Original Research Article

Research on the Coordinated Relationship between China's Provincial Environment and Economy

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Abstract: The aim of the paper is to study the coordinated relationship between environment and economy among provinces in China. The environmental total factor productivity of 30 provinces and cities in China from 2003 to 2017 are measured using sequential ML methods, and the influencing factors of environmental total factor productivity are analyzed in a panel. It is found that: environmental total factor productivity has no obvious regional distribution characteristics, and is highly consistent with the change pattern of environmental technological progress rate, with oscillating upward characteristics; foreign capital utilization, capital increase per capita, and long-term education and science investment all have positive effects on environmental total factor productivity.

Keywords: Environmental total factor productivity; Sequential ML; Regional patterns; Influencing factors.

1. Introduction

In the process of rapid global economic development, mankind is facing increasingly severe environmental problems: frequent occurrence of extreme weather such as typhoons and droughts; rapid melting of the Earth's coolers such as North and South Polar glaciers and Greenland glaciers; frequent occurrence of forest fires.... As a member of the Earth’s ecosystem, the survival and development of human beings are closely related to the Earth's environment. The signing of the Paris Agreement in April 2016 is both a manifestation of the fact that human beings have begun to pay attention to environmental issues, and an important attempt by human beings to jointly manage environmental issues.

As one of the current major global economies, China’s attitude towards environmental governance has a significant impact on global environmental governance. On the international front, the Standing Committee of the National People’s Congress (NPC) formally approved China’s accession to the Paris Agreement in September 2016, reflecting China’s willingness to participate in global environmental governance; on the domestic front, the Eighth Session of the Standing Committee of the Twelfth National People’s Congress (NPCSC) in April 2014 voted to adopt the “Revision of Environmental Protection Law Revision” at the Eighth Session of the Standing Committee of the Twelfth National People’s Congress in April 2014, and the new Environmental Protection Law gives China’s environmental protection authorities more enforcement tools and stronger penalties, reflecting China’s firm determination to address internal environmental issues.

According to Figure 1(a), with the slowdown in GDP growth in 2011, total energy consumption and wastewater discharges, while maintaining growth, are on a slowing trend, with sulfur dioxide emissions declining significantly.

Figure 1(b) shows that the total energy consumption intensity, fixed asset intensity and urban employment intensity remained high during the period of 2003-2017, while the wastewater emission intensity and sulfur dioxide emission intensity have a decreasing trend, of which the sulfur dioxide emission intensity has decreased very significantly. The combination of Figure 1(a) and Figure 1(b) reflects, on the one hand, that in recent years, China has increased its efforts to combat environmental pollution and effectively curbed the emission of pollutants, and on the other hand, it also reflects that China’s current inefficiency in total energy consumption, capital and labor can still not be ignored.

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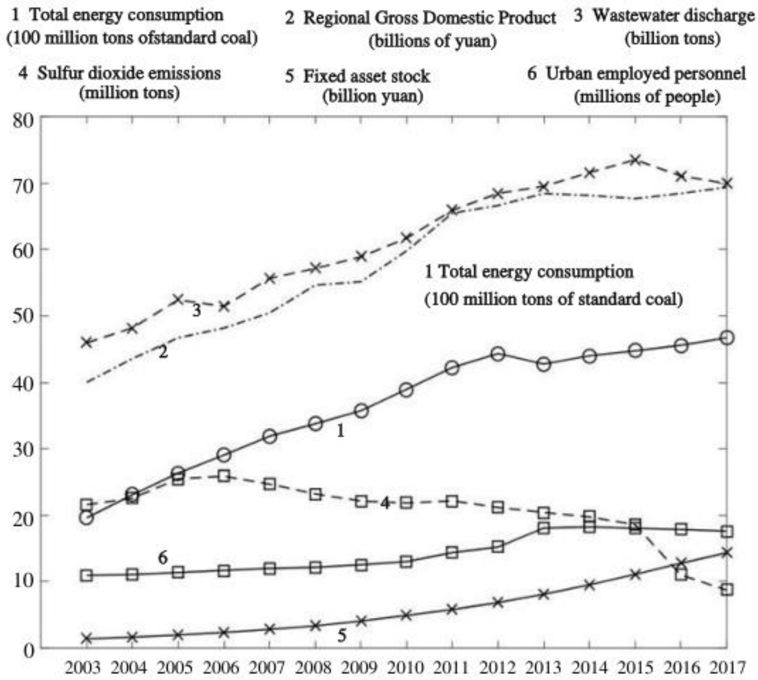
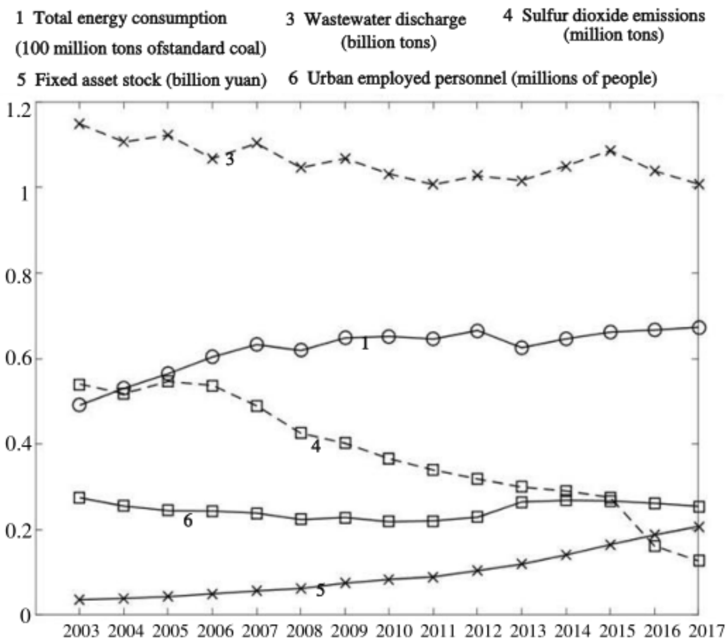


