proportion of environmental word frequency to the total number of full-text to do robustness tests.

* This environmental dictionary includes : saving, environmental protection, environmental protection law, environmental friendly, ecology, ecosystem, ecological balance, ecological restoration, environmental monitoring, air, pollution, pollution control, pollution treatment, coal, energy, energy consumption, conservation, recycling, renewable, natural gas, solar energy, wind energy, emission reduction, sewage, garbage, waste, green, green land, clean, low carbon, carbon dioxide, sulfur dioxide, PM2.5, dust, haze.

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This paper uses Yciyun software to draw a word cloud view (Figure 3). In the government work reports of 30 provinces and cities from 2010 to 2019, the word ' ecology ' has the highest frequency of 5313 times. Followed by ' coal ', ' energy ', ' green ', ' saving ', the total number of each word is more than 1000 times.

Figure 3: Cloud view of environmental vocabulary.

3.2.3. Mediating variable and moderating variable

In this paper, the mediating variable is the quality of economic development (HQD). Referring to the research results of Sun Hao et al. [28], the index system is constructed from such five dimensions as innovation, coordination, green, open and sharing. A total of 10 indicators are selected (table 2), and the entropy method is used to measure the quality of economic development. The moderating variable is income gap (GINI), which is measured by Gini coefficient, and the calculation process is referred to Tian Weimin [29].

Table 2: Index system of economic development quality measurement.

First grade indexes	Second grade indexes	Indicator description
innovation	R&D investment intensity (+)	R&D expenditure of industrial enterprises above scale / regional GDP
	efficiency of investment (-)	investment rate / regional GDP growth rate
coordination	urban and rural structure (+)	urban population / total population
	industrial structure (+)	proportion of tertiary industry to GDP
green	wastewater (-)	total wastewater discharge / regional GDP
	exhaust gas (-)	sulfur dioxide emissions / regional GDP
open	foreign investment (+)	actual use of foreign investment / regional GDP
	marketization degree (+)	regional marketization index
sharing	resident income growth (+)	per capita disposable income growth rate / regional GDP growth rate
	urban and rural consumption gap (-)	urban per capita consumption expenditure / rural per capita consumption expenditure

Notes: The calculation of regional marketization index refers to the practice of Fan et al. [30].

3.2.4. Control variables

The control variables include industrial structure upgrading (ISA), industrial structure rationalization (ISR), environmental regulation (ER), technology output (PA), energy efficiency (EE) and economic contribution rate (ECR). The specific variables are defined in table 3. Among them, the rationalization of industrial structure measurement is referred by the practices of Gan et al. [31] and Yang et al. [32], and measured by the reciprocal of the Theil index. The measurement formula of the Theil index is shown in Equation 11. Among them, TL is the Theil index, i is the industrial sector, n is the number of sectors, Y is the regional GDP, Y_i is the output value of each sector, L is the number of employees, and L_i is the number of employees in each sector. The smaller the Theil index is, the more reasonable the industrial structure is. The larger the reciprocal of the Theil index is, the more reasonable the industrial structure is.

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$$TL = \sum_{i=1}^{n} \frac{Y_i}{L_i} \ln(\frac{Y_i}{L_i} / \frac{Y}{L}) \quad (11)$$

Table 3: Index system of influencing factors.

Variable type	Variable name	Variable definition
core variable	government environmental willingness (lnEWF)	number of environmental words
	government environmental willingness (EWFR)	proportion of environmental word frequency in total word frequency
mediating variable	quality of economic development (HQD)	economic development quality index measured by entropy method
moderating variable	income differential (GINI)	gini coefficient
control variable	advanced stage of industry structure (ISA)	third industry added value / second industry added value
	rationalization of industrial structure (ISR)	the reciprocal of Theil index
	environmental regulation (ER)	proportion of industrial pollution control investment to GDP
	technological output (lnPA)	number of patent applications for industrial enterprises above scale
	energy efficiency (EE)	GDP / total energy consumption
	economic contribution rate (ECR)	the proportion of GDP in 30 provinces

3.3. Data sources and description

The research object of this paper is 30 provincial administrative units in China (exclude Tibet, Hong Kong, Macao and Taiwan) from 2010-2019. The data are derived from China Statistical Yearbook, China Energy Statistical Yearbook, China Environmental Statistical Yearbook, China Science and Technology Statistical Yearbook and statistical yearbooks of provinces and cities. The missing data is obtained by linear interpolation.

