Analysis of the Ecological Efficiency of Chinese Provincial Based on the Three-stage DEA Model

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<요 약>

Ecological efficiency is an important index measuring and reflecting the sustainable development level of economy, resources and environment in a region. This paper makes an empirical study on the ecological efficiency of 31 provinces in China in 2014 with the three-stage DEA model. The results show that the three indexes, the total investment in environmental governance (Unit: hundred million Yuan), the second industry proportion(%), and per capita automobile ownership (car/ten thousand people) functioning as the external environmental variables have significantly impacted the regional ecological efficiency. Excluding the impact of the external environment and statistical noise, the technical efficiency of regional ecological efficiency has increased from 0.526 to 0.639, and the pure technical efficiency has increased from 0.650 to 0.858, with the scale efficiency decreased from 0.833 to 0.740, accurately reflecting the regional ecological efficiency level. 31 Chinese provinces are classified into four different types according to the pure technical efficiency and scale efficiency. Every region shall, according to the characteristics of its efficiency, emphasize differently on improving the management level or expanding the scale of production so as to improve the ecological efficiency.

Keywords: regional ecological efficiency, three-stage DEA model, technical efficiency, scale efficiency

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Ⅰ. Introduction

Chinese economy has been greatly developed ever since the reform and opening up, with the GDP increased from 365,020 million Yuan in 1978 to 2,253,250 million Yuan in 2014(with the constant prices in 1978); and meanwhile, resources and environmental problems in China have become increasingly prominent. For example, during 1990 to 2014, the total energy consumption was increased from 980 million tons to 4,260 million tons, with an increase of 435%; wastewater emissions rose from 35,400 million tons up to 71,600 million tons, with an increase of 103%; industrial emissions expanded from 8.5 trillion cubic meters to 69.419 trillion cubic meters, with an increase of 717%; industrial solid waste was yielded from 580 million tons to 3,290 million tons, with a growth of 467%. Moreover, the rapid consumption of resources and environmental issues has become increasingly prominent due to the rapid expansion of Chinese economy. Resource depletion and environmental degradation have become the insurmountable economic development "bottleneck" of China, which results in urgent concerns on environmental problems due to the rapid economic development, and makes people aware that the driving power of Chinese economic development should be transformed from the pure pursuit of capital and labor efficiency to the pursuit of resource efficiency and environmental efficiency, namely, striving to achieve the economic and environmental sustainable development. As an effective measure and management method for the sustainable development of economy and resource environment, ecological efficiency can comprehensively reflect the actual level of the coordinated development of the complex system of economic-resources-environment.

Based on the analysis of the regional ecological efficiency in China in 2014, this paper analyzes the regional differences, and evaluates the economic, resource and environmental situations of each province from the perspective of ecological efficiency. The purpose of the study is to identify, using the three-stage DEA model, whether efficiency differences before and after eliminating the influences of external factors and statistical noise exist, and to confirm which region is influenced most by external factors and statistical noise. The thesis not only can help reveal more realistic Chinese regional eco-efficiency, but it can also display the influences of external factors and statistical noise on eco-efficiency. It studies the influencing factors on ecological efficiency and seeks ways to improve regional ecological efficiency, which provides some policy references for China to actively change the mode of economic development and realize the coordinated development of economy, resources and environment.

Ⅱ. Literature Review

In 1990 Schaltegger and Sturm first proposed the concept of ecological efficiency, that is, the ratio of the added value and the added environmental impact. The pursuit of ecological efficiency is the economic development under the condition of low consumption and low pollution. The wide recognition and acceptance of the concept of ecological efficiency was due to the famous article "Changing the Course: A Global Business Perspective on Development and the Environment" by the World Business Council for Sustainable Development (WBCSD) in 1992. The WBCSD defines eco-efficiency as "ecological efficiency shall price goods and services by providing the competitiveness both meeting human needs and improving the quality of life, and meanwhile, drop the environmental impact of the entire life cycle to at least the same level of the estimated carrying capacity of the earth. Simply put it, we shall realize the minimized impact and the maximized value". The expression of the concept of ecological efficiency is:

$$\text{Ecological efficiency} = \frac{\text{value of the product or service}}{\text{environment impact}} = \frac{\text{added value}}{\text{added environment impact}}$$

Where the value of the product and service hasn't received a uniform measurement method, but appropriate economic indexes can be adopted to indicate the value of products or services. Environmental impact refers to resources and energies consumption and waste discharge.

In recent years, the research on Chinese ecological efficiency has made positive progress. By means of the eco-efficiency indexes in German environmental economic account, Zhu Dajian and Qiu Shoufeng(2008) constructed the eco-efficiency indexes of Chinese circular economic development and analyzed the development trend of Chinese ecological efficiency from 1990 to 2005. Li Liping et. al.(2000) introduced the concept of ecological efficiency and the strategic objectives and measures to improve ecological efficiency.

In the literature on ecological efficiency study, the DEA method is frequently adopted. When calculating the eco-efficiency with the DEA method, we usually target at a set of decision unit, regarding the resource consumption and environmental impact as input index, and the value of the product or service as the output index. Based on the principle of minimum input and maximum output, the relative eco-efficiency of the evaluated decision unit is calculated by means of the mathematical programming model. Yang Bin (2009) adopted the DEA method to measure and evaluate the regional ecological efficiency of China from 2002-2006 from the macroscopic perspective. Zhou Yang et al.(2016) adopted the super efficiency DEA model to measure the ecological efficiency of 17 prefecture-level cities in Shandong province during 2010-2014.