(a) Trends in inputs and outputs, 2003-2017 (1990 base prices)



(b) Trends in input-output intensity, 2003-2017 (1990 basis prices, unit output = hundreds of billions of dollars)

Figure 1 Trends in China's inputs and outputs and their intensities, 2003-2017.

2. Literature Review

The research results of previous researchers have found that the studies related to this paper can be roughly be divided into three categories: The research and measurement of the characteristics of the digital economy, the research and measurement of economic high-quality development, the study and measurement of and research and measurement on the relationship between digital economy and high-quality economic development.

Due to the advantages of Data Envelopment Analysis (DEA), such as no need to assume the functional form and the ability to decompose the total factor productivity, the DEA method has become one of the important methods for economic efficiency measurement. Economic efficiency research based on the DEA method is mainly carried out from two perspectives: first, the horizontal perspective, i.e., estimating the relative economic efficiency among different decision-making units (DMUs) at the same time. The second is the vertical perspective, i.e., the evolution of economic efficiency of the same decision-making unit (DMU) on the time axis. Compared to traditional economic efficiency, which only considers capital and labor inputs and desired outputs of the economy, environmental economic efficiency additionally introduces non-desired outputs of the economy.

The most important and fundamental theoretical model in cross-sectional research is the CCR model created by Charnes, which is an ideal model for evaluating whether a decision unit with multiple inputs and one or more outputs is technologically effective and scale effective from the perspective of production effectiveness in economics. Subsequently, Banker established the BCC model, which is mainly used to evaluate the technical validity of the decision unit. the CCR model and the BCC model are the important cornerstones of the other DEA models, but there are still shortcomings, these two models are based on the premise that the input or output variables are scaled down or scaled up in equal proportions, which does not reflect the flexibility of changes in actual inputs and outputs. Considering the shortcomings of the CCR model and BCC model, Tone proposed a slack variable-based efficiency measurement model (i.e., the SBM model), which is a non-radial, non-angle DEA model that not only makes up for the shortcomings of the radial-angle DEA method that cannot reflect the flexible variations in inputs and outputs, but also has the advantage of the measurements relying on the reference set only. In view of the fact that the previously mentioned models cannot effectively solve the efficiency evaluation among DMUs with non-expected outputs, the non-expected SBM model proposed by Tone and the RAM model proposed by Cooper effectively solve this problem.

In longitudinal research, the most important and fundamental theoretical model is Shephard's Malmquist (M) index method based on the output distance function. However, in evaluating environmental economic efficiency, the M index method requires that the output variables of ineffective decision-making units be increased proportionally and simultaneously in order to realize the efficient state, which is contrary to the concept of environmental economic efficiency that requires that the desired output increase and the non-desired output decrease coexist. The Malmquist-Luenberger index method (ML) proposed by Chung based on the directional output distance function effectively solves the problem of the direction of change of undesired output while retaining the advantages of the M index method. Although the M-index method and ML-index method are the most widely used methods to study the economic efficiency changes on the time axis, their theoretical methods are still difficult to fully reflect the reality, so the problem of unsolved linear programming will occur in some cases. In order to eliminate the technical pseudo-regression problem from the macroeconomic point of view, Donghyun proposed the serial ML index method. The common frontier ML index method proposed by Battese takes into account the heterogeneity between groups and groups the frontiers in different periods for efficiency measurement, which can also avoid the problem of unsolvable linear programming under the assumption of constant returns to scale.

