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THE IMPACT OF ECONOMIC GROWTH ON ENVIRONMENTAL EFFICIENCY IN CHINA WITH EXTENDED SBM MODEL

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ABSTRACT

An extended SBM model is proposed to measure the provincial environmental efficiency including undesirable input and undesirable output in window analysis. In the index system, energy consumption is used as an undesirable input as a new approach and undesirable output is a different combination of three kinds of pollution emissions (SO_2, COD, and CO_2), and the dataset covers 30 provinces in China from 2005 to 2017. It is found that there is a big gap in the environmental efficiency scores among different provinces and higher scores in the east region and lower scores in the west region. In the long run, it has the property of a generally upward trend and regional convergence and there is a strong positive relationship with economic growth. Then, a variety of econometric models, including panel data model, GMM model, and panel Tobit model test the N-shape curve reflecting the relationship between environmental efficiency and economic growth, and the conclusions are consistent with robust results.

Keywords: Environmental Efficiency; Extended SBM Model; Window Analysis; EKC

1. INTRODUCTION

It is inarguably that the environment plays an increasingly important role in the modern economy and society. Due to different developmental strategies and industrial structures, there are different environmental management strategies. The philosophy of "polluting first and treating later" and the notion that "the quality of the environment will deteriorate first and then improve with economic development" have become the normal phenomenon all over the world. The inverted U-shaped environmental Kuznets curve depicts this phenomenon, which has been verified by many studies (Grossman and Krueger, 1995; Shafik, 1994; Farhani et al., 2014).

In the last three decades, the Chinese economy has experienced enormous growth. Its gross

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domestic product (GDP) has leaped to the second place in the world since 2010, reaching 99 trillion RMB (about 14.1 trillion US dollars) in 2019, which is about 2/3 of the United States GDP, and its GDP per capita has reached 10,276 US dollars, close to the world's average[1]. At the same time, China's rapid industrialization and urbanization have produced so many serious environmental problems. Pollution emissions have been increasing rapidly, which have seriously impacted the environmental quality and people's living.

The fundamental reason that leads to the degradation of the environment quality is that we are in the pursuit of economic benefits while pollution emissions and environmental damage have been neglected. In the production process, attention has only been paid to the assessment of economic outputs while pollution emissions that damage the environment have not been included in the national input-output accounting system. Only by taking into account both energy consumption and bad pollution output and measuring environmental efficiency comprehensively, can we be able to measure the real economic efficiency more accurately and find out the relationship between environmental efficiency and economic growth.

The remainder of the paper is organized as below. Section 2 is a literature review discussing environmental efficiency evaluation with the DEA model; Section 3 discusses the new approach of the extended SBM model with undesirable input and undesirable output for evaluating environmental efficiency. Section 4 evaluates the environmental efficiency using windows analysis of extended SBM model and tests the N-curve relationship between environmental efficiency and economic growth using various econometric models. Section 5 summarizes the results and puts forward some policy implications.

2. LITERATURE REVIEW

Environmental efficiency also called ecological efficiency and ecological-economy efficiency was proposed as a measure to reflect the environmental performance of economic activities (Schaltegger and Sturm, 1990). Environmental efficiency is defined as "the efficiency with which ecological resources are used to meet human needs" (OECD, 2008). It can be regarded as the ratio of economic output to input as well as environmental factors, which emphasizes coordinated green development by reducing the negative impact on the environment while producing economic value.

The proposition of environmental efficiency provides a scientific criterion for the study of economic growth and environmental problems (Zhu et al., 2006), which has drawn widespread attention. In the early time, environmental efficiency was used to measure enterprise

[1]National Bureau Statistic of China: http://www.stats.gov.cn/tjsj/zxfb/202002/t20200228_1728913.html

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performance on the ecological environment (Kuosmanen et al., 2006). However, due to the external nature of environmental pollution, it is impossible to study and solve ecological problems focusing only on enterprises. Then, the study on environmental efficiency turned to industry, region and even country more and more (Kielenniva et al., 2012; Lorenzo-Toja et al., 2015).

How to quantitatively evaluate environmental efficiency is also the research focus. The basic method to measure efficiency is comparing the indicators of output and input. Because economic activities are often multi-factor inputs, and the form of outputs is also diversified, so the simple form of single output indicator divided by single input indicator cannot meet the real facts. Therefore, the multi-indicator approach is often used, mainly including three categories: The first one is to calculate the comprehensive index of environmental efficiency with an index system. The difficulty lies in how to select the indicators and set the weight for each indicator. The challenge is the subjectivity and randomness when constructing the index system. The second one involves the parameterized frontier analysis method, namely stochastic frontier analysis (SFA) proposed by Aigner et al. (1977). This kind of method can decompose the technical inefficiency from the stochastic residual of a regression, but it is necessary to define the specific form of a production function. Battese and Coelli(1992) proposed a stochastic frontier production function model for panel data. The third one is the data envelopment analysis (DEA), which is solved by linear programming to measure the relative efficiency of decision-making units (DMUs). It is suitable for multi-input and multi-output situations without a specific form of the production function. It was not until 1978 when Charnes et al. (1978) proposed the CCR model that the DEA method was formally proposed and widely used.

As to evaluating environmental efficiency, some environmental indicators as bad outputs must also be considered, such as pollution emissions, which are important factors affecting environmental quality. In the existing studies, there are usually two ways to incorporate undesirable output into DEA model when evaluating environmental efficiency. The first one is to change the undesirable output to desirable output by indicators transformation with the traditional DEA model. Seiford and Zhu (2002) summarized four feasible solutions to this kind of method, each with its advantages and disadvantages. The second one is to assume that the undesirable output conforms to the weak free disposal, and to construct the corresponding set of environmental production possibilities. Färe and Grosskopf (2004), Tyteca (1997) separately proposed a non-linear Slack-Based Measure(SBM) model considering the undesirable output, which can measure both the increase of desirable output and the decrease of undesirable output (pollution emissions, etc). For the SBM model is good at dealing with pollution emissions, it has become the main method to evaluate environmental efficiency.