4. Empirical analysis

4.1. Descriptive statistics

The descriptive statistics of each variable are shown in Table 4. In order to avoid the influence of extreme data on the results, 1 % tail reduction is performed on the left and right sides of the data in the regression. In order to avoid the influence of heteroscedasticity on the results, the ewf and pa are logarithmically processed.

Table 4: Descriptive statistics of variables.

Variable	Numbers	Mean	S.D.	Min	Max
tfce	300	0.9157	0.1056	0.6232	1.2485
lnewf	300	4.1892	0.3334	3.0910	5.2574
ewfr	300	1.0916	0.3339	0.4939	2.7458
hqd	300	0.3524	0.1524	0.0891	0.8283
gini	300	0.4264	0.0452	0.3502	0.5096
isa	300	1.2638	0.7020	0.5270	5.2340
isr	300	8.7409	10.2328	1.2864	57.2658
er	300	0.1186	0.1079	0.0020	0.9918
lnpa	300	9.0055	1.4905	4.6347	12.5158
ee	300	1.5578	0.7183	0.4590	4.8058
ecr	300	3.3333	2.4984	0.3015	10.9462

4.2. Spatial autocorrelation test

Taking the spatial adjacent matrix as the weight matrix, if the two provinces are adjacent, the weight

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is 1, and vice versa is 0. Stata17 software is used to calculate the Moran index of the total factor carbon efficiency of provinces and cities in China from 2010 to 2019 (Table 5), and the results correspond to Equation 5. The Moran index of total factor carbon efficiency is significant in most years, and is positive in most years, indicating that total factor carbon efficiency is positively spatially correlated, that is, high efficiency provinces and cities are adjacent to each other.

Table 5: Spatial autocorrelation test results.

Year	2010	2011	2012	2013	2014
TFCE	0.154^{**}	-0.015	0.143^{*}	0.078	0.160^{**}
P value	0.041	0.427	0.055	0.139	0.038
Year	2015	2016	2017	2018	2019
TFCE	0.320^{***}	0.152^{**}	0.041	0.165^{**}	0.229^{***}
P value	0.001	0.018	0.238	0.033	0.008

Note: * p < 0.1, ** p < 0.05, *** p < 0.01.

4.3. Spatial econometric regression

The regression part uses Stata 17 software. The spatial econometric regression results are shown in table 6 and the corresponding formula 6. In the regression, lnewf and ewfr are used to measure government environmental willingness. In terms of spatial matrix selection, columns (1) and (2) adopt geographical distance matrix, and columns (3) and (4) adopt economic distance matrix to enhance the robustness of the results. The regression results show that lnewf and ewfr are significantly negative, indicating that government environmental willingness inhibits total factor carbon efficiency, H1b is confirmed. The spatial correlation coefficient Rho was significantly positive, indicating that the total factor carbon efficiency was positively correlated, which verified the results of spatial autocorrelation test.

Table 6: Spatial econometric regression results.