Simple application of the DEA model to evaluate eco-efficiency doesn't take the external environment's impact on the efficiency value into account, so some scholars, after adopting the DEA model to evaluate the efficiency, regard the efficiency values as dependent variables and the factors affecting the efficiency value as explanatory variables. They apply Tobit regression model to analyze the factors affecting the efficiency value, naming it the two-stage DEA model. Wang Dong et al.(2011) conducted the overall analysis and evaluation of the industrial eco-efficiency of Chinese provinces and districts with the data envelopment analysis model, and analyzed the influencing factors of industrial eco-efficiency with the truncated normal regression model(Tobit model). Wu Mingran and Ma Chun(2016), with the DEA method, calculated the ecological efficiency of 31 Chinese provinces during 2009-2013, and then analyzed the factors affecting the ecological efficiency with the Tobit model.

However, the research on the ecological efficiency by the two-stage DEA model can not eliminate the influence of statistical noise, resulting in the deviation of the calculation results, which can not objectively reflect the decision-making and management level of the production unit. Fried(2002) pointed out that the traditional DEA model did not consider the influence of environmental factors and statistical noise on the efficiency evaluation of the decision making units, and put forward a new evaluation method to more accurately calculate the efficiency of decision making unit based on the three-stage DEA model. The prominent characteristic of the three-stage DEA model is that it can eliminate the impact from non operating factors(external environment and statistical noise) on efficiency, which resulted in the calculated efficiency value reflecting the internal management level of decision making units to a more authentic level. Deng Bo et al.(2011) analyzed Chinese regional ecological efficiency with the three-stage DEA, and the results showed that after removing the impact of external environment factors and statistical noise on the efficiency value, large changes on regional ecological efficiency have taken place. However, the environmental impact indexes neglect the water resources and land resources in themselves. Yang Jun et al.(2012) studied the investment efficiency of environmental governance in the eastern, middle, and western regions of China in 2004-2008 by using the three-stage DEA, and analyzed the key factors restricting the regional ecological efficiency, but they did not analyze the eco-efficiency of each administrative region, which will have defects in practice.

The core idea of eco-efficiency is to realize as much value output as possible in the economic development with less consumption of resources and pollution emissions, and to analyze the influencing factors of eco-efficiency to seek the best combination of economic growth and ecological environment improvement in the development process. This paper uses the three-stage DEA to evaluate the regional Chinese ecological efficiency in 2014, with 31 provinces of China (due to missing data, Hongkong, Macao and Taiwan were not included) as the decision making units for evaluation of eco-efficiency, and thus the relative eco-efficiency in each administrative region can be more accurately gained and the influencing factors on regional ecological efficiency in China can be explored to be a reference for regional ecological efficiency improvement in China.

Ⅲ. Research Model

Fried (2002) pointed out that the traditional DEA model did not consider the influence of environmental factors and statistical noise on the efficiency evaluation of the decision making units, and put forward a new evaluation method to more accurately calculate the efficiency of decision making unit based on the three-stage DEA model. The model retains the advantages of traditional DEA model, and combines the SFA(Stochastic Frontier Analysis) and makes up for the defects of DEA, excluding the environmental effects and statistical noise, and thus the decision making units can evaluate their efficiency with the same environment and statistical noise. The model consists of three stages.

1. Stage 1: Traditional DEA(CCR, BCC) Model

Data envelopment analysis(DEA) is a non parametric statistical method adopted by the American scientists Charnes, Cooper et al. evaluating the relative efficiency of the decision making units(DMU) with the same types of multi input and multi output in 1978 with the linear programming model. Its essence is to evaluate the frontier of the effective production based on a set of multi input and multi output observation values, and then the multi-objective comprehensive evaluation is carried out. DEA method is one of the most widely used mathematical methods to estimate the relative efficiency and scale gain of DMU unit in the case of multi input and multi output.

The basic models of DEA are CCR and BCC models. In this paper, we use CCR and BCC models to calculate the technical efficiency and pure technical efficiency of China's regional ecological efficiency, and further calculate the scale efficiency. DEA model includes input oriented (D model) and output oriented (P model), where D model refers to the seeking of the minimum input while output remains unchanged, and P model refers to the fact that investment must seek the maximum output. Because the regional ecological efficiency refers to achieve as much value output as possible with less resource consumption and pollution emissions in economic development, the investment oriented model is selected. Since the CCR and BCC models have been more mature, they won't be mentioned here.