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In terms of current research on evaluation of national environmental efficiency, Zhou and Ang (2008) proposed several non-radial evaluation models, using carbon dioxide as the undesirable product to measure the environmental efficiency of 21 OECD countries. Halkos and Petrou (2019) evaluated the environmental efficiency of 28 EU members. Dong et al. (2008) analyzed the efficiency of environmental governance in China from the perspective of international comparison. Shabani et al. (2015) proposed a DEA model that took into account inaccurate data, desirable and undesirable output to measure the environmental efficiency of 163 countries.

As to regional environmental efficiency in China, Song and Wang (2014) used SBM model to calculate China's regional environmental efficiency from the perspective of technology development and government rules. Li and Chen(2008) estimated the provincial environmental efficiency in China from 1990 to 2006 with SBM model. It was found that the average efficiency score in China significantly reduced by introducing environmental indicators into the model and the central and western regions were more sensitive than that in eastern regions. Li et al. (2015) evaluated the environmental efficiency of 30 provinces in China from 2000 to 2010 based on the eco-efficient DEA model. Lu and Zhao (2016) used the proportional DEA model to calculate the environmental efficiency of China's provinces from 2005 to 2012. They all found that pollution emission significantly reduced the average efficiency score of each region, with the highest environmental efficiency in the western regions, the second in the eastern regions and the lowest in the central regions. Qu (2018) implied that there were significant regional differences in environmental efficiency in China. Environmental efficiency shows a gradient decreasing pattern of "East-Central-West-Northeast" and significant positive spatial correlation and agglomeration characteristics. The environmental efficiency of provinces and regions near the geographic area affects each other, and the spatial diffusion effect is significant.

DEA model calculates the relative efficiency among units, but not the absolute score. Taken into account the change of technology, the static regional environmental efficiency comparison cannot reflect its dynamic change. To compare dynamically the environmental efficiency in different periods, Total Factor Productivity(FTP) or Malmquist index is widely used, with which change in environmental efficiency can be decomposed into a change in technological efficiency, technological progress, and change in scale efficiency. According to Yang(2009), the change in environmental efficiency mainly comes from Hicks' neutral technological progress and the deterioration of relative environmental efficiency. Tang and Zhu(2012) found that the inter-provincial environmental efficiency differences experienced a process of year-by-year decrease followed by year-by-year expansion. Li and Luo(2016) showed that there was absolute convergence of regional environmental efficiency in China, and there were obvious differences among the three regions of the eastern, the central and the western.

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In summary, there are many studies on environmental efficiency in China with the Malmquist index method for dynamic analysis. However, the decomposition of the Malmquist index method is not a real technological progress, but a referential result and the decomposition results deviate from the real value. The window analysis approach of DEA model meets the needs for efficiency comparison in different periods and regions in case of environmental efficiency (Halkos and Tzeremes, 2009; Sueyoshi et al., 2013). Wang et al. (2013) analyzed the energy and environmental efficiency of 29 provinces in China from 2000 to 2008 and found that the efficiency of the three regions was rising and the highest was in the eastern regions. Halkos and Polemis(2018) studied the environmental efficiency of the electric power industry in the United States with different emission indicators and analyzed their impact on economic growth. However, there are few papers about regional environmental efficiency in China using the window analysis method of DEA model.

3. METHODOLOGY AND DATA

3.1 Extended SBM model

The DEA model is a non-parametric mathematical programming approach considered to be an effective method for evaluating the efficiency of different decision-making units (DMUs). Based on the traditional CCR model (Charnes et al., 1978) or BCC model (Banker et al., 1984), both radial and non-radial inputs and outputs can be incorporated into the model to evaluate both desirable and undesirable outputs (Tone, 2004). Suppose there are n DMUs, denoted by DMU_j (j=1,……,n). Let n, m, and k be the number of DMUs, inputs, and outputs, respectively, $X \in R^{m\times n}$ be the input matrix and $Y \in R^{k\times n}$ be the output matrix of the observed data. Then, the input matrix can be decomposed into a radial input matrix $X^R \in R^{m_1\times n}$ and a non-radial input matrix $X^{NR} \in R^{m_2\times n}$ with $m = m_1 + m_2$. Correspondingly, the output matrix can be decomposed into a radial output matrix $Y^R \in R^{k_1\times n}$ and a non-radial output matrix $Y^{NR} \in R^{k_2\times n}$ with $k = k_1 + k_2$. They can be expressed as $X=(X^R,X^{NR})^T$ and $Y = (Y^R,Y^{NR})^T$. Normally, input and output data sets are positive, so the production possibility set for a constant returns to scale formulation can be expressed as (*Simar& Wilson, 2002*):

$$P=\{(x,y) \mid x \geq X\lambda, y \leq Y\lambda, \lambda \geq 0\}$$

For a special $DMU_0(x_0,y_0)=(x_0^R,x_0^{NR},y_0^R,y_0^{NR}) \in P$, we have：

$$\alpha x_0^R = X^R\lambda + s^{R-};\ x_0^{NR} = X^{NR}\lambda + s^{NR-};\ \gamma y_0^R = Y^R\lambda - s^{R+};\ y_0^{NR} = Y^{NR}\lambda - s^{NR+}.$$

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with $\alpha \leq 1, \gamma \geq 1$, and $\lambda, s^{R-}, s^{NR-}, s^{R+}, s^{NR+} \geq 0$. The s^{R-}, s^{NR-} represent radial and non-radial input slacks vectors separately, and s^{R+}, s^{NR+} represent radial and non-radial output slacks vectors separately. Efficiency index can be defined as (Cooper et al., 2001):

$$\rho = \frac{1 - \frac{m_1}{m}(1-\alpha) - \frac{1}{m}\sum_{i=1}^{m_2} \frac{s_i^{NR-}}{x_{i0}^{NR}}}{1 + \frac{k_1}{k}(\gamma - 1) + \frac{1}{k}\sum_{p=1}^{k_2} \frac{s_p^{NR+}}{y_{p0}^{NR+}}} \quad (1)$$

where $\alpha = 1, \gamma = 1$, and all the slacks equal zero implies that DMU_0 is DEA efficient.