Dependent variables	(1) tfce	(2) tfce	(3) tfce	(4) tfce
lnewf	-0.0715^{***}		-0.0511^{***}	
	(0.0150)		(0.0154)	
ewfr		-0.0736^{***}		-0.0537^{***}
		(0.0140)		(0.0146)
isa	-0.0447^{***}	-0.0486^{***}	-0.0409^{***}	-0.0437^{***}
	(0.0128)	(0.0125)	(0.0129)	(0.0126)
isr	-0.0022^{***}	-0.0020^{***}	-0.0023^{***}	-0.0022^{***}
	(0.0006)	(0.0006)	(0.0007)	(0.0006)
er	-0.1504^{***}	-0.1301^{***}	-0.0564	-0.0416
	(0.0478)	(0.0450)	(0.0429)	(0.0409)
lnpa	-0.0546^{***}	-0.0541^{***}	-0.0274^{***}	-0.0271^{***}
	(0.0078)	(0.0078)	(0.0073)	(0.0073)
ee	0.1154^{***}	0.1165^{***}	0.1278^{***}	0.1286^{***}
	(0.0148)	(0.0146)	(0.0158)	(0.0157)
ecr	-0.0005	-0.0015	-0.0064^{*}	-0.0071^{*}
	(0.0034)	(0.0034)	(0.0037)	(0.0038)
_cons	1.4416^{***}	1.2226^{***}	0.8255^{***}	0.6725^{***}
	(0.0734)	(0.0518)	(0.1094)	(0.0880)
Rho	6.4129^{***}	6.3673^{***}	0.5064^{***}	0.5035^{***}
	(0.7384)	(0.7265)	(0.0639)	(0.0644)
Sigma	0.0831^{***}	0.0830^{***}	0.0831^{***}	0.0830^{***}
	(0.0035)	(0.0034)	(0.0038)	(0.0038)
r2	0.6143	0.6165	0.4341	0.4418
Observations	300	300	300	300

Notes: Regression using robust standard error, robust standard errors in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01.

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4.4. Mediating effect analysis

The mediating effect results are shown in Table 7, which corresponds to Equation 7. Among them, columns (1) and (2) adopt the geographical distance matrix, and columns (3) and (4) adopt the economic distance matrix. In the regression results, lnewf and ewfr are significantly negative, indicating that the increase of government environmental willingness will inhibit the quality of economic development. The results of table 6-7 show that the mediating effect is established, and there is a channel of "enhanced government environmental willingness-reduced quality of economic development-reduced total factor carbon efficiency". So far, H2b is proved.

Table 7: Mediating effect results.

Dependent variables	(1) hqd	(2) hqd	(3) hqd	(4) hqd
lnewf	-0.0777***		-0.0546***	
	(0.0146)		(0.0132)	
ewfr		-0.0526***		-0.0414***
		(0.0137)		(0.0130)
Controls	Yes	Yes	Yes	Yes
Rho	13.5904***	13.5121***	0.6221***	0.6407***
	(1.5350)	(1.5377)	(0.0658)	(0.0651)
Sigma	0.0798***	0.0818***	0.0762***	0.0768***
	(0.0050)	(0.0051)	(0.0056)	(0.0055)
r2	0.7761	0.7746	0.6804	0.6644
Observations	300	300	300	300

Notes: Regression using robust standard error, robust standard errors in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01.

4.5. Moderating effect analysis

Table 8: Moderating effect results.

Dependent variables	(1) tfce	(2) tfce	(3) tfce	(4) tfce
gini	0.2507**	0.2392**	0.1871*	0.1813*
	(0.1016)	(0.1004)	(0.1045)	(0.1033)
lnewf	-0.0706***		-0.0495***	
	(0.0142)		(0.0148)	
lnewf×gini	-0.6240**		-0.7094**	
	(0.3055)		(0.3145)	
ewfr		-0.0659***		-0.0458***
		(0.0131)		(0.0142)
ewfr×gini		-0.7653***		-0.7655***
		(0.2840)		(0.2808)
$\gamma_1 lnewf + \gamma_2 lnewf \times gini / \gamma_1 ewfr + \gamma_2 ewfr \times gini$				
gini25%	-0.3119***	-0.3618***	-0.3238***	-0.3418***
Quantile results	(0.1166)	(0.1065)	(0.1184)	(0.1046)
gini50%	-0.3358***	-0.3911**	-0.3510***	-0.3712***
Quantile results	(0.1283)	(0.1174)	(0.1304)	(0.1153)
gini75%	-0.3604**	-0.4212**	-0.3789***	-0.4013***
Quantile results	(0.1402)	(0.1285)	(0.1427)	(0.1263)
Controls	Yes	Yes	Yes	Yes
Rho	6.3350***	6.3285***	0.4972***	0.4952***
	(0.7148)	(0.7050)	(0.0641)	(0.0647)
Sigma	0.0818***	0.0815***	0.0820***	0.0818***
	(0.0034)	(0.0034)	(0.0037)	(0.0037)
r2	0.6258	0.6264	0.4721	0.4731
Observations	300	300	300	300

Notes: Regression using robust standard error, robust standard errors in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01.