As one of the important economies in the world, China's environmental-economic efficiency has been a research hotspot for scholars at home and abroad. Important empirical studies include: Tu Zhengge used the directional environmental distance theory to analyze the coordination of environment, resources and industrial growth in 30 provinces and cities in China; Nie Yuli and Wen Huwei measured and analyzed the green economic efficiency of 286 cities above prefecture level in China from 2005 to 2011 by using the non-expectation SBM model; Wang Bing and Wu Yanrui analyzed the environmental efficiency, environmental total factor efficiency, and environmental productivity of 30 provinces and cities in China from 1998 to 2007 by using the directional distance function and Luhnberg productivity index of the SBM. Wang Bing and Wu Yanrui analyzed the environmental efficiency and total factor productivity of 30 provinces and cities in China from 1998 to 2007 by using the SBM directional distance function and Luhnberg productivity index; Zhu Wentao measured the green total factor productivity of 29 provinces and cities in China from 2003 to 2015 by using the SBM directional distance function and the ML index, and examined the impact of outward foreign direct investment and reverse technological spillovers on China's green total factor productivity empirically factor productivity in China. Chen and Golley used the radial distance function and ML index method to measure and analyze the changing patterns of environmental total factor productivity of 38 industrial sectors in China during 1980-2010.

This paper is based on the serial ML index method to measure the environmental total factor productivity value of each province and city, and analyze the influencing factors. Compared with the existing literature, this paper introduces the serial ML index method, eliminates the technical pseudo-regression problem, and hopes to obtain more reliable conclusions. The structure of the article is organized as follows: Chapter 2 is the model and data description, Chapter 3 is the results of empirical analysis of environmental total factor productivity, Chapter 4 is the results of the analysis of influencing factors of environmental total factor productivity, and Chapter 5 is the conclusions and recommendations.

3. Model and Data

3.1 Environmental Total Factor Productivity Measurement Model

The production frontier in the traditional ML index depends on the linear combination of inputs and outputs of each decision unit in the current year, and due to the high volatility of inputs and outputs in each year, technological regressions often occur. In this regard, the sequential ML index methodology eliminates the possibility of technological regressions because its technological frontier for each year depends on the linear combination of all inputs and outputs of the overall decision unit for the current and previous years. The serial ML index model from period t to $t+1$ can be formulated as follows:

$$SML_t^{t+1} = \left[\frac{1 + D_{sq}^t\left(x^t, y^t, b^t; -y^t, -b^t\right)}{1 + D_{sq}^t\left(x^{t+1}, y^{t+1}, b^{t+1}, -y^{t+1}, -b^{t+1}\right)} \times \frac{1 + D_{sq}^{t+1}\left(x^t, y^t, b^t; -y^t, -b^t\right)}{1 + D_{sq}^{t+1}\left(x^{t+1}, y^{t+1}, b^{t+1}, -y^{t+1}, -b^{t+1}\right)} \right]^{\frac{1}{2}} \tag{Eq.1}$$

The four distance functions in the sequential ML index method have similarities, only one of which is exemplified here, and for the decision unit $k^{'}$, the measurement expression is as follows:

$$\begin{aligned} & D_{sq}^t\left(x_{k^{'}}^t, y_{k^{'}}^t, b_{k^{'}}^t, y_{k^{'}}^t, -b_{k^{'}}^t\right) = \max \beta \\ & s.t. \quad \sum_{T=origion}^{t} \sum\nolimits_{k=1}^{n} \lambda_k^T x_{i,k}^T \le x_{i,k'}^T, i = 1, 2, \cdots, m \\ & \qquad \sum_{T=origion}^{t} \sum\nolimits_{k=1}^{n} \lambda_k^T y_{z,k}^T \ge \left(1+\beta\right) y_{z,k'}^t, z = 1, 2..., s1 \\ & \qquad \sum_{T=origion}^{t} \sum\nolimits_{k=1}^{n} \lambda_k^T b_{j,k}^T \le (1-\beta) b_{j,k'}^t, j = 1, 2..., s2 \\ & \qquad \lambda_k^T \ge 0, k = 1, \cdots n, T = origion, origion+1, \cdots, t \end{aligned} \tag{Eq.2}$$

The above equation "origin" is the starting year of the data, t is the year in which the target decision unit is located, n is the number of decision units, x, y and b are the input, desired output, and non-desired output variables, and $m, s1$ and $s2$ are the number of inputs, desired outputs, and non-desired outputs, respectively. The serial ML index can be further decomposed into the product of efficiency progress and technical progress:

$$SML_T^{t+1} = SMLEFFCH_t^{t+1} \times SMLTECH_t^{t+1}$$
$$SMLEFFCH_t^{t+1} = \frac{1 + D_{sq}^{t}\left(x^{t}, y^{t}, b^{t}; -y^{t}, -b^{t}\right)}{1 + D_{sq}^{t+1}\left(x^{t+1,} y^{t+a}, b^{t+1}; -y^{t+1}, -b^{t+1}\right)} \quad \text{(Equ.3)}$$
$$SMLEFFCH_t^{t+1} = \left[\frac{1 + D_{sq}^{t}\left(x^{t+1}, y^{t+1}, b^{t+1}; -y^{t+1}, -b^{t+1}\right)}{1 + D_{sq}^{t}\left(x^{t+1,} y^{t+a}, b^{t+1}; -y^{t+1}, -b^{t+1}\right)} \times \frac{1 + D_{sq}^{t+1}\left(x^{t}, y^{t}, b^{t}; -y^{t}, -b^{t}\right)}{1 + D_{sq}^{t}\left(x^{t,} y^{t}, b^{t}; -y^{t}, -b^{t}\right)}\right]^{\frac{1}{2}}$$