2. The Second Stage: The Establishment of Similar SFA Regression Model

Through the analysis of the first stage DEA model, we can get the input slack variable. Fried (2002) believes that the decision unit is invalid managerial inefficiencies and environmental effects and the statistical noise effect, so it is necessary to separate the three kinds of effects. In the second stage, The input slack variables of decision making units are functioned as dependent variables, and environmental factors, management inefficiency and statistical noise are used as explanatory variables, which form the SFA regression equation seen in formula 1:

$$S_{ni} = f(Z_k;\beta_k) + v_{ni} + \mu_{ni};\quad n = 1,2,\cdots,N;\ i = 1,2,\cdots,I \tag{1}$$

Among them, i=,2,..., I means the I decision making unit; n=1,2,..., N means the N input variable; S_{ni} means the slack value of the n input of the i decision making unit; $f(Z_i;\beta_n)$ indicates the effect of the environment variables on the input slack variables, which is usually $f_i(Z_k;\beta_k) = \beta_0 + \sum_{k=1}^{k} Z_k \times \beta_k$; Z_k is the k environment variable, β_0 is the constant coefficient, and β_k is the coefficient of the k environment variable; $v_{ni} + \mu_{ni}$ is the mixed error, where v_{ni} indicates the statistical noise, and μ_{ni} the management inefficiency. $v_{ni} \sim N(0,\sigma_v^{2})$ is the statistical noise term, indicating the influence of statistical noise on the input slack variables; μ_{ni} meaning the effects of management factors on the input slack variables. Suppose it obeys the normal distribution in zero truncation, i.e. $\mu_{ni} \sim N^{+}(0,\sigma_\mu^{2})$; v_{ni} and μ_{ni} are independent from each other. Then the maximum likelihood estimation is applied to calculate the estimated values of the parameters of β_k, σ^2, and γ. The values of σ_v and σ_μ are calculated with the formulas $\sigma^2 = \sigma_v^2 + \sigma_\mu^2$ and $\gamma = \frac{\sigma_\mu^2}{\sigma_v^2 + \sigma_\mu^2}$. The values of γ lie between 0 and 1. When it approaches 1, it shows that the influence of management factors is dominant; when it approaches 0, it indicates that the influence of statistical noise is dominant.

According to the idea of Chen Weiwei(2014) in her paper, the separation formula of management inefficiency is derived, and the formula of separation is shown in formula 2:

$$E\left(\mu_{ni} \middle| \mu_{ni} + v_{ni}\right) = \sigma_* \left[\frac{\phi(\lambda \frac{\varepsilon}{\sigma})}{\Phi(\frac{\lambda\varepsilon}{\sigma})} + \frac{\lambda\varepsilon}{\sigma} \right] \tag{2}$$

$\sigma_* = \frac{\sigma_\mu \sigma_v}{\sigma}, \sigma = \sqrt{\sigma_\mu^{2} + \sigma_v^{2}}$, $\lambda = \sigma_\mu / \sigma_v$ and ϕ are the standard normal distribution density function, and Φ is the distribution function of standard normal distribution.

The statistical noise can be calculated according to formula 1 and formula 2, and the formula calculated is shown in formula 3:

$$E\left(v_{ni} \middle| \mu_{ni} + v_{ni}\right) = \boldsymbol{S}_{ni} - \beta_0 - \sum_{k=1}^{k} Z_k \times \beta_k - E\left(\mu_{ni} \middle| \mu_{ni} + v_{ni}\right) \tag{3}$$

The purpose of SFA regression is to eliminate the influence of environmental factors and statistical noise on efficiency measurement so as to adjust all the decision-making units in the same external environment. The adjustment formula is seen in formula 4:

$$X_{ni}^{A} = X_{ni} + [\max(f_i(Z_k;\beta_k)) - f(Z_k;\beta_k)] + [\max(v_{ni}) - v_{ni}]$$
$$i = 1,2,\cdots,I; n = 1,2,\cdots,N \tag{4}$$

Where X_{ni}^{A} is the adjusted input variable; X_{ni} is the input variable before the adjustment; $[\max(f_i(Z_k;\beta_k)) - f(Z_k;\beta_k)]$ is to adjust the external environmental factors so that all decision-making units are in the same influencing environment; $[\max(v_{ni}) - v_{ni}]$ indicates that the statistical noise of all decision making units are adjusted to the equal level so that each decision unit is at the same level of external environment and luck.

3. The Third Stage: The Adjusted DEA Model

The relative efficiency of each decision making unit is re-measured while the input variable X_{ni}^{A} eliminating environmental and statistical noise is substituted into the DEA model, and the obtained efficiency value has eliminated the influences from environmental factors and statistical noise, which can more clearly reflect the management inefficiency of the decision making units. They are relatively true and accurate.

Ⅳ. Index Selection and Data Sources

The research object of this paper is Chinese regional eco-efficiency whose core idea is: to realize as much value output as possible in the economic development with less consumption of resources and pollution emissions, and to analyze the influencing factors of eco-efficiency to seek the best combination of economic growth and ecological environment improvement in the development process. This is consistent with the requirements of the input and output indexes of the DEA model. There are many factors that affect the regional ecological efficiency in China, and we shall start from the core idea of ecological efficiency, and take into account the principles like scientifically, systematicness, operability and data availability for indexes selection. The construction of the input and output indexes and environmental impact indexes are shown in Table 1.

This paper selects the data from China Energy Statistical Yearbook 2015, China Statistical Yearbook 2015 and Hebei Economic Statistical Yearbook 2015.