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In order to further study the reasons why government environmental willingness inhibits the total factor carbon efficiency, this paper takes the income gap (Gini coefficient) as the moderating variable to study whether there is a moderating effect between income gap and government environmental willingness. In this paper, gini, lnewf and ewfr are centralized respectively, then lnewf×gini and ewfr×gini are obtained by multiplying them. Finally, they are substituted into the model for regression. The results are shown in table 8. Among them, columns (1) and (2) adopt geographical distance matrix, and columns (3) and (4) adopt economic distance matrix. In table 8, lnewf, ewfr, lnewf×gini and ewfr×gini are all negative, indicating that the income gap strengthens the inhibitory effect of government environmental willingness on total factor carbon efficiency ; the sum of the main effect and the moderating effect at different quantiles was significantly negative, and with the increase of the Gini coefficient, the absolute value of the coefficient gradually increased, indicating that with the expansion of the income gap, the inhibitory effect of government environmental willingness on total factor carbon efficiency continued to increase. H3b is confirmed.

4.6. Machine learning

The machine learning section of this article uses Python software. The total factor carbon efficiency is taken as the response variable, and the core variables, mediating variable, moderating variable and control variables are taken as the characteristic variables. This paper uses seven machine learning methods, Python programs refer to Chen [33]. The data is randomly divided into 70 % training set and 30 % test set. The results are shown in table 9. The results show that machine learning method can effectively improve the goodness of fit of regression, and the extreme gradient boosting method (XGBoost) has the highest goodness of fit among all algorithms, which is about 3 times of linear regression.

Table 9: Comparison results of machine learning models.

Serial number	Model name	R2
1	XGBoost	0.6746
2	Gradient Boosting	0.6624
3	Bagging	0.6536
4	Random Forest	0.6114
5	Neural Network	0.4879
6	Support Vector Machine	0.4520
7	Decision Tree	0.1782
8	Linear Regression	0.2186

This paper uses XGBoost method to draw the importance map of variables. Figure 4 shows the importance map of feature variables, and Figure 5 shows the importance map of feature variables replacement obtained by random replacement of training set. Both figures show that industrial structure upgrading (ISA) is the most important to improve total factor carbon efficiency.

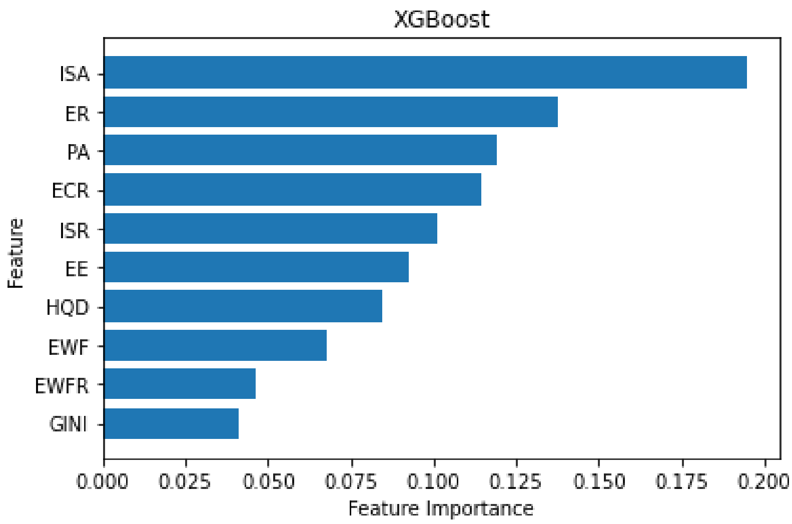

Figure 4: Importance of variables.