3.2 Data

In terms of the selection of provinces and cities, due to institutional differences and data availability, this article excludes Hong Kong, Macao, Taiwan and Tibet, and finally retains 30 provinces and cities. The data of the variables involved in the article come from the China Statistical Yearbook:

(1) Desired output: the real GDP of the 30 provinces and cities with 1990 as the base period is selected; (2) Undesired output: since wastewater, exhaust gas and solid waste are the three main types of pollutants discharged in the real production activities, which have negative external effect on the environment, this article adopts sulfur dioxide and wastewater emissions, which are relatively complete, as the non-desired output indicators of the provinces and cities; (3) Capital inputs: this paper takes 1990 as the starting period, and calculates the capital stock of each province and city in each year by using the “perpetual inventory method”, and the depreciation rate of fixed assets is set at 5%. It is worth noting that It is worth noting that the capital stock calculated with 1990 as the starting period ignores the capital investment before 1990, but since the capital investment before 1990 is relatively low and depreciated year by year, the fixed capital stock calculated in this paper can still fully reflect the real size of capital stock in each province and city. (4) Labor input: due to the difficulty of obtaining data on the total labor of the whole society, this paper adopts the number of employed persons in urban units as the indicator of labor input; (5) Resource input: the traditional total factor productivity measurement generally does not consider the resource input, but after considering the environmental constraints, some scholars have begun to include resource inputs, such as energy, into the productivity measurement to serve as the main source of non-desired outputs. In this paper, total energy consumption is chosen as an indicator of resource inputs. Table 1 shows the descriptive statistics of the input-output variables.

Table 1 Descriptive statistics of input-output variables.

Variate	Units	Observed number	Average	Standard error	Minimum value	Maximum value
Stock of capital	Billion yuan	450.00	20275.47	20572.55	630.43	125000.00
Employment in urban units	Million people	450.00	476.21	325.06	42.50	1973.28
Total energy consumption	Ten thousand tons of standard coal	450.00	12194.09	8000.41	684.00	38899.25
gross regional domestic product	Billion yuan	450,00	1938.58	1532.70	112.23	7355.32
discharge amount of wastewater	Million ton	450.00	205000.00	164000.00	111000.00	938000.00
Sulfur dioxide emission	ton	450.00	687000.00	441000.00	14300.00	2000000.00

4. Empirical Analysis of Environmental Total Factor Productivity

4.1 Environmental Total Factor Productivity Versus Traditional Total Factor Productivity

Based on the Serial ML index model (SML), this article measures the environmental total factor productivity (TFP) and its decomposition for 30 provinces and cities in China from 2003 to 2017. Meanwhile, in order to compare with the traditional total factor productivity, this paper also measures the corresponding traditional total factor productivity and its decomposition value based on the serial M index model (i.e., SM), which does not take into account the non-expected output. The results are shown in Table 2, and the values in Table 2 are the second square root of the product of total factor productivity for each year in the time period, reflecting the average value of total factor productivity in the time period, according to which we can find that.

(1) The average of the errors of the SML values on the SM values measured in the four time phases of 2003-2005, 2005-2010, 2010-2015, and 2015-2017 are 0.049, 0.405, 0.327, and 0.319, respectively, and the average of the errors is greater than 0, which indicates that the environmental total factor productivity is higher than the traditional total factor productivity as a whole, i.e., total factor productivity is increasing after taking into account the undesired outputs, indicating that the environmental policies do promote the coordination between environment and economy. After considering the non-expected output, the total factor productivity is rising, indicating that China's environmental policy does promote the coordinated development between the environment and the economy. (2) In terms of average values, the SML and SM values measured in the four phases of 2003-2005, 2005-2010, 2010-2015, and 2015-2017 show an overall upward trend, indicating that the quality of China's economy has been getting higher during the period of 2003-2017, and that the efficiency of environmental management and the efficiency of capital and labor tends to rise, especially in the most recent phase of 2015-2017, in which the growth of environmental total factor productivity and traditional total factor productivity are higher than that of traditional total factor productivity. In particular, in the recent 2015-2017 period, both environmental total factor productivity growth and traditional total factor productivity growth hit record highs since 2003.

Table 2 Two Total Factor Productivity Measures for Four Stages in Each Province and City.