For a simple case, assuming we have n DMUs using m inputs $X = [x_1, \cdots, x_n] \in R^{m \times n}$ with a desirable and an undesirable output expressed by $Y^G = [y_1^G, \cdots, y_n^G] \in R^{k_1 \times n}$ and $Y^B = [y_1^B, \cdots, y_n^B] \in R^{k_2 \times n}$ respectively, the production possibility set is presented as follows with $X, Y^G, Y^B > 0$:

$$P = \left\{ \left(x, y^G, y^B\right) \mid x \geq X\lambda, y^G \leq Y^G\lambda, y^B \geq Y^B\lambda, \lambda \geq 0 \right\}$$

So, the SBM model for environmental efficiency can be expressed as (Halkos and Polemis, 2018):

$$\rho^* = \frac{1 - \frac{1}{m}\sum_{i=1}^{m} \frac{s_i^-}{x_{i0}}}{1 + \frac{1}{k_1 + k_2}\left(\sum_{p=1}^{k_1} \frac{s_p^{G+}}{y_{p0}^G} + \sum_{q=1}^{k_2} \frac{s_q^{B-}}{y_{q0}^B}\right)} \quad (2)$$

s.t. $x_0 = X\lambda + s^-;\ y_0^G = Y^G\lambda - s^{G+};\ y_0^B = Y^B\lambda + s^{B-};\ s^- \geq 0, s^{G+} \geq 0, s^{B-} \geq 0, \lambda \geq 0$

with $s^-, s^{G+} \in R^{k_1}, s^{B-} \in R^{k_2}$ representing slacks for inputs, desirable outputs, and undesirable outputs, respectively.

Furthermore, we are considering undesirable input. Although the increase of both the desirable input and the undesirable input will reduce the efficiency when the output is constant, they play different roles in the process of production. For example, capital and labor are necessary for production as desirable input, and they get profit or salary in income redistribution. Part of the final products can be transformed into capital and labor again as inputs in the next production stage. The undesirable input, one the other way, is permanent consumption in production, and its

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consumption should be reduced as much as possible. The energy consumption in the production process can be considered as undesirable input. Here we extend the SBM model with undesirable input as the following form:

$$\rho^* = \frac{1 - \frac{1}{m_1 + m_2}\left(\sum_{i=1}^{m_1} \frac{s_i^{D-}}{x_{i0}^{R}} + \sum_{j=1}^{m_2} \frac{s_j^{N-}}{x_{j0}^{NR}}\right)}{1 + \frac{1}{k_1 + k_2}\left(\sum_{p=1}^{k_1} \frac{s_p^{G+}}{y_{p0}^{G}} + \sum_{q=1}^{k_2} \frac{s_q^{B-}}{y_{q0}^{B}}\right)} \qquad (3)$$

s.t. $x_0^R = X^R\lambda + s^{D-}$; $x_0^{NR} = X^{NR}\lambda + s^{N-}$; $y_0^G = Y^G\lambda - s^{G+}$; $y_0^B = Y^B\lambda + s^{B-}$; $s^{D-} \geq 0, s^{N-} \geq 0, s^{G+} \geq 0, s^{B-} \geq 0, \lambda \geq 0$

with $s^{D-} \in R^{m_1}, s^{N-} \in R^{m_2}$ representing slacks for desirable inputs and undesirable inputs, and $s^{G+} \in R^{k_1}, s^{B-} \in R^{k_2}$ representing slacks for desirable outputs and undesirable outputs, respectively.

3.2 Windows analysis approach

DEA window analysis introduced by (Charnes et al., 1984) is a variation of the traditional DEA approach that can handle cross-sectional and time-varying data to measure the dynamic efficiency of DMUs with panel data. It operates on the principle of moving averages and establishes efficiency measures by treating each DMU in different periods as a sole unit. Under the window analysis framework, the efficiency score of a unit in a period can be contrasted to the others as well as to its own in other periods. So we can apply this approach to explore the environmental efficiency of different regions in different periods through a sequence of overlapping windows.

Assuming there are N DMUs with γ inputs and δ outputs in T time periods（t=1,…,T）, so there are samples of $N \times T$. Then DMU$_0$ has inputs vector of $x_0^t = (x_0^{1t}, \cdots, x_0^{mt})^T$ and outputs vector of $y_0^t = (y_0^{1t}, \cdots, y_0^{kt})^T$ in period t. If the start point of the widow is v such that $(1 \leq \mathrm{v} \leq \mathrm{T})$ and width of the widow is w such that $(1 \leq \mathrm{w} \leq \mathrm{T} - \mathrm{v})$, inputs vector and outputs vector will be：

$$x_{vw} = \begin{bmatrix} x_1^v & \cdots & x_N^v \\ \vdots & \ddots & \vdots \\ x_1^{v+w} & \cdots & x_N^{v+w} \end{bmatrix} \text{ and } y_{vw} = \begin{bmatrix} y_1^v & \cdots & y_N^v \\ \vdots & \ddots & \vdots \\ y_1^{v+w} & \cdots & y_N^{v+w} \end{bmatrix}$$

For the efficiency estimation changes through time, DEA window analysis is applied to rely on the idea of a moving average of appropriate width. In this paper, we have 30 provinces (N=30)

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over 13 years (t=2005,…,2017) and with the imposition of a 3-year window(w=3). We assume that there was no technical change within each of the same widows and all DMUs in each window can be compared against each other, so a narrow window width should be chosen and each DMU placed in the same window can be treated as different.