<Table 1> The Evaluation Indexes System of Eco-efficiency

Index types	Primary Indexes	Secondary Indexes	Variable Definition
Input indexes	Resource input	Water consumption	X1 Water consumption (hundred million cubic meters)
		Energy consumption	X2 Total energy consumption (ten thousand tons of standard coal)
		Land consumption	X3 Land for construction (ten thousand hectares)
	Environmental input	Wastewater discharge	X4 Chemical oxygen demand (ten thousand tons)
		Exhaust emissions	X5 Sulfur dioxide emissions (ten thousand tons)
		Solid waste emissions	X6 Common industrial solid wastes produced (ten thousand tons)
Output indexes		Total economic development	Y District GDP (hundred million Yuan)
External environment variables		Environmental governance	Z1 Total investment in environmental pollution treatment (hundred million Yuan)
		Industrial structure	Z2 Secondary industry share (%)
		Other factors	Z3 Per capita car ownership (car/ ten thousand Yuan)

1. Selection of Input and Output Indexes

The ecological efficiency is to obtain the maximum economic value with the least resource input and the minimum environmental cost, which is consistent with the connotation of the DEA method to the input output. According to the concept of eco-efficiency, we select 7 indexes reflecting input and output. The input indexes include the resources input and environment input. The water consumption X1(hundred million cubic meters), the total energy consumption X2(ten thousand tons of standard coal) and land for construction X3(ten thousand hectares) are selected as the resource input indexes; chemical oxygen demand X4(ten thousand tons), sulfur dioxide emissions X5(ten thousand tons) and the common industrial solid wastes produced X6(ten thousand tons) are selected as the environment input indexes; the administrative regions' GDP Y (hundred million Yuan) is selected as the output index; the 31 administrative regions of China are the decision-making units.

The water consumption X1 refers to gross water used by various water users, including losses during distribution.

The total energy consumption X2 refers to the total consumption of energy of various kinds by the production sectors of the economy and the households in a given period of time.

Land for construction X3 refers to the land of construction of buildings and structures. It represents the input of land resources.

Chemical oxygen demand(COD) X4 is an important measuring index than monitor organic pollution. COD was select as wastewater discharge.

Given that sulfur dioxide(SO_2) X5 was specified by the Chinese government as a stringent control pollutant, SO_2 emission is treated as an input variable.

Common industrial solid wastes produced X6 refers to the industrial solid wastes that are not listed in the 《National Catalogue of Hazardous Wastes》, or not regarded as hazardous according to the national hazardous waste identification standards(GB5085), solid waste-Extraction procedure for leaching toxicity (GB5086) and solid waste-Extraction procedure for leaching toxicity (GB/T 15555).

The DEA model requires that the input and output indexes should have the same tropism. The input and output indexes were detected with the Pearson correlation test, and the test results were shown in Table 2, from which we might realize that except the general industrial solid waste production, other input indexes and output indexes have got positive correlation coefficients, and could pass the bilateral test at the significant level of 0.01 or 0.05. Since the input variable X6 failed the Pearson correlation test, the X6 general industrial solid waste output was excluded from the indexes system.

<Table 2> Correlation Analysis of Input and Output Variables

		X1	X2	X3	X4	X5	X6
Y	Pearson	0.552** (0.001)	0.864** (0.000)	0.723** (0.000)	0.748** (0.000)	0.482** (0.006)	0.200 (0.280)

Note : *Significance level is<0.05; **significance level is<0.01; ***significance level is<0.001; Values in parentheses are p-values

2. Selection of Environmental Variables

Environmental variables should be those impacting the ecological efficiency, but beyond the subjective control scope of the sample, including the composition of the regional industrial structure, the government investment in environmental governance and other factors. In this paper, the total amount of environmental governance investment Z1 (hundred million Yuan), the secondary industry share Z2(%) and per capita car ownership Z3(car/ten thousand people) function as the environmental variables, whose details can be seen in Table 1.

Total investment in environmental governance Z1 (hundred million Yuan): A large part of the total investment in environmental governance (hundred million Yuan) in China is from government funds. There is a wide range of investment in environmental pollution governance, which can comprehensively cover all aspects of pollution control, mainly including the old industrial pollution source control, construction project "three simultaneous", and urban environmental infrastructure construction. Environmental governance investment is bound to effectively control pollution emissions, protect the ecological environment, and improve ecological efficiency. Therefore, the total amount of investment in environmental governance is selected as the environmental variables of ecological efficiency.

The secondary industry share Z2(%): Xu Zhengsong et al.(2014) analyzed the relationship between industrial structure and environmental pollution, realizing that the secondary industry share had a significantly positive impact on environmental pollution. This paper adopts the secondary industry share to represent the industrial structure components to analyze the influence of the secondary industry share on the slack variables of ecological efficiency. The industrial structure is the main link for human being to act on the ecosystem environment, and the rationality of the industrial structure determines the economic benefit, the resource utilization efficiency and the ecological environment.

Per capita civilian car ownership Z3(car/ten thousand people): By 2014, China's per capita civilian car ownership had reached 1,067 vehicles/ten thousand people. Qu Lingfu(2010), by analyzing the causes of urban pollution discovered that the pollution caused by automobile had become one of the main pollution sources to the urban environment and air environment. The study showed that the automobile environmental pollution had become an important issue in the world, and the impact of the automobile on the ecological environment was enormous. Therefore, per capita civilian car ownership is selected as the external environmental variable of ecological efficiency.