Provinces	2003-2005		2005-2010		2010-2015		2015-2017	
	SML	SM	SML	SM	SML	SM	SML	SM
Beijing	1.017	0.927	1.307	0.934	1.037	0.962	1.216	1.006
Tianjin	1.018	0.979	1.025	1.016	1.014	0.964	1.117	1.036
Hebei	1.011	0.957	1.004	0.992	0.976	0.954	1.076	1.096
Shanxi	0.937	0.908	0.979	0.891	0.979	0.955	1.020	1.041
Nei Menggu	0.995	0.860	1.033	1.045	0.986	0.972	0.956	0.916
Liaoning	0.932	0.870	1.022	0.998	0.989	0.973	0.978	0.922
Jilin	0.937	0.888	1.006	0.968	1.002	0.976	1.006	0.979
Hei Longjiang	0.970	0.927	0.974	0.882	0.979	0.992	1.012	1.032
Shanghai	1.019	1.058	1.018	0.982	1.011	0.911	1.215	1.056
Jiangsu	0.999	1.011	1.022	1.012	0.992	0.893	1.077	1.032
Zhejiang	0.977	0.913	0.996	0.937	0.995	0.964	1.085	1.034
Anhui	0.933	0.877	1.002	0.970	0.994	0.970	1.060	1.027
Fujin	0.929	0.905	1.001	0.934	1.006	0.974	1.076	1.042
Jiangxi	0.916	0.862	0.997	0.963	0.983	0.937	1.044	1.023
Shandong	1.015	0.917	0.998	0.996	0.984	0.962	1.041	1.020
Hengnan	0.950	0.933	0.965	0.924	0.991	0.932	1.066	1.038
Hubei	0.978	0.930	1.011	0.978	1.002	0.970	1.063	1.025
Hunan	0.917	0.910	0.992	0.946	1.011	1.003	1.067	1.025
Guangdong	0.991	0.973	1.016	0.964	0.989	0.909	1.084	1.025
Guangxi	0.912	0.912	0.970	0.943	1.025	0.977	1.025	0.991
Hainan	1.013	0.934	1.013	0.979	1.005	0.987	1.082	1.023
Chongqing	0.960	0.909	1.009	0.973	1.014	0.965	1.011	1.052
Sichuan	0.963	0.908	1.005	0.979	1.000	0.961	1.033	1.040
Guizhou	0.993	0.909	1.002	0.922	0.986	1.009	1.011	1.041
Yunnan	0.973	0.896	0.997	0.926	0.975	0.991	1.012	1.012
Shanxi	0.988	0.930	0.997	0.947	0.986	0.962	1.030	1.033
Gansu	1.005	0.915	0.997	0.913	0.988	0.955	1.000	0.980
Qinghai	0.932	90943	1.012	1.000	1.007	0.995	0.973	0.970
Ningxia	0.960	0.885	1.020	1.036	1.014	0.983	1.014	1.031
Xinjiang	0.998	0.924	0.993	0.947	0.996	0.977	1.001	0.979
Average value	0.971	0.922	1.004	0.963	0.977	0.965	1.048	1.017
Average value of error	0.0490		0.0405		0.03327		0.0319	

4.2 Patterns of Change in Environmental Total Factor Productivity and Its Decomposition

In this section, based on the environmental total factor productivity values measured above, the regional distribution maps of 30 provinces and cities in the four period stages of 2003-2005, 2005-2010, 2010-2015 and 2015-2017 are plotted, in which the environmental total factor productivity is categorized into less than 0.900, 0.901-1.000, 1.001-1.100, and more than 1.100, and the plotting results are shown in Figure 2. It can be found that:

(1) On the basis of Figure 2, it can be seen that the regional distribution of environmental total factor productivity is not characterized by a decreasing order from east to west, and there are still a lot of provinces and municipalities with a low degree of economic development and geographic remoteness that have achieved environmental total factor productivity growth; (2) The environmental total factor productivity has the characteristics of fluctuations in the four periods of low, high, low, high, and the environmental total factor productivity has the characteristics of a seismic rise on the whole, which is probably related to the The time cycle of production technology updating and upgrading is related, and it is worth affirming that the vast majority of provinces and municipalities realized environmental total factor productivity growth in 2015-2017; (3) According to Figure 3(b), it can be seen that the efficiency progress rate fluctuates slightly above and below 1, and there is no obvious pattern. While the rate of technological progress in Figure 3(a) is generally greater than 1, which is due to the fact that this paper adopts the serial ML index method to avoid technological regression, and according to Figure 3(a) it is visible that the rate of technological progress has two fluctuation phases that are obviously greater than 1 during 2003-2017, and the time of fluctuation is consistent with the time of oscillating upward movement in environmental total factor productivity in Figure 2, which indicates that the current technological progress is the ability of environmental total factor productivity to realize growth is a decisive factor.