Therefore, the first window contains the years of 2005, 2006 and 2007, the second window contains the years of 2006, 2007 and 2008, and the last window contains years of 2015, 2016 and 2017. We have 990 different DMUs ($30\times3\times11$) in total.

3.3 *Environmental Kuznets Curve* (*EKC*)

To capture the impact of economic growth on environmental efficiency, we can use different econometric models. The inverted U-shaped curve named after Kuznets(1955) explains that income inequality rises and falls according to economic development. The *Environmental Kuznets Curve*(*EKC*) postulates an inverted U-shaped function relationship between different pollution missions and per capita income, i.e. Environmental pressure increases up to a certain level as income goes up, then it decreases (Grossman and Krueger, 1995). Many existing studies also focus on the examination of the relationship between environmental efficiency and economic growth (Zaim and Taskin, 2000; Managi, 2006; Jayanthakumaran and Liu, 2012). Following the above papers, we use a cubic specification of the following form based on EKC:

$$EF_{it} = \alpha_i + \beta_t + b_1 GDPP_{it} + b_2 GDPP_{it}^2 + b_3 GDPP_{it}^3 + \varepsilon_{it} \quad (i=1,2,\ldots,30;\ t=1,2,\ldots,13) \qquad (4)$$

where EF is a vector that includes environmental efficiency scores, GDPP is real GDP per capita (in constant 2000 prices), i for province and t for the period. The parameters α_i and β_t are individual and time fixed effects used to capture common factors across the cross-section element, and ε_{it} are zero mean i.i.d. In the processing, we use fixed-effect and random-effect respectively on whether the individual effect is related to independent variables and then choose which model is better decided by Hausman test.

Considering the endogeneity of the independent variable GDPP, an OLS estimator may be biased (Hausman and Ros, 2013), and cannot reflect the impact of economic growth on environmental efficiency. To deal with this kind of possible problem, it is feasible to estimate the model by applying two dynamic GMM estimators known as DIF-GMM (Arellano and Bond, 1991) and SYS-GMM (Blundell and Bond, 1998). In these models, we use investment intensity of environmental governance, the ratio of environmental investment on GDP, as an instrument variable.

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3.4 Panel Tobit Model

The maximum score of environmental efficiency estimated by DEA model (Non-Super DEA model) is 1 for the DMUs which are considered DEA efficient, so the scores for all DMUs range from 0 to 1. Since the dependent variable in Equation 4, environmental efficiency score, is a random variable with values that fall between 0 and 1, it is more suitable to use the following Panel Tobit model for the censored dependent variable(*Tobin,1956;Maddala,1987;Baltagi, 2008*):

$$EF_{it}^{*} = \alpha_i + \beta_t + b_1 GDPP_{it} + b_2 GDPP_{it}^{2} + b_3 GDPP_{it}^{3} + \varepsilon_{it} \quad (i=1,2,\ldots,30;\ t=1,2,\ldots,13) \qquad (5)$$

where $EF_{it} = 0 \quad if \quad EF_{it}^{*} \leq 0$

$EF_{it} = EF_{it}^{*} \quad if \quad 0 < EF_{it}^{*} < 1$

$EF_{it} = 1 \quad if \quad EF_{it}^{*} \geq 1$

3.5 Indicators and Data

Capital stock and labor force are two desirable inputs. As to capital stock, for there are no data published by the national statistical bureau of china, a common method is used to estimate data using the following equation: $K_t = (1-\delta)K_{t-1} + I_t/P_t$, where K_t is capital stock in period t, K_{t-1} is the capital stock of the previous year, δ is depreciation rate, I is fixed capital investment, and P is price index of fixed capital investment. Following Shan(2008), we obtain the initial data of capital stock and average depreciation rate of 10.96%, then calculate the capital stock from 2000 to 2017 with the new dataset from the statistical bureau of China. The number of labor in the middle of the year is used as labor input, which equals the average number of employed persons at the beginning and the end of the year. Energy consumption is considered as undesirable inputs, and all types of energy consumption are converted to standard coal consumption in the same unit.

Gross domestic product (GDP) at the price of 2000 is desirable output, as many other studies do. We use pollution missions as undesirable outputs, including sulfur dioxide(SO_2) emissions as air pollution and chemical oxygen demand (COD) as water pollution. Although carbon dioxide (CO_2) is not a pollution emission in a strict sense, as a greenhouse gas which mainly affects climate change, its impact on the environment is becoming more and more obvious, and it is also the main indicator of energy consumption, emission reduction, and environmental management in many countries. Therefore, carbon dioxide (CO_2) is also regarded as one kind of undesirable outputs in this paper. Without the data of CO_2 emissions of each province in the statistical

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yearbook, we estimate the data from the amounts of fossil energy consumption, e.g., coal, oil, and natural gas by following *Liu et al.(2010)*. Table 1 presents the summary statistics of input and output variables of 30 provinces of China from 2000 to 2017. As we can see, from the relative values of the skewness and kurtosis, the variables do not follow the normal distribution.

Table 1: Descriptive statistics of variables.

Statistical measures	Desirable Inputs		Undesirable Inputs	Desirable outputs	Undesirable outputs			Dependent variable	Instrument variable
	Capital Stock	Labor	*Energy*	*GDP*	SO_2	*COD*	CO_2	Real *GDP/capita*	Investment intensity
Units	RMB Billion	Million	Million Ton	RMB Trillion	Mt	Mt	Mt	RMB	%
Observations	390	390	390	390	390	390	390	390	390
Mean	889.8	15.24	126.0	1.206	0.679	0.56	328.13	27420	17.29
Median	572.0	11.59	104.0	0.916	0.573	0.46	257.49	22966	13.22
Standard deviation	915.2	11.96	80.0	1.073	0.437	0.40	254.63	17004	16.17
Maximum	4750.8	58.69	389.0	6.204	2.002	1.98	1754.37	95599	63.7
Minimum	23.7	1.05	8.2	0.047	0.014	0.06	16.74	4216	0.8
Skewness	1.83	1.41	1.02	1.89	0.61	1.12	1.83	1.33	3.13
Kurtosis	3.65	1.72	0.57	4.26	-0.38	0.90	4.79	1.72	14.67