Ⅴ. Empirical Analysis

1. The First Stage: Traditional DEA Analysis

DEAP2.1 software is used to analyze the ecological efficiency and scale returns of 31 provinces and cities in China. The results are shown in Table 3. The analysis results show that without considering the external environment variables and statistical noise, the average technical efficiency value of the eco-efficiency in 31 Chinese provinces in 2014 was 0.526, the average pure technical efficiency was 0.65, and the average scale efficiency was 0.833. According to the three efficiency values, 31 Chinese provinces are divided into three categories, the first of which is that the technical efficiency, pure technical efficiency and scale efficiency are all 1. The three efficiency values in Beijing, Tianjin and Shanghai are 1, indicating that they are in the technical efficiency frontier, and that Beijing, Tianjin and Shanghai have got their ecological technology efficiency and scale efficiency effective and the scale returns constant. It shows that the input and output of the resources and environment are compared in a reasonable manner; The second is that the pure technical efficiency value is 1, while the technical efficiency and scale efficiency values are less than 1. There are a total of six provinces and cities including Jiangsu in such category, which indicates the low technical efficiency is due to scale efficiency, so the key of the reform lies in how to better play its scale efficiency; the third is that the three efficiency values are less than 1, with a total of 23 provinces and cities including Hebei involved, indicating that the allocation capacity of resources and resources application efficiency are low, and there are redundant environmental input. There exist different improvements in the pure technical efficiency and scale efficiency. Overall, China's ecological efficiency is relatively low. The result includes interference from environmental factors and statistical noise, which can not reflect the true level of ecological efficiency in the provinces and cities. Therefore, it is necessary to further adjust and calculate.

<Table 3> The First Stage of Ecological Efficiency in 31 Provinces of China in 2014

Region	TE1	PTE1	SE1	Returns to scale	Region	TE1	PTE1	SE1	Returns to scale
Beijing	1	1	1	-	Hubei	0.537	0.6	0.895	drs
Tianjin	1	1	1	-	Hunan	0.565	0.628	0.9	drs
Hebei	0.321	0.429	0.749	drs	Guangdong	0.734	1	0.734	drs
Shanxi	0.297	0.376	0.791	irs	Guangxi	0.527	0.54	0.976	irs
Inner Mongolia	0.311	0.315	0.987	irs	Hainan	0.616	0.828	0.744	irs
Liaoning	0.42	0.552	0.762	drs	Chongqing	0.532	0.549	0.968	irs
Jilin	0.516	0.535	0.964	irs	Sichuan	0.46	0.521	0.882	drs
Heilongjiang	0.403	0.414	0.973	irs	Guizhou	0.306	0.356	0.858	irs
Shanghai	1	1	1	-	Yunnan	0.393	0.41	0.957	irs
Jiangsu	0.698	1	0.698	drs	Tibet	0.811	1	0.811	irs
Zhejiang	0.683	1	0.683	drs	Shaanxi	0.505	0.512	0.986	irs
Anhui	0.556	0.557	0.998	irs	Gansu	0.291	0.333	0.875	irs
Fujian	0.636	0.674	0.943	drs	Qinghai	0.185	1	0.185	irs
Jiangxi	0.625	0.64	0.976	irs	Ningxia	0.178	0.509	0.35	irs
Shandong	0.521	1	0.521	drs	Xinjiang	0.199	0.216	0.919	irs
Henan	0.489	0.651	0.751	drs	Mean	0.526	0.65	0.833	

Note : TE1 is the first stage technical efficiency, PTE1 is the first stage pure technical efficiency, SE1 is the first stage scale efficiency; IRS is the increasing returns to scale, DRS is the decreasing returns to scale, is the constant returns to scale.

2. The Second Stage: Similar SFA Regression Analysis

The slack variables of each input variable in the decision making units concluded with the BCC model in first phase are regarded as explanatory variables, and the three external environment variables in Table 1 are set as the explanatory variables. The similar SFA regression analysis is carried out with the Frontier4. 1 software, with the results shown in Table 4, from which we know that the three external environment variables′ regression coefficients to the five slack variables can pass the test at the 10% significance level, indicating that the external environment variables has significant influence on the redundant ecological efficiency input of all provinces and cities. The ɣ of three external environmental variables to the five input variables are 0.999, and pass the test at the significant level of 1%, meaning that in the influence of input slack variables, management inefficiency dominates, and has a significant influence on the ecological efficiency, and that it is necessary to eliminating the influence of management inefficiency and statistical noise with the SFA analysis. The LR tests of the one-sided error for the five SFA model pass the examining of significant 5% level (the c2 distribution 5% significant test value is 7.045), so we reject the “zero assumption without invalid term″, which indicates that the SFA model is reasonable.