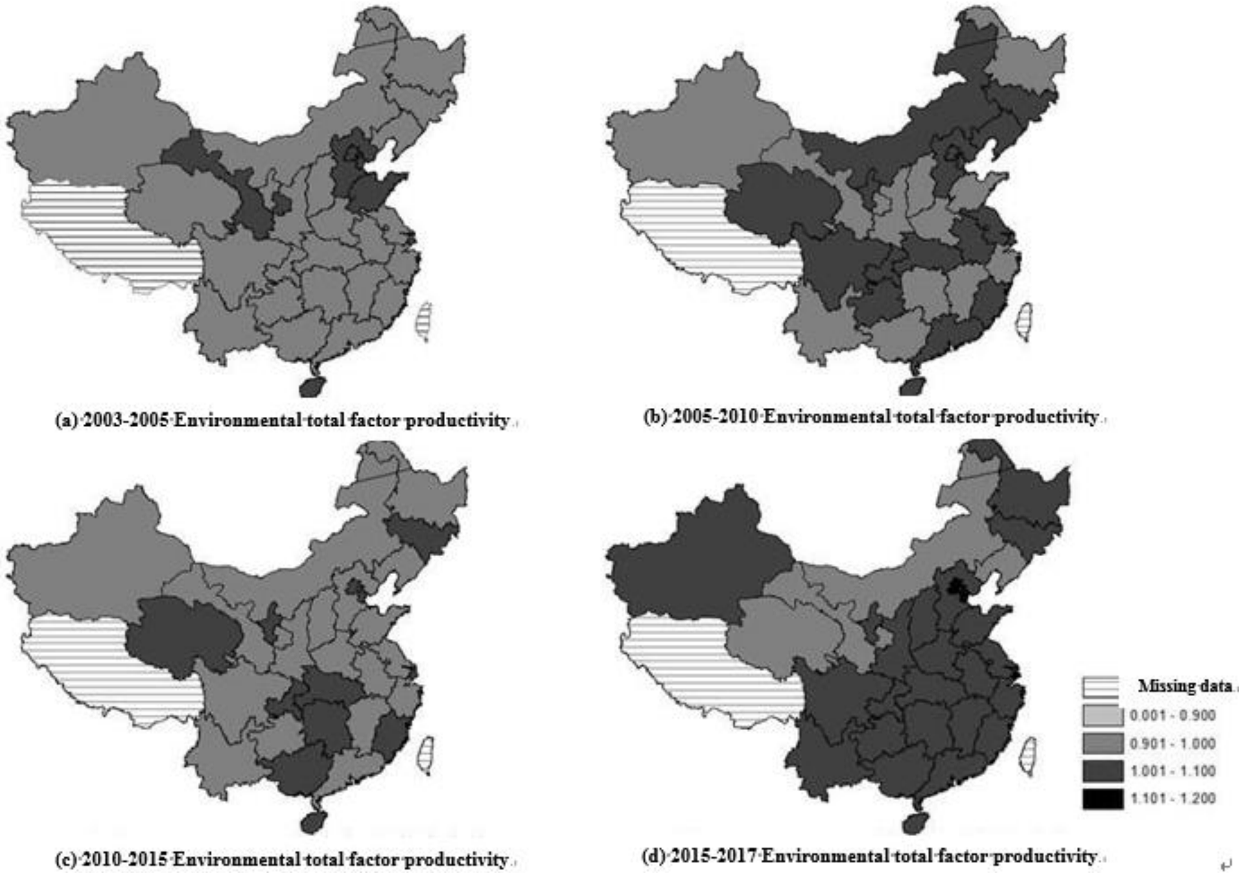


Figure 2 Regional distribution of four-stage environmental total factor productivity by province and city.

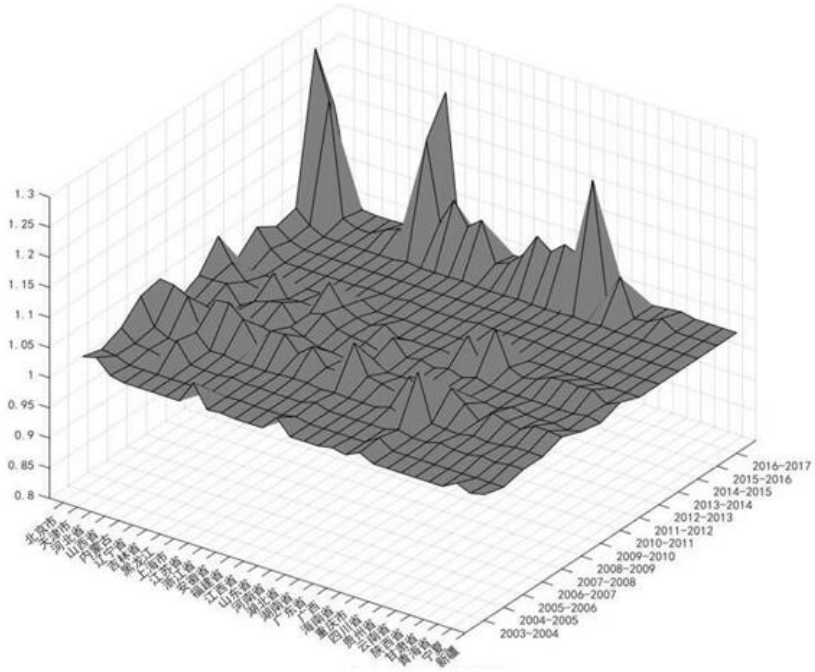
5. Analysis of Influencing Factors of Environmental Total Factor Productivity