Date source: data.stats.gov.cn

4. RESULT AND DISCUSSION

4.1 Provincial environmental efficiency score

We first use the extended SBM model to compute the efficiency score of 30 provinces in China. The DEA window analysis is then applied and Beijing is taken as an example in Table 2. The calculations for the other 29 provinces are similar and are omitted here. Through the sequence of 11 overlapping windows from 2005 to 20017, we can explore the evolution of environmental efficiency for each province of China. Viewing the column data of Table 2, we can test the stability of the environmental efficiency score for each province across the different datasets. And the row data enable us to examine the trends across the same dataset. According to the last row of Table 2, we can see that Beijing experienced an improvement in its environmental efficiency score from 2005 to 2017 while it fluctuated during 2010 and 2015.

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Table 2: A three-year window analysis of environmental efficiency of an example of Beijing.

Window/Year	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Window 1	0.821	0.910	1.000										
Window 2		0.805	0.899	1.000									
Window 3			0.797	0.898	1.000								
Window 4				0.841	0.937	1.000							
Window 5					0.937	1.000	1.000						
Window 6						1.000	0.961	1.000					
Window 7							0.926	0.959	1.000				
Window 8								0.933	0.975	1.000			
Window 9									0.947	0.978	1.000		
Window 10										0.798	0.830	1.000	
Window 11											0.791	0.919	1.000
Average	0.821	0.858	0.899	0.913	0.958	1.000	0.962	0.964	0.974	0.926	0.873	0.960	1.000

Table 3 presents the results of the provincial environmental efficiency score derived from the extended SBM model broken down by three pollution models (SO_2, COD, CO_2), and Table 4 presents another situation of two pollution models (SO_2, COD). The results reveal that in all of the specifications, 5 out of 30 provinces (Liaoning, Fujian, Hainan, Yunnan, and Qinghai) are reported to be DEA efficient or near efficient in terms of the pollution emissions since their scores are 1 or close to 1. The environmental efficiency scores of 9 more developed provinces (Beijing, Tianjin, Shanghai, Zhejiang, Anhui, Shandong, Guangdong, Chongqing, and Sichuan) were increasing before 2010 then fluctuated close to 1 in recent years. On the other hand, 6 provinces (Shanxi, Inner Mongolia, Guizhou, Shaanxi, Gansu, and Xinjiang) report the lowest efficiency scores below 0.4 in many years.

The descriptive statistics reveal that the environmental efficiency scores of economically developed provinces are often higher than those of less developed provinces, but there is no absolute regional distribution property because the provinces with the highest score locate everywhere. Although most of the central and western provinces had lower scores, there are also provinces with higher scores, such as Chongqing, Sichuan, and Yunnan. It is shown that there are high disparities of scores among different provinces since the standard deviation and the coefficient of variation (CV) appear to be relatively high over 0.2 and 0.3 respectively. It is worth mentioning that similar results are obtained in the two specifications in Table 3 and Table 4.

In terms of the time series analysis, the average annual scores of each province reveal a general

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improvement for most cases and a slight decline for a few cases (Jilin, Ningxia, and Xinjiang). Some provinces had a significant increase in the past 13 years, especially Sichuan, Hunan, Henan and Shandong had doubled their scores in table 3. A similar situation occurred in table 4. The increasing of the score and the decline of the coefficient of variation (CV) can indicate two findings, one is the improvement of provincial environmental efficiency overall, another is that the disparities of environmental efficiency of each province have been shrinking, showing a convergence trend.

Table 3: Environmental efficiency scores with three undesirable outputs (SO_2, COD, and CO_2).