<Table 4> SFA Analysis Results

	X1	X2	X3	X4	X5
beta 0	127.46*** (126.74)	−4802.75*** (−4802.75)	23.26*** (21.58)	20.97*** (20.99)	−28.24*** (−21.48)
Z1	0.07*** (93.98)	2.40** (4.86)	0.03** (3.84)	0.01** (5.26)	0.02* (2.41)
Z2	0.03* (2.88)	146.25** (146.3416)	1.15* (3.08)	0.44* (2.37)	1.23* (2.84)
Z3	−0.14*** (−80.54)	−3.09* (−8.37)	−0.07* (−4.33)	−0.04* (−3.02)	−0.03* (−2.57)
σ^2	3.06E+03*** (3.06E+03)	4.45E+07*** (4.45E+07)	3.68E+02*** (3.68E+02)	2.15E+02*** (2.15E+02)	2.55E+02*** (2.55E+02)
ɣ	0.999*** (5.17E+07)	0.999*** (3.36E+05)	0.999*** (1.81E+07)	0.999*** (1.11E+06)	0.999*** (1.76E+07)
log likelihood function	−179.24	−297.44	−156.71	−143.68	−146.50
LR test of the one-sided error	20.92	10.22	8.96	9.65	9.33

Note : *Significance level is<0.05: **significance level is<0.01; ***significance level is<0.001 ; Values in parentheses are p-values.

With further investigation of the regression coefficients in the external environment variables to the five slack variables, and with the help of formula 1,we know that the external environment variable is the regression of the input slack variable, so when the regression coefficient is negative, it shows that adding the external environment variable value is conducive to reducing the input amount of slack, which helps to reduce the waste of input variables or to reduce the negative output; conversely, when the regression coefficient is positive, the external environment variables will increase the investment slacks, which contributes to the waste of the input variables. Specific analyses are as follows:

2.1 Total environmental governance investment Z1(hundred million Yuan)

The positive coefficients of the total investment in environmental governance to the five input variables show that increasing the total investment in environmental governance will enhance the input variables, while lower the ecological efficiency. The coefficient of the environmental variable Z1 to the total energy consumption X2 is 2.4, and the coefficients to other input variables are rather small, less than 0.07, which indicates that the environmental variable Z1 has little effect on the other four input variables. This conclusion is contrary to the theoretical expectation, but it reflects that China's environmental governance investment does not play the due role in the improvement of ecological efficiency. Water consumption, energy consumption, construction land, chemical oxygen demand and sulfur dioxide emissions did not decrease with the increase of environmental governance investment. Therefore, we should pay attention to the effective allocation of environmental governance investment, and give full play to the role of total environment investment.

2.2 The secondary industry share Z2

The second industry has the positive regression coefficients to the slack variables of five input variables, and is significant at the level of 10% or 1%, indicating that when the second industry proportion in the total economy increases, the input of X1 water consumption, X2 the total energy consumption, X3 construction land, X4 chemical oxygen demand, and X5 sulfur dioxide emissions will increase, which will reduce the ecological efficiency; this is consistent with the theoretical expectations. In recent years, China has been committed to the adjustment of industrial structure and vigorously developed the third industry, one of whose role is to protect the ecological environment and reduce energy consumption.

2.3 Per capita civilian car ownership Z3 (car / ten thousand people)

The regression coefficients of the per capita civilian car ownership to the five variables are negative, and are significant at the significant level of 10% or 1%. The results show that when the per capita car ownership increases, the input variables of the five input indexes will be reduced, which is inconsistent with the theoretical expectations. The regression coefficients of the per capita car ownership to construction land, chemical oxygen demand, and sulfur dioxide emissions are below 0.07, indicating that the per capita civilian car ownership has little influence on the three input indexes, but its regression coefficient to energy consumption input slacks is -3.09, with great influence. The reason is that the per capita car ownership reflects the economic development level of a region. The higher economic development level will improve the efficiency of energy application accordingly, which is consistent with the findings of Xue Jingjing et al.(2013).

Since the influences of various environmental variables on ecological efficiency are different in all provinces and cities, the ecological efficiency of some regions with better external environment and luck will be higher, while some regions with poor external environment and luck will get lower ecological efficiency. Therefore, formula 4 shall be applied so that all regions are facing the same external environment and luck, and then the true level of ecological efficiency in various regions is investigated.

3. The Third Stage DEA Model Results Analysis

After adjusting the input variables in the second stage, using the DEA-CCR and BBC models again to analyze Chinese regional ecological efficiency and the real ecological efficiency of China is obtained. The calculated results are shown in Table 5. Comparing Table 3 and Table 5, we know that the ecological efficiency got in the third stage has an obvious change over that in the first stage. After eliminating the influence of external environment variables and statistical noise, the technical efficiency of regional ecological efficiency in 31 provinces has increased; the average pure technical efficiency has increased obviously from 0.65 to 0.858, while the scale efficiency has decreased from 0.833 to 0.74. This shows that before the environmental factors and statistical noise are excluded from China's regional ecological efficiency, the pure technical efficiency is underestimated, while the scale returns are overvalued.

