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Full Length Research Paper

Assessing the sustainable performance of Chinese industrial sector

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Sustainability management is a subject of growing interest in economic development, business management, and environmental management. Data envelopment analysis (DEA) has been widely used to integrate this diverse nature of sustainable performance in economy. However, existing DEA frameworks suffer from two critical limitations: First, they follow traditional radial assumptions, which may lead to difficulties in characterizing the real production process. Second, they do not estimate the determinants of sustainable performance. In this regard, this paper presents a two-stage DEA model that can overcome these limitations. In the first stage, non-radial and non-oriented DEA frameworks with the slacks-based measure (SBM) are introduced. In the second stage, the truncated bootstrap regression identifies the determinants of sustainable performance with industries in 30 regions of China. The eastern region showed the highest sustainable performance, whereas the western region showed the lowest performance. The level of industrialization had no effect on sustainability management. However, GDP per capita, the promotion of the service industry, energy efficiency, public investment in environmental pollution control, and the waste reuse technology level had positive effects on sustainable performance.

Key words: Sustainability management, Two-stage DEA, truncated bootstrap regression, China, SBM-DEA.

INTRODUCTION

China's reform and open policy have allowed it to achieve remarkable progress in economic and social development. In particular, China has been referred to as the "global factory." This implies the rapid development of China's industrial sector, particularly its manufacturing sector, as well as China's contribution to global economic progress. Unfortunately, the scale-oriented economic development of China has led to the inefficient use of natural resources and energy in the production process, resulting in high consumption and serious pollution. Industrial pollutants and energy consumption have increased steadily. For instance, China's GDP grew rapidly from 1981 to 2004 (an average annual growth rate of 10%), and its energy consumption in 2008 was 3.42 times that in 1981. The amounts of industrial solid waste produced, waste gas emissions, and wastewater discharge in 2004 were 3.19, 1.64, and 1.65 times those in 1981, respectively (Bian and Yang, 2010).

Since the UN Conference on Environment and Development (UNCED) in 1992, sustainable development has been a fundamental paradigm for many countries, including China. To harmonize the trade-off between economic growth and negative effects on the environment, we can use sustainable performance as a tool for quantifying this harmonized management because it indicates healthy economic activities by clarifying the empirical relationship between environmental outputs and economic performance (Yilmaz and Flourish, 2010). Lee and Kim (2009) indicated that environmental provisions and standards are widely accepted and implemented in the industrial sector. By contrast, social provisions and standards are not widely used, and there is a missing link in the environmentally sustainable implementation of economic development in the industry.

Data envelopment analysis (DEA), proposed by Charnes et al. (1978) and extended by Banker et al. (1984), is a well-established linear programming method for measuring the relative performance of each decision-

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making unit (DMU) that has multiple inputs and outputs. DEA has recently been widely applied to evaluate economic and business management performance. Sufian and Shah Habibullah (2009) used DEA to examine the impact of M&A on the technical performance of the Malaysian banking sector. Chen et al. (2010a) also used DEA to measure the management performance of financial holding companies in Taiwan. Lin et al. (2010) used DEA to analyze the debt-paying management performance of Taiwan's shipping industry. Although these studies used DEA to measure the performance of multiple DMUs, they did not consider the environmental impact from a sustainable perspective. As Lee (2009) argued, previous business management research has largely ignored green management practices. Chen et al. (2010b) suggested a three-stage DEA method incurporating environmental factors, but their study was not empirical proved, but just theoretic proposition-oriented.

Sustainable development research has increasingly focused on environmental issues such as climate change, and thus, DEA, which can incorporate undesirable outputs such as industrial pollutants, has become a popular method for measuring environmental management performance. As Zhou et al. (2008b) indicated, there are a number of methods for incorporating undesirable outputs into DEA models.