provinces	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	Mean
Beijing	0.82	0.86	0.90	0.91	0.96	1.00	0.96	0.96	0.97	0.93	0.87	0.96	1.00	0.93
Tianjin	0.90	0.88	0.88	0.95	1.00	1.00	1.00	1.00	1.00	0.91	0.87	1.00	1.00	0.95
Hebei	0.35	0.34	0.33	0.37	0.55	0.61	0.62	0.61	0.64	0.64	0.60	0.59	0.62	0.53
Liaoning	1.00	0.95	1.00	0.91	0.96	1.00	1.00	1.00	1.00	0.98	0.92	0.95	1.00	0.97
Jilin	0.53	0.48	0.43	0.44	0.56	0.55	0.53	0.54	0.52	0.48	0.46	0.48	0.48	0.50
Heilongjiang	0.62	0.60	0.57	0.58	0.69	0.73	0.67	0.67	0.68	0.68	0.71	0.78	0.79	0.67
Shanghai	0.78	0.81	0.84	0.81	0.85	1.00	0.94	0.94	0.92	0.85	0.78	0.92	1.00	0.88
Jiangsu	0.60	0.60	0.60	0.61	0.69	0.70	0.69	0.77	0.88	0.81	0.81	0.88	0.95	0.74
Zhejiang	0.66	0.65	0.65	0.66	0.73	0.78	0.73	0.78	0.88	0.84	0.78	0.90	1.00	0.77
Fujian	1.00	1.00	0.95	1.00	0.97	1.00	0.98	0.99	0.99	0.95	0.96	1.00	1.00	0.98
Shandong	0.50	0.50	0.63	0.66	0.81	1.00	0.69	0.80	0.97	0.92	0.94	1.00	1.00	0.80
Guangdong	0.84	0.82	0.84	1.00	1.00	1.00	1.00	1.00	1.00	0.99	1.00	1.00	1.00	0.96
Hainan	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.97	1.00	1.00	1.00
East Mean	0.74	0.73	0.74	0.76	0.83	0.87	0.83	0.85	0.88	0.84	0.82	0.88	0.91	0.82
Shanxi	0.38	0.36	0.32	0.34	0.41	0.42	0.42	0.42	0.43	0.41	0.38	0.37	0.38	0.39
Anhui	0.57	0.53	0.52	0.55	0.81	0.85	0.87	0.89	0.92	0.87	0.78	0.84	1.00	0.77
Jiangxi	0.25	0.23	0.21	0.23	0.34	0.35	0.33	0.33	0.32	0.32	0.30	0.30	0.30	0.29
Henan	0.27	0.26	0.26	0.29	0.53	0.55	0.50	0.50	0.51	0.50	0.48	0.59	0.63	0.45
Hubei	0.40	0.38	0.38	0.42	0.57	0.59	0.56	0.56	0.55	0.50	0.47	0.53	0.56	0.50
Hunan	0.38	0.37	0.35	0.41	0.64	0.66	0.63	0.65	0.68	0.65	0.62	0.78	0.88	0.59
Center Mean	0.38	0.35	0.34	0.37	0.55	0.57	0.55	0.56	0.57	0.54	0.51	0.57	0.62	0.50
Inner Mongolia	0.35	0.32	0.30	0.35	0.45	0.45	0.44	0.42	0.38	0.35	0.34	0.37	0.38	0.38
Guangxi	0.40	0.38	0.34	0.37	0.53	0.50	0.51	0.51	0.53	0.51	0.48	0.49	0.50	0.47
Chongqing	0.55	0.54	0.54	0.59	0.80	0.86	0.83	0.89	0.95	0.88	0.80	0.93	1.00	0.78
Sichuan	0.41	0.41	0.41	0.47	0.63	0.70	0.77	0.82	0.81	0.79	0.83	0.92	1.00	0.69
Guizhou	0.29	0.27	0.24	0.26	0.45	0.45	0.44	0.43	0.43	0.41	0.38	0.34	0.33	0.36
Yunnan	1.00	0.99	0.96	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Shaanxi	0.28	0.26	0.24	0.27	0.39	0.39	0.39	0.40	0.39	0.37	0.36	0.37	0.37	0.34
Gansu	0.26	0.24	0.22	0.24	0.38	0.38	0.36	0.37	0.37	0.35	0.33	0.32	0.32	0.32
Qinghai	1.00	1.00	0.94	1.00	1.00	1.00	0.88	0.91	1.00	1.00	1.00	1.00	1.00	0.98

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Ningxia	1.00	0.74	0.63	0.57	0.68	0.63	0.56	0.57	0.60	0.61	0.59	0.58	0.56	0.64
Xinjiang	0.43	0.39	0.35	0.35	0.41	0.42	0.42	0.42	0.42	0.41	0.39	0.37	0.34	0.39
West Mean	0.54	0.50	0.47	0.50	0.61	0.62	0.60	0.61	0.62	0.61	0.59	0.61	0.62	0.58
Mean	0.59	0.57	0.56	0.59	0.69	0.72	0.69	0.71	0.72	0.70	0.67	0.72	0.75	0.67
CV	0.46	0.47	0.49	0.47	0.32	0.33	0.33	0.33	0.34	0.35	0.36	0.37	0.38	0.36

Table 4: Environmental efficiency scores with two undesirable outputs (SO_2, COD).

provinces	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	Mean
Beijing	0.78	0.84	0.89	0.91	0.95	1.00	0.95	0.96	0.97	0.80	0.62	0.90	1.00	0.89
Tianjin	0.89	0.87	0.88	0.95	0.97	1.00	1.00	1.00	1.00	0.90	0.84	1.00	1.00	0.95
Hebei	0.36	0.34	0.34	0.38	0.57	0.63	0.62	0.62	0.64	0.63	0.59	0.58	0.61	0.53
Liaoning	1.00	0.94	1.00	0.90	0.95	1.00	1.00	1.00	1.00	0.97	0.90	0.94	1.00	0.97
Jilin	0.52	0.46	0.42	0.43	0.54	0.52	0.50	0.51	0.49	0.46	0.43	0.46	0.46	0.48
Heilongjiang	0.62	0.59	0.57	0.58	0.68	0.73	0.65	0.66	0.67	0.65	0.67	0.75	0.76	0.66
Shanghai	0.77	0.80	0.83	0.80	0.84	1.00	0.95	0.94	0.93	0.84	0.77	0.90	1.00	0.87
Jiangsu	0.60	0.60	0.61	0.62	0.69	0.72	0.70	0.79	0.88	0.84	0.80	0.88	0.95	0.74
Zhejiang	0.66	0.65	0.67	0.67	0.75	0.80	0.74	0.80	0.88	0.82	0.74	0.90	1.00	0.77
Fujian	0.84	0.81	0.81	0.82	0.96	1.00	0.97	0.96	0.99	0.91	0.79	0.94	1.00	0.91
Shandong	0.51	0.52	0.65	0.67	0.83	1.00	0.69	0.81	0.96	0.90	0.92	1.00	1.00	0.80
Guangdong	0.81	0.80	0.82	0.90	0.94	1.00	1.00	1.00	1.00	0.99	1.00	1.00	1.00	0.94
Hainan	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.99	0.96	1.00	1.00	1.00
East Mean	0.72	0.71	0.73	0.74	0.82	0.88	0.83	0.85	0.88	0.82	0.77	0.87	0.91	0.81
Shanxi	0.39	0.37	0.34	0.35	0.42	0.43	0.43	0.44	0.45	0.42	0.39	0.38	0.39	0.40
Anhui	0.57	0.52	0.53	0.55	0.82	0.86	0.88	0.90	0.93	0.86	0.75	0.83	1.00	0.77
Jiangxi	0.22	0.20	0.19	0.21	0.30	0.30	0.29	0.30	0.30	0.29	0.28	0.28	0.28	0.27
Henan	0.26	0.25	0.25	0.29	0.52	0.53	0.48	0.49	0.50	0.48	0.46	0.59	0.64	0.44
Hubei	0.39	0.37	0.37	0.41	0.56	0.59	0.56	0.57	0.55	0.48	0.43	0.50	0.55	0.49
Hunan	0.35	0.34	0.32	0.36	0.58	0.60	0.61	0.63	0.64	0.59	0.53	0.69	0.83	0.54
Center Mean	0.36	0.34	0.33	0.36	0.53	0.55	0.54	0.55	0.56	0.52	0.47	0.55	0.62	0.48
Inner Mongolia	0.34	0.32	0.30	0.35	0.45	0.45	0.43	0.41	0.37	0.34	0.33	0.37	0.38	0.37
Guangxi	0.33	0.31	0.26	0.27	0.45	0.44	0.49	0.50	0.51	0.48	0.44	0.46	0.47	0.42
Chongqing	0.45	0.46	0.42	0.46	0.69	0.73	0.74	0.83	0.95	0.85	0.72	0.62	0.63	0.66
Sichuan	0.35	0.34	0.35	0.38	0.58	0.62	0.69	0.75	0.76	0.72	0.65	0.68	0.77	0.59
Guizhou	0.29	0.27	0.24	0.26	0.45	0.45	0.45	0.44	0.44	0.41	0.38	0.33	0.33	0.37
Yunnan	1.00	0.99	0.97	1.00	1.00	1.00	1.00	1.00	1.00	0.99	1.00	1.00	1.00	1.00
Shaanxi	0.27	0.25	0.23	0.26	0.37	0.37	0.36	0.38	0.37	0.35	0.35	0.37	0.37	0.33
Gansu	0.26	0.24	0.22	0.24	0.37	0.37	0.35	0.36	0.36	0.34	0.32	0.32	0.31	0.31
Qinghai	1.00	1.00	0.95	1.00	1.00	0.94	0.87	0.91	1.00	1.00	1.00	1.00	1.00	0.97
Ningxia	1.00	0.74	0.63	0.58	0.68	0.63	0.57	0.57	0.62	0.62	0.60	0.59	0.58	0.65
Xinjiang	0.42	0.38	0.34	0.35	0.41	0.42	0.41	0.41	0.42	0.40	0.39	0.37	0.34	0.39
West Mean	0.52	0.48	0.45	0.47	0.59	0.58	0.58	0.60	0.62	0.59	0.56	0.56	0.56	0.55
Mean	0.57	0.55	0.55	0.57	0.68	0.70	0.68	0.70	0.72	0.68	0.63	0.69	0.72	0.65