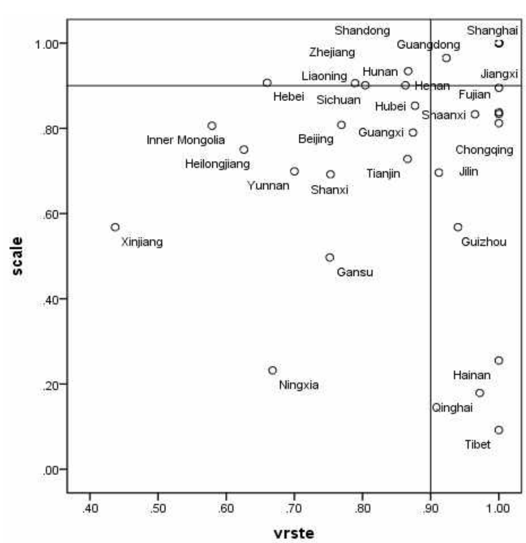
Further comparison between Table 3 and Table 5 shows that after eliminating the influence of environmental variables and statistical noise, the provinces at the technical efficiency frontier have risen from 3 to 4, of which only Shanghai is still in the technical efficiency frontier, indicating that the ecological efficiency of Shanghai is indeed in a sound state. Compared to the first stage, Jiangsu, Shandong and Guangdong rose to the efficiency frontier, meaning that Jiangsu, Shandong and Guangdong are highly effective in eliminating the ecological efficiency of environmental factors and statistical noise; Beijing and Tianjin withdrew from the technical efficiency frontier after eliminating the environmental factors and statistical noise, so their previous high efficiency can not reflect the true technical management level, indicating the more favorable external environments of Beijing and Tianjin compared to those of other provinces. From the ecological efficiency changes of other provinces, the overall technical efficiency of Hainan, Tibet, Qinghai and Ningxia was declined, indicating that their previous high efficiency was closely related to their favorable environment and good luck, while their technical management level did not appear so high. There are 24 provinces with a rising regional eco-efficiency in the third stage compared with that of the first stage, suggesting that the previous low technical efficiency in these areas is indeed due to adverse environment or bad luck, rather than their low level of technical management. From the change of scale returns of eco-efficiency, there are 17 provinces with the increasing returns in ecological efficiency in the first stage, 11 diminishing their returns, and 3 remaining constant, indicating that only three provinces and cities have the optimal scale in terms of the ecological efficiency scale. After eliminating the influences of external environment variables and statistical noise, there are 27 provinces with an increasing scale returns of the ecological efficiency in the third stage, 4 remaining unchanged, which indicates that the economic development scales in the provinces are irrational, but the input the model selected is resource consumption and pollutant emissions, which obviously won't achieve effective scale by increasing the input. Therefore, we should improve the utilization rate of resources and reduce their adverse impact on the environment.

<Table 5> The Third Stage of Ecological Efficiency in 31 Provinces of China in 2014

Region	TE3	PTE3	SE3	Returns to scale	Region	TE3	PTE3	SE3	Returns to scale
Beijing	0.621	0.769	0.808	irs	Hubei	0.748	0.877	0.853	irs
Tianjin	0.631	0.866	0.728	irs	Hunan	0.778	0.863	0.901	irs
Hebei	0.599	0.66	0.907	irs	Guangdong	1	1	1	-
Shanxi	0.521	0.753	0.692	irs	Guangxi	0.69	0.874	0.79	irs
Inner Mongolia	0.466	0.579	0.806	irs	Hainan	0.255	1	0.255	irs
Liaoning	0.715	0.789	0.906	irs	Chongqing	0.812	1	0.812	irs
Jilin	0.634	0.912	0.696	irs	Sichuan	0.725	0.804	0.901	irs
Heilongjiang	0.47	0.626	0.75	irs	Guizhou	0.534	0.94	0.568	irs
Shanghai	1	1	1	-	Yunnan	0.49	0.7	0.699	irs
Jiangsu	1	1	1	-	Tibet	0.092	1	0.092	irs
Zhejiang	0.89	0.923	0.965	irs	Shaanxi	0.804	0.965	0.833	irs
Anhui	0.834	1	0.834	irs	Gansu	0.374	0.752	0.497	irs
Fujian	0.838	1	0.838	irs	Qinghai	0.174	0.972	0.179	irs
Jiangxi	0.895	1	0.895	irs	Ningxia	0.155	0.668	0.232	irs
Shandong	1	1	1	-	Xinjiang	0.248	0.437	0.568	irs
Henan	0.81	0.867	0.934	irs	Mean	0.639	0.858	0.74	

Note : TE3 is the third stage technical efficiency, PTE3 is the third stage pure technical efficiency, SE3 is the third stage scale efficiency; IRS is the scale of increasing returns, DRS is the scale of decreasing returns, - is the scale of unchanged returns.

The regional ecological efficiency of China can be divided into four types with the efficiency value of 0.9 the critical point, and the spatial refraction map is shown in Figure 1 where the first type is "high-high", namely, provinces and cities with the pure technical efficiency and scale efficiency over 0.9, including Shanghai, Jiangsu, Zhejiang, Shandong and Guangdong whose ecological efficiency needs little improvement in ecological efficiency. The second type includes provinces and cities with high pure technical efficiency but low scale efficiency, namely, the "high-low", including 10 provinces like Jilin, Anhui, Fujian, Jiangxi, Hainan, Chongqing, Guizhou, Tibet, Shaanxi and Qinghai, whose pure technical efficiency is larger than 0.9 but the scale efficiency is below 0.9, especially Tibet and Qinghai with the scale efficiency below 0.2. The improvement direction for ecological efficiency is the scale efficiency, and the focus of future development is to improve the scale economy to centralize the allocation of resources. The third type is the "low high" with the pure technical efficiency below 0.9 but the scale efficiency over 0.9, including 5 provinces like Hebei, Liaoning, Henan, Hunan and Sichuan, which shall emphasize the improvement of pure technical efficiency in the subsequent development, that is, to improve the technological management level in production and business activities. The fourth type is the "low-low", including 10 provinces and cities like Beijing, Tianjin, Shanxi, Inner Mongolia, Heilongjiang, Hubei, Guangxi, Yunnan, Gansu, Ningxia and Xinjiang whose ecological technical efficiency and scale efficiency are of great potential for improvement. In the future development, they should pay attention to improving the management level and promoting the expansion of the production scale.