In general, these methods can be classified into three types. The first type is based on a simple translation of data and the use of traditional DEA models. Lovell et al. (1995) treated undesirable outputs as normal outputs after taking their reciprocals. Similarly, Seiford and Zhu (2002) developed a radial DEA model with a negative sign assigned to all undesirable outputs (i.e., each undesirable output is multiplied by "-1") and applied a suitable transition vector by linear programming to all negative undesirable outputs into the integrated output vector. Using this approach, Yeh et al. (2010) compared the sustainable development performance of Taiwan with that of China. However, the way in which they modified their data did not reflect the reality of production processes, and thus, their approach has a difficulty to explain real production activities.

The second type treats undesirable outputs as inputs in traditional DEA models, assuming that undesirable outputs have the same characteristic of the inputs as "the less the better" in the production process (Hu and Wang, 2006; Zhang et al., 2008). Clearly, a method that treats undesirable outputs such as pollutants simply as inputs can take the traditional DEA approach. However, undesirable outputs are byproducts, not inputs, of production, and thus, this simple method cannot reflect the actual production process.

The third type is based on the concept of weak disposability technology, which was proposed by Färe and Grosskopf (2004) and applied by Zhou et al. (2008a). More studies measuring sustainable performance have adopted this method than the simple data translation method because this method can consider desirable as well as undesirable outputs both simultaneously and systematically, allowing the method to reflect the actual production process more accurately. However, this approach ignores slack variables and it is a radial efficiency measure.

Although there are a number of methods for measuring environmental management performance, most follow the concept of the traditional radial DEA model, which has weak discriminating power in ranking and comparing decision-making units (DMUs) when many DMUs have the same efficiency score of 1. In addition, radial models adjust all undesirable inputs and outputs by the same proportion to the efficient targets. However, the obtained efficient targets may not be preferred by decision makers or managers because of various political, economic, or even practical considerations. Taking this circumstance into consideration, the present study fills the gap in previous research by presenting an alternative non-radial slacks-based measure-DEA (SBM-DEA) framework that incorporates undesirable and desirable outputs simultaneously to quantify the sustainable management performance (SMP) of China's industrial sector. Here the industrial sector refers to the mining and manufacturing sectors as well as the provision of electricity, gas, and water.

Further, as suggested by Chen et al. (2010b), the present study conducts a regression analysis to identify the determinants of DEA performance scores in the second stage. Because dependent variables for DEA scores are not continuous but limited to the interval between 0 and 1, the ordinary least squares (OLS) method is not appropriate, Tobit regression was also used as an alternative to OLS in the past studies. For instance, Lu et al. (2010) employed it in the second stage to determine the determinants of the R&D management performance of the high-technology industry. Wei et al. (2009) also used Tobit regression to determine the factors influencing China's energy performance. However, according to Simar and Wilson (2007), Tobit regression has some limitations as follows: First, efficiency scores can be estimated empirically, but they cannot be observed directly. Thus, the assumption of the Tobit model with independently distributed error terms is not valid. Second, even if empirical estimates of the efficiency frontier can be obtained from the selected sample of DMUs, the model eliminates some efficient production possibilities not observed in the sample.

Therefore, this study employs the truncated bootstrap regression suggested by Simar and Wilson (2007) to select a set of representative factors to identify the determinants of sustainability performance. The proposed two-stage model provides more reliable results than existing models in practical terms.

METHODOLOGY

In this paper, an alternative two-stage DEA model is introduced to assess the sustainable performance and its determinants. In the first stage, the new sustainability data envelopment analysis (SDEA) framework is employed with the slacks-based measure (SBM), which was firstly introduced by Tone (2001) and extended by Zhou et al. (2006). Based on these two studies, non-radial and non-oriented measures are simultaneously incorporated for sustainability factors. Since the output of the first stage just tells the efficiency, not its determinants, in the second stage, the truncated bootstrap regression, suggested by Simar and Wilson (2007), is used to identify the determinants of performance scores.

Sustainability DEA framework

SBM-DEA, a non-radial, non-input/output-oriented approach, makes direct use of input and output slacks to measure efficiency. We assume that more outputs than inputs is a general criterion for performance. If there are undesirable outputs, then technologies with more good (desirable) outputs than bad (undesirable) outputs and inputs can be seen as efficient. Suppose that there are n regions and that each has three factors—inputs, good outputs, and bad outputs—which are denoted by the three vectors $x \in R^m$, $y^g \in R^{s1}$, and $y^b \in R^{s2}$, respectively. Define the matrices Y^g, Y^b, and X as $Y^g = [y^g{}_{ij}] = [y_1^g,..., y_n^g] \in R^{s1\times n}$, $Y^b = [y_{ij}^b] = [y_1^b,..., y_n^b] \in R^{s2\times n}$, and $X = [x_{ij}] = [x_1,..., x_n] \in R^{m\times n}$, respectively. The production possibility set (PPS) is as follows:

$$P(x) = \left\{ (y^g, y^b) \mid x \text{ produce } (y^g, y^b), x \ge X\lambda, y^g \le Y^g\lambda, y^b \ge Y^b\lambda, \lambda \ge 0 \right\}$$

Where λ is the non-negative intensity vector, which indicates that the above definition corresponds to the CRS (constant returns to scale) situation. We can employ the sensitivity analysis by imposing constraints on the matrix λ.

By imposing $\lambda = 1$, we have $P(x)$ in a VRS (variant returns to scale) situation. By imposing $\lambda \ge 1$, we have $P(x)$ in an NDRS (non-decreasing returns to scale) situation. By imposing $0 \le \lambda \le 1$, we have $P(x)$ in an NIRS (non-increasing returns to scale) situation. Bian and Yang (2010) showed that the CRS situation satisfies all production technologies and that it also meets the requirements for environmental performance, and thus, we consider only the CRS situation in this paper. Tone (2001) developed the SBM-DEA model as follows, considering slack variables which overcome the shortcoming of traditional CCR model:

$$\begin{aligned}
&\phi^* = \min \frac{1 - \frac{1}{m}\sum_{i=1}^{m} \frac{s_i^-}{x_{i0}}}{1 + \frac{1}{s}\sum_{r=1}^{s} \frac{s_r^g}{y_{r0}^g}} \\
&S.T. \\
&x_0 = X\lambda + s^- \\
&y_0^g = Y^g\lambda - s^g \\
&s^- \ge 0, s^g \ge 0, \lambda \ge 0
\end{aligned} \qquad (1)$$

When bad outputs are considered, our sustainability SBM-DEA model can be measured as follows:

$$\begin{aligned}
&\phi^* = \min \frac{1 - \frac{1}{m}\sum_{i=1}^{m} \frac{s_i^-}{x_{i0}}}{1 + \frac{1}{s_1 + s_2}\left(\sum_{r=1}^{s_1} \frac{s_r^g}{y_{r0}^g} + \sum_{r=1}^{s_2} \frac{s_r^b}{y_{r0}^b}\right)} \\
&S.T. \\
&x_0 = X\lambda + s^- \\
&y_0^g = Y^g\lambda - s^g \\
&y_0^b = Y^b\lambda + s^b \\
&s^- \ge 0, s^g \ge 0, s^b \ge 0, \lambda \ge 0
\end{aligned} \qquad (2)$$

The vector s^g denotes the shortage of good outputs, whereas the vectors s^- and s^b denote surpluses of inputs and bad outputs, respectively. The DMU is efficient in the presence of undesirable outputs if ϕ^*=1, indicating that all slack variables are 0, ($s^- = 0, s^g = 0, s^b = 0$), but that the object model (2) is not a linear function. Using the transformation suggested by Tone (2001), we can establish an equivalent linear programming model for t, φ, s^b and s^g as follows:

$$\begin{aligned}
&r^* = \min t - \frac{1}{m}\sum_{i=1}^{m} \frac{s_i^-}{x_{i0}} \\
&1 = t + 1 + \frac{1}{s_1 + s_2}\left(\sum_{r=1}^{s_1} \frac{s_r^g}{y_{r0}^g} + \sum_{r=1}^{s_2} \frac{s_r^b}{y_{r0}^b}\right) \\
&S.T \\
&x_0 t = X\varphi + s^- \\
&y_0^g t = Y^g\varphi - s^g \\
&y_0^b t = Y^b\varphi + s^b \\
&s^- \ge 0, s^g \ge 0, s^b \ge 0, \varphi \ge 0, t > 0.
\end{aligned} \qquad (3)$$

Let the optimal solution to Model (3) be (t^*, φ^*, s^{-*}, s^{g*}, s^{b*}) to solve the optimizing model (1) defined by $\rho^* = t^*$, $\lambda^* = \frac{\varphi^*}{t^*}$, $s^{-*} = \frac{s^{-*}}{t^*}$, $s^{g*} = \frac{s^{g*}}{t^*}$, $s^{b*} = \frac{s^{b*}}{t^*}$. The existence of ($t^*$, φ^*, s^{-*}, s^{g*}, s^{b*}) with t^*>0 is guaranteed by Model (3). The reader is referred to Cook and Seiford (2009) for more detailed solutions to other DEA models, including CCR.

By combining Model (2) with Model (3), we can consider bad outputs without any methodological constraint to evaluate sustainable performance.

Two-stage truncated bootstrap regression

Because of the biased disadvantages of the OLS model or Tobit regression, the second-stage regression model should be employed to identify the unbiased determinants of sustainable performance. The first disadvantage comes from the fact that efficiency scores are not observed directly but obtained through the empirical estimation. Thus, OLS models (including the Tobit model), which assume independently distributed error terms, are not valid. In addition, empirical estimates of the efficiency frontier are obtained based on a selected sample of DMUs, which eliminates some efficiency production possibilities not observed in the sample. Further, the two-stage regression model depends on explanatory variables that are not directly observed but estimated in the first stage. This implies that the error term is correlated with second-stage explanatory variables.

To overcome these disadvantages, the truncated bootstrap approach of Simar and Wilson (2007), by employing a double bootstrap method, enables consistent inferences within models, explaining efficiency scores while simultaneously producing standard errors and their confidence intervals. The truncated bootstrap model is defined as follows:

$$\phi^{\wedge} = z_i \beta + \varepsilon_i \qquad (3)$$

Our aim is to recognize the relationship between DEA scores $\phi^{\wedge}$ and explanatory variables z_i, which refer to the vector of parameters with some statistical noise ε_i in Equation (3). Previous studies have suggested some estimation procedures based on the OLS or Tobit model. However, because of the biased estimation as mentioned above, our approach follows the following steps:

1. Calculate the DEA score $\phi^{\wedge}$ for each DMU by using the DEA model according to Models (1) and (2);

2. Conduct the truncated regression of $\phi^{\wedge}$ and z_i by using the maximum likelihood function to estimate $\beta^{\wedge}$ and $\sigma_{\varepsilon}^{\wedge}$ of β and σ_{ε}, respectively;

3. Repeat the following steps B times (B=2000) to obtain a set of bootstrap estimates $\{\phi_{i,b}^{\wedge *}, b = 1, \ldots B\}$:

a. Draw ε_i from the N (0, $\hat{\sigma}^2$) distribution with left truncation at (1- $\beta^{\wedge} z_i$);

b. Calculate $\phi_i^* = z_i \beta^{\wedge} + \varepsilon_i$;

c. Make a pseudo data set (x_i^* y_i^*), where $x_i^* = x_i$ and $y_i^* = y_i$ $\phi_i^{\wedge} / \phi_i^*$;

d. Substitute a new DEA estimate θ_i^* with the set of pseudo data (x_i^* y_i^*).

4. For each DMU, calculate the bias-corrected estimate $\phi^{\wedge\wedge}{}_i = \phi^{\wedge}{}_i -$ $bia^{\wedge}s_i$, where $bia^{\wedge}s_i$ is the bootstrap estimator of bias defined as $bia^{\wedge}s_i = 1/B \sum_{b=1}^{B} \phi^{\wedge *}{}_{i,b} - \phi^{\wedge}{}_i$;

5. Conduct the truncated regression of $\phi^{\wedge\wedge}{}_i$ on z_i to obtain the estimates ($\beta^{\wedge\wedge}$, $\sigma^{\wedge\wedge}$) of (β, σ);

6. Repeat the following three steps *B2 (B2=2000)* times to obtain a set of bootstrap estimates $\{\beta_b^{\wedge\wedge *}, \sigma^{\wedge\wedge *}, b = 1, \ldots B2\}$:

a. For i=1,…,n, ε_i is drawn from N (0, $\sigma^{\wedge\wedge}$) with left truncation at (1- $\beta^{\wedge\wedge} z_i$);

b. For i=1,…,n, execute $\phi^{**} = \beta^{\wedge\wedge} z_i + \varepsilon_i$;

c. Again, conduct the truncated regression of $\phi^{**}{}_i$ on z_i to obtain the estimates of ($\beta^{\wedge\wedge *}$, $\sigma^{\wedge\wedge *}$).

For simplicity, the reader is referred to Simar and Wilson (2007) for more information on the estimation algorithm. Some researchers, including Barros and Dieke (2008) and Barros and Assaf (2009), have conducted empirical analyses to verify that in the two-stage DEA model, truncated bootstrap regression can account for efficiency scores better than the Tobit model and result in smaller standard errors and less variance. Panayides et al. (2009) suggested that in the two-stage DEA model, truncated bootstrap regression is a new trend in DEA research.

RESULTS

We presented the data on inputs and outputs for our DEA framework and illustrate how our model can be used to evaluate sustainable performance. We also address the determinants of sustainable performance by examining the industries operating in 30 regions of China in 2009.

Inputs and outputs in DEA

Choi et al. (2010) propose three indicators of economic performance in the systematic output evaluation: gross domestic product (GDP), industrial value added (IVA), and the employment rate. Because our research focuses on the regional industrial sector, IVA based on the present price (unit: RMB 100 million) was selected as the only desirable output. Many studies have taken this approach, including Zhang (2008) and Shi et al. (2010). The two basic inputs we considered were labor and capital. For labor, we used the employed labor number (LN) (unit: 10,000 persons), that is, the number of individuals employed in the industrial sector. Because there were no capital stock statistics for China, we used fixed

Table 1. Descriptive statistics for DEA inputs and outputs.

Input and output	Variable	Mean	Max	Min	Std. dev.
Non-resource inputs	CS	2353.2	9453.3	54.4	2284.9
	LN	116.4	443.5	7.5	108.4
Resource input	EC	9473.6	26809.9	785.5	7259.3
Desirable output	IAV	5248.8	18091.5	300.6	4750.7
Undesirable outputs	WG	14534.9	50779.4	1353.2	10679.2
	WW	78097.2	256159.9	7031.3	67539.5
	WS	6797.7	21975.8	200.8	5160.8

Table 2. Correlation matrix for input and output data.

Input and output	IVA	LN	CS	EC	WG	WW	WS
IVA	1.00						
LN	0.93*	1.00					
CS	0.84*	0.68*	1.00				
EC	0.75*	0.55*	0.79*	1.00			
WG	0.68*	0.51*	0.72*	0.90*	1.00		
WW	0.85*	0.84*	0.80*	0.63*	0.58*	1.00	
WS	0.37*	0.20*	0.54*	0.78*	0.85*	0.29*	1.00

*denotes significance at the 5% level.

fixed capital investment (unit: RMB 100 million) for the capital stock (CS) input, following Shi et al. (2010), Bian and Yang (2010), and Zhang (2008), among others. The energy consumption (EC) of the industrial sector was selected for the resource input, which included all types of energy sources (such as coal, oil, and gas). All inputs were converted into tons of standard coal equivalent (SCE) in terms of the corresponding standard of energy integration. The amount of industrial waste gas (WG) emissions (unit: 100 million m^3), the volume of industrial wastewater (WW) (unit: 10,000 tons), and the amount of industrial solid waste (SW) generated (unit: 10,000 tons), referred to as the “three types of industrial waste” in China, were used for the three undesirable outputs. All of the data were drawn from the 2010 Statistics Year Book of China.

As shown in Table 1, the variables varied substantially, and thus, we determined whether large inputs are important for