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CV	0.47	0.48	0.50	0.48	0.33	0.35	0.34	0.34	0.35	0.35	0.37	0.37	0.38	0.37

When comparing the specification of three undesirable outputs (Table 3) to two undesirable outputs (Table 4), the environmental efficiency scores of each province seem very similar except for a few provinces. There are two opposed situations: one is that the scores in the model of three undesirable outputs are lower, mainly in 4 provinces of Hebei, Shanxi, Jiangsu, and Zhejiang, but the difference is small; the other one is that the scores in the model of three undesirable outputs are higher, mainly in5 provinces of Fujian, Hunan, Guangxi, Chongqing, and Sichuan, and the difference is relatively larger. The reason for the score gap is the difference in energy consumption and carbon emissions among provinces. Compared with sulfur dioxide and other pollution emissions, the provinces with relatively high carbon emissions get a greater negative impact on environmental efficiency in the first case, which leads to lower scores, and vice versa.

4.2 Test on the impact of economic growth on environmental efficiency

To model the relationship between the environmental efficiency and economic growth with various econometric methods, we defined environmental efficiency scores as dependent variable (EFSCC) in the first situation of three undesirable outputs and EFSC in the second situation of two undesirable outputs. Then the gross domestic product per capita (GDPP) and its extra polynomial terms (e.g. GDPP squared and GDPP cubed) are used as independent variables.

The unit root test is carried out for each variable. As to the dependent variables of EFSCC and EFSC, the original variables are tested with the intercept term. The LLC test with the same unit root and Fisher-ADF test with different unit root show the similar results of rejecting the assumption that there is a unit root. Hence, the two variables are stationary. As to the independent variable of GDPP, the original variable is tested with the intercept term and slope. The tests of LLC and Fisher-ADF indicate that there is no unit root. So, the parameters of the equation 4 and equation 5 can be estimated without the cointegration test.

Firstly, we estimate the cubic equation with a panel data model using STATA for fixed effects and random effects respectively. We end up choosing the random effects model justified by the Hausman test to the results for the different dependent variables of EFSCC and EFSC shown in Table 5 under Model I. We find significant evidence consistent with an N-shaped relationship between environmental efficiency score and economic growth. More specifically, the coefficients on the GDPP terms (i.e.GDPP, GDPP squared and GDPP cubed) for two dependent variables (EFSCC and EFSC) are statistically significant alternating their signs starting from positive to negative. This suggests the existence of an N-shaped curve. It is worth mentioning that the existence of non-linear effects generated by a cubic and not a quadratic specification is justified under the Wald test, which tests the restrictions that the extra polynomial terms (e.g.

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GDPP squared and GDPP cubed) are zero (H0: b2 =b3 = 0). The result of F test and χ^2 test all reject the null hypothesis under which the restricted model is nested to the unrestricted one (third-degree polynomial model).

Table 5: Results of econometric analysis.