5.1 Tests for Variables and Steady

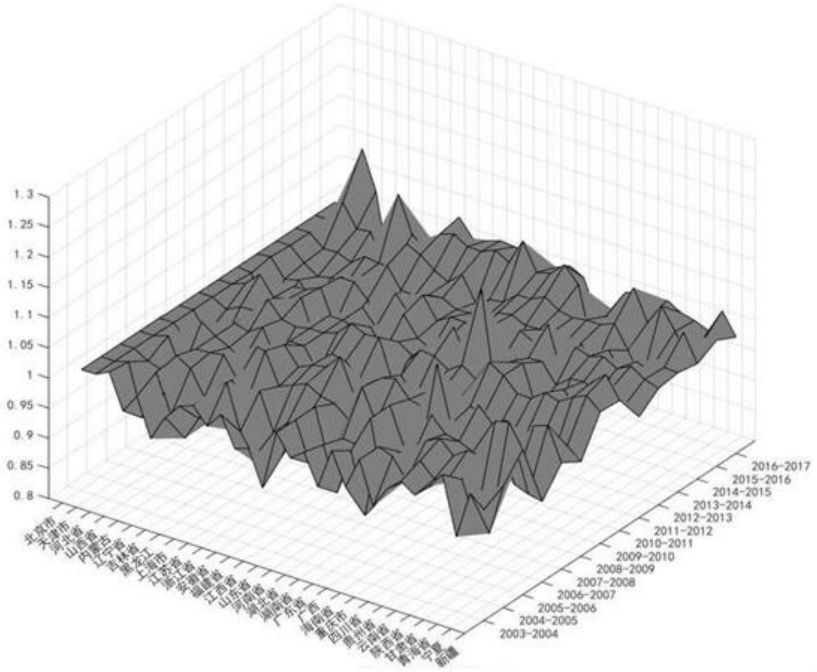
In the process of analyzing the influencing factors of the coordinated relationship between the environment and the economy, the dependent variable selects the environmental total factor productivity (sml) measured in the text, and the independent variable selects representative influencing factors based on the existing studies by Tu Zhengge, Nie Yuli, Wang Bingcao, Qian Zhengming, and Qiu Shilei:

(1) Endowment structure factor: logarithm of fixed capital per unit of labor (In_mcap); (2) Industrial structure factor: share of output value of the secondary industry (per_gdp2); (3) Economic development level factor: logarithm of GDP per capita (ln_mgdp) and its squared term (1n_mgdp2); (4) Factor of foreign investment: logarithm of registered capital of foreigners (ln_fdi); (5) Factor of education investment: logarithm of fiscal education expenditure (ln_edu) and its lagged variable; (6) Factor of technological investment: logarithm of fiscal science expenditure (ln_sci) and its lagged value.

In order to avoid the pseudo-regression problem in the model, this paper is based on LLC and ADF unit root test method to test the smoothness of the panel data, the results are shown in Table 3, which shows that the panel data is smooth.



(a) Environmental technology progress



(b)Environmental efficiency improvement

Figure 3 Progress in environmental technology and progress in environmental efficiency between 2003 and 2017 by province and city.

Table 3 Steady test of panel data.

Variate	LLC		ADF		Conclusion
	Statistical magnitude	**P value**	**Statistical magnitude**	**P value**	
Sml	-11.369	0.000	-11.369	20.6.236	Steady
In_edu	-10.735	0.000	-10.735	148.217	Steady
In_sci	-8.277	0.000	-8.277	135.270	Steady
In_for	-10.178	0.000	-10.178	138.826	Steady
Per_gdp2	-13.354	0.000	-13.354	203.562	Steady
In_mgdp	-11.318	0.000	-11.318	179.767	Steady
In_mgdp2	-11.135	0.000	-11.135	182.123	Steady
In_mcap	-14.662	0.000	-14.662	231.731	Steady

5.2 Model Construction and Empirical Analysis

The panel model for analyzing the factors affecting environmental total factor productivity mainly contains: fixed effect model, random effect model and mixed effect model. In the process of experimental data, the mixed regression model performs best among the three models, so this paper takes the results of the mixed regression model as the main object of analysis, and at the same time lists the regression results of the fixed effect model as a reference, and the regression results are shown in Table 4.