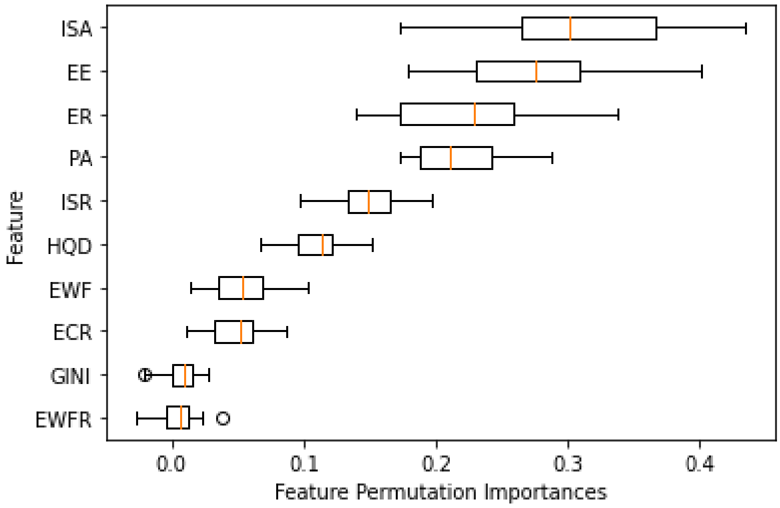

Figure 5: Importance of variable substitution.

5. Discussion and conclusions

5.1. Discussion

There are three main contributions of this paper. (1) The paper enriches the understanding of total factor carbon efficiency. Common sense tells that the environmental protection willingness of a regional government usually plays a role in improving the ecological environment, but the empirical results are exactly the opposite. The environmental protection willingness of the government inhibits the total factor carbon efficiency. When analyzing the text of the government report, it is found that the word frequency of “carbon dioxide” is low. From 2010 to 2019, a total of 81 times have appeared in the government work reports of 30 provinces and cities in China, and individual provinces have not even once. In contrast, “environmental protection” has appeared 835 times. The focus of total factor carbon efficiency is carbon emissions, which does not exclude the possibility that the frequency of “carbon dioxide” words is less, which leads to the government’s environmental protection willingness to inhibit total factor carbon efficiency. At present, China pays more and more attention to the reduction and governance of carbon dioxide, and puts forward the goal of carbon peak, carbon neutralization. It is believed that in the future, when scholars re-examine relevant topics, government environmental willingness will promote total factor carbon efficiency, or a U-shaped relationship between the two variables. (2) The paper expands the existing theoretical mechanism, and the mediating effect results show that there is a channel of “enhanced government environmental willingness-reduced quality of economic development-reduced total factor carbon efficiency”; the moderating effect shows that income gap strengthens the inhibitory effect of government environmental willingness on total factor carbon efficiency. The above results show some reasons why the government’s willingness to protect the environment inhibits the total factor carbon efficiency, and pave the way for further research. In the future, scholars can design mechanism paths from other perspectives and conduct empirical tests to expand relevant theoretical understanding. (3) The paper tries to apply the emerging machine learning method to the field of environmental economics. At present, few scholars in the field of environmental economics in China adopt the machine learning method to carry out research. This paper attempts to apply the machine learning method to the case study of environmental economics in China to help more scholars understand and master the machine learning method, so that the machine learning method can be better integrated into the study of environmental economics in China.

5.2. Conclusions

Based on the panel data of 30 provinces in China from 2010 to 2019, this paper measures the government’s environmental willingness, total factor carbon efficiency and economic development quality index. The results show that: The government’s environmental protection willingness will inhibit the total factor carbon efficiency, and there is a channel of enhancing the government’s environmental protection willingness-reducing the quality of economic development-reducing the total factor carbon efficiency. The income gap strengthens the inhibitory effect of government’s environmental protection willingness on total factor carbon efficiency, indicating that there may be problems in the practice of local government's environmental protection willingness. The machine learning method can improve the goodness of fit of the regression. The importance map of variables shows that the most important thing for improving the total factor carbon efficiency is to optimize the industrial structure.

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