Model	Model I CUBIC		Model II DIF-GMM		Model III SYS-GMM		Model IV Tobit	
Dependent variable	EFSCC	EFSC	EFSCC	EFSC	EFSCC	EFSC	EFSCC	EFSC
Constant	0.422 (8.94)***	0.410 (8.65)***	0.259 (6.89)***	0.270 (7.60)***	0.164 (5.66)***	0.122 (4.17)***	0.412 (7.82)***	0.409 (7.96)***
GDPP	1.39E-02 (5.89)***	1.39E-02 (5.72)***	7.48E-03 (3.58)***	7.28E-03 (3.22)***	6.80E-03 (3.10)***	6.87E-03 (3.33)***	1.54E-02 (5.44)***	1.43E-02 (5.10)***
GDPP^2	-1.67E-5 (-2.71)***	-1.76E-5 (-2.78)***	-1.16E-4 (-2.13)**	-1.22E-4 (-2.1)**	-1.49E-4 (-2.62)***	-1.55E-4 (-2.89)***	-1.86E-4 (-2.42)**	-1.76E-4 (-4.24)**
GDPP^3	7.33E-10 (1.61)**	8.16E-10 (1.75)**	7.54E-10 (1.89)*	8.31E-10 (1.96)**	1.16E-9 (2.76)***	1.20E-9 (3.03)***	8.84E-10 (1.57)*	8.61E-10 (1.55)*
DF(-1)			0.499 (9.6)***	0.416 (7.59)***	0.644 (18.43)***	0.720 (19.59)***		
Observations	390	390	330	330	360	360	390	390
	Rho		Instruments		Instruments		Rho	
	0.876	0.868	136	136	158	158	0.871	0.858
	Hausman test		Sargantest		Sargan test		LR	
	0.128	0.152	216.0***	251.0***	429.2***	357.6***	206.6***	218.4***

Note: Significance test t in parentheses; Significant at ***1%, **5% and *10% respectively.

The estimated equations in the cubic specifications appear to be performing well under the t tests. However, the probability of existence of autocorrelation reveals that the error terms in the model are not i.i.d, leading to the serial dependence of errors. To avoid the influence of autocorrelation on the unbiasedness of estimated parameters, the difference generalized method of moments (DIF-GMM) is used to estimate parameters. According to the significance of the t-test, the first-order difference of dependent variables is selected, and the first, second and third terms of independent variables are preserved. The results are shown in model II in Table 5. The empirical evidence in favor of an N-shaped curve does not dramatically change when employing a dynamic panel data analysis. More specifically, the income polynomial coefficients (i.e. GDPP, GDPP squared) are statistically different from zero at the $p < 0.01$ level of significance for the two dependent variables and the coefficients of GDPP cubed are statistically different from zero at the $p < 0.05$ level of significance. As to the values of the estimated parameters, b1s and b3s are positive while b2s are negative (alternating signs) suggesting the existence of a stable N-shaped relationship between environmental efficiency and economic growth. Additionally, the lagged efficiency score indicators of DF(-1) are significant at the 1% level in nearly all cases and their

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high magnitude implies the suitability of the dynamic panel data estimation.

In cases where the lagged dependent variables are poor instruments for the first-differenced regression improving the accuracy of the estimates dramatically in the DIF-GMM model, the SYS-GMM estimator should be employed for this reason, and the results are reported as model III in Table 5. As we can see, the results support the previous empirical findings leading to the confirmation of an N-shaped relationship. The income polynomial coefficients (i.e. GDPP, GDPP squared and GDPP cubed) are statistically different from zero at the $p < 0.01$ level of significance in the two situations of (EFSCC and EFSC).

Since the environmental efficiency score is in the specific range of 0 to 1, the truncated dependent variable model (Tobit model) is used to re-estimate the parameters. Since the parameters estimated from the fixed effect of the panel data model of the truncated dependent variable may be biased and invalid, the random effect model is used here, and the results are reported in model IV in Table 5. As can be seen, similar to the results of the above models, all the coefficients are statistically different from zero, and the value of coefficients are close to those of model I respectively, which dedicated the N-shaped curve reflecting the relationship between environmental efficiency score and economic growth again.

The above results estimated by different econometric models consistently show an N-shaped curve reflecting the relationship between environmental efficiency and economic growth. There are many possible reasons for this phenomenon. The most plausible explanation is that in the early stage of economic development, the underdeveloped areas absorbed ‘dirty industries’ because of their low technology level and lack of capital, and became ‘pollution paradise’, which had a greater impact on the environment and a naturally lower environmental efficiency. With the improvement of economic and technology, experience accumulated in environmental governance and environmental efficiency improved. However, at a certain stage of economic growth, adjustment of industrial structures and capital accumulation began to appear. Under the effect of a significant increase in capital input, economic efficiency and environmental efficiency would decline. Eventually, industrial upgrading and rising technology along with the improvement of environmental governance will ultimately improve environmental efficiency, and completed the internalization of external pollution, thus showing an N-shaped curve reflecting the relationship between environmental efficiency and economic growth.

5. BRIEF CONCLUSIONS AND POLICY IMPLICATIONS

This paper uses the extended SBM model to measure the provincial environmental efficiency score including desirable and undesirable inputs-output in the window analysis framework. The results show that the environmental efficiency score of each province exhibits a strong

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relationship with economic growth. It has the property of general ascent and regional convergence. Then, the N-shape curve reflecting the relationship between environmental efficiency and economic growth is analyzed by using a variety of econometric models, including panel data model, GMM model, and panel Tobit model. The conclusions obtained by various methods are consistent, and the results are robust.

Based on the results, we believe that it is necessary to strengthen environmental management and take improving environmental efficiency as an important part of environmental protection. Firstly, it is very important to apply environmental efficiency. We should not only consider the higher requirements for the environment, but also the reality of the economic development stage and the upgrading and transformation of industrial structure. It is necessary to understand the dynamic relationship between economic growth and environmental protection and implement the improvement of environmental efficiency into environmental protection. Secondly, it is time to improve the working mechanism of environmental protection. Aiming at improving environmental efficiency, we should improve various environmental protection mechanisms. For different provinces in the east, central and western regions, for developed and underdeveloped provinces, different environmental rules and measures should be adopted according to the specific conditions of economy, industry, and ecology, to avoid the wholly same kinds of environmental protection. At last, it is necessary to apply the evaluation of environmental efficiency in environmental protection. We can find out the law of environmental efficiency change, and formulate scientific environmental protection policies according to key information such as inflection point and vertex according to the EKC.

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