Table 4 Regression results on factors affecting environmental total factor productivity.

sml	Mixture regression model			ADF		
	Coef.	**St.Err.**	**Sig**	**Coef.**	**St.Err.**	**Sig**

1n-edu	-0.017	0.025	***	-0.002	0.028	***
L.1n-edu	0.092	0.034	***	0.09	0.035	***
L2.1n-edu	-0.089	0.025		-0.086	0.027	
1n-sci	0.005	0.007	*	-0.002	0.008	*
L.1n-sci	0.016	0.008	*	0.017	0.009	**
L2.1n-sci	-0.013	0.007	*	-0.015	0.008	***
1n-for	0.005	0.003	***	0.30	0.008	
Per-gdp2	-0.118	0.03		-0.018	0.087	
1n-mgdp	-0.200	0.164		-0.377	0.301	
1n-mgdp2	0.012	0.01		0.021	0.018	
1n-mcap	0.020	0.006	***	0.016	0.014	**
Constant	1.870	0.687	***	2.456	1.236	
R-Squared	0.239			0.163		
F-test	9.922			5.647		
S-Observations	360			360		

Note: *“***”p＜0.01, “**”p＜0.05, “*”＜0.1*

In addition, considering that an increase in the lag order of the variables will lead to a rapid decrease in the amount of available data, this paper only introduces two-period lagged variables for educational inputs and technological inputs to investigate whether there is a lagged effect of the two inputs. According to Table 4, it can be found:

(1) In terms of education and technology input factors, education input has obvious lag effect, that is, the current education input will not immediately affect the total factor productivity of the current year, but significantly promote the growth of environmental total factor productivity in the second year, although the results in Table 4 reflect that the current education input has a suppression effect on the environmental total factor productivity in the third year, but the cumulative effect of two years of education input is still greater than 0. And when education input increases by 1% every year, environmental total factor productivity will increase by 0.092% every year, which shows that the promotion effect of education input maintaining long-term growth is more obvious. When the education input increases by 1% every year, the environmental total factor productivity increases by 0.092% every year, which shows that the promotion effect of the education input to maintain long-term growth is more obvious. Technology investment, on the other hand, has a similar lag effect with education investment; (2) In terms of foreign investment factors, the total registered investment of foreign-invested enterprises in 2003-2017 has a significant positive impact on technological progress, indicating that under the policy of the state emphasizing the development of environmental economy, the introduction of foreign enterprises in line with China’s environmental protection policy has a positive impact on China’s technological progress, but the impact is limited, and for every 1% increase in total registered investment of foreign-invested enterprises, environmental total factor productivity only increases by about 0.005%; (3) In terms of industrial structure factors, for every increased by 1%, the environmental total factor productivity only increased by about 0.005%; in terms of industrial structure factors, the proportion of total output value of the secondary industry in 2003-2017 had a significant negative impact on the environmental total factor productivity, and for every 1% increase in the proportion of total output value of the secondary industry, the environmental total factor productivity approximated to be reduced by 0.118%, which is the same as the research expectation, because the secondary industry contains the mining industry, construction and other highly polluting industries; (4) In terms of endowment structure factors, per capita capital had a significant positive effect on environmental total factor productivity from 2003 to 2017, and for every 1% increase in per capita capital, environmental total factor productivity approximated an increase of 0.02%, a possible reason for this result being that technological advances in recent years in capital-intensive firms have offset their negative impact on the environment.

6. Conclusions and Recommendations

6.1 Conclusion

Simple analysis based on environmental total factor productivity: during the period of 2003-2017, environmental total factor productivity is generally higher than traditional total factor productivity, that is, after considering the non-desired output, total factor productivity is rising, which indicates that China's environmental policy is effective; environmental total factor productivity does not have obvious geographic distribution characteristics, which indicates that provinces and municipalities with a low degree of economic development and geographic remoteness can also achieve Environmental total factor productivity growth; environmental total factor productivity and technological progress rate of the change law is highly consistent with the oscillation of the characteristics of the rise, while the efficiency of the progress of the lack of a clear pattern and fluctuations in the amplitude of the smaller, indicating that the technical progress during the period of 2003-2017 is the determining factor of the environmental total factor productivity can achieve growth. Based on the analysis of the influencing factors of environmental total factor productivity: long-term education and technology input, foreign investment, and per capita capital have significant positive effects on environmental total factor productivity, of which education and technology input has a significant lag effect; the proportion of secondary industry has a significant negative effect on environmental total factor productivity.

6.2 Recommendations

Based on the findings of the empirical analysis in this paper, the following policy recommendations can be made:

As environmental total factor productivity is highly consistent with the evolutionary pattern of technological progress, it is characterized by an oscillating upward trend. On the one hand, provinces and municipalities should take technological progress as a breakthrough point and strive to raise total factor productivity. On the other hand, they should encourage technological research and development and updating to shorten the cycle of technological progress as much as possible, thus reducing the shock cycle of the oscillating rise of total factor productivity.

In addition, in order to improve the quality of economic development more quickly, provinces and municipalities can also: upgrade labor capital both qualitatively and quantitatively; accelerate the technological upgrading of related industries in the secondary sector; welcome foreign investment that meets environmental protection conditions; and increase investment in education and science in the long term.

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