<Fig. 1> Distribution Chart of Regional Ecology Pure Technical Efficiency and Scale Efficiency in China

Ⅵ. Conclusions

An eco-efficiency research method based on the three-stage DEA model would be constructed in this paper, which can not only evaluate the regional eco-efficiency, but also clearly judge the main external environmental factors for the regional eco-efficiency, and furthermore provide explicit direction to improvement of eco-efficiency. Therefore, the three-stage DEA model can provide a new attempt for the quantitative study of ecological efficiency, and has better practical application value. The main conclusions are as follows:

First, External environment and statistical noise have a significant impact on ecological efficiency. Among the external environment factors, the proportion of the second industry is the adverse factor for ecological efficiency, so we should reduce the proportion of the second industry, improve the utilization rate of resources and environment of the second industry, and vigorously develop the third industry. The regression coefficient of the total investment in environmental governance and the input variables is positive, indicating that when the total investment in environmental governance increases, the input variables will increase, but the ecological efficiency will be reduced, which is not consistent with the theoretical expectations. It shows that the environmental fiscal expenditure does not play a due role in promoting the ecological efficiency; instead, there is a waste of investment. It is necessary to strengthen the unified management of environmental expenditure to improve the efficiency of its allocation. The regression coefficient of per capita car ownership and input variables is negative, which indicates that the ecological efficiency will increase when the per capita car ownership increases.

Second, Compared to the ecological efficiency of the first and the third stages, the ecological efficiency of the provinces and cities before and after the adjustment has changed significantly. Excluding the impact of external environment variables and statistical noise, the nationwide average technical efficiency has increased from 0.526 to 0.639, and the average pure technical efficiency has increased from 0.65 to 0.858, while the average scale efficiency has decreased from 0.833 to 0.74, all of which show that external environmental effects and statistical noise do have important effects on the ecological efficiency, and the efficiency value obtained by means of the three-stage DEA model can reflect the actual level of ecological efficiency in various provinces and cities.

Third, With the efficiency value of 0.9 the critical point, the ecological efficiency of all Chinese provinces and cities is divided into four types, namely "high-high", "high-low", "low-high" and "low-low". For the "high-high" areas, the pure technical efficiency and scale efficiency are high, with limited promotion space. For the "high-low" areas, the focus should be the improvement of the scale efficiency so that the production scale can be the optimal. For the "low-high" areas, the pure technical efficiency should be improved, namely, to improve the management level of production technology. For the "low-low" areas, the pure technical efficiency and scale efficiency are low, so the management level should be improved and the production scale should be expanded so as to improve the ecological efficiency.

Finally, there are some limitations in our research as mentioned above. Further work remains to be done in this area.

First, while using the DEA model to compute the technical efficiency, the selection of input and output indicators are often influenced by some subjective factors such as personal preferences etc. If we use the proper combination of qualitative and quantitative methods to select the indicators, the result will become more accurate and convincing. Similarly, there is similar problem in the environmental factors' selecting.

Second, this present study applies the radial DEA model to evaluate the eco-efficiency value, meanwhile the environmental pollution is taken as an input variable. However, such approach doesn't correspond to the actual production process. In future studies, we will try to apply non-radial DEA model to calculate the eco-efficiency value and take environmental pollution as undesirable outputs.

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요약

3단계 DEA모델을 이용한 중국의 에코 효율성 측정에 관한 연구

나상균* · 우건광**

에코 효율성은 경제 및 자원 환경의 지속가능한 발전의 중요한 요인이다. 에코 효율성은 중국의 지역 경제 및 자원 환경의 평가 척도가 된다. 본 연구는 3단계 DEA 모델을 이용하여 2014년도의 중국에 있는 31개성의 에코 효율성을 분석 하였다. 분석결과, 외부환경변수인 환경 거버넌스의 총 투자액, 2차 산업 및 1인당 자동차 소유량이 중국 지역의 에코 효율성에 많은 영향을 미치고 있는 것으로 분석되었다. 외부환경 및 임의오류를 제외한 후 중국 지역의 에코 효율성은 0.526에서 0.639로 증가하였고, 순수 기술 효율성은 0.650에서 0.858로 증가하였으며, 규모 효율성은 0.833에서 0.740로 감소하였다. 또한 순수 기술 효율성 및 규모 효율성의 측정을 위해서 중국에 있는 31개성을 4가지 유형으로 구분하였다. 분석결과, 중국의 각 성은 에코 효율성을 개선하기 위해 각성의 특성에 적합한 에코 효율성 유형에 따라 관리수준을 제고하거나 생산규모를 확대해야 하는 것으로 분석되었다.

핵심주제어 : 에코 효율성, 3단계 DEA 모델, 기술 효율성, 규모 효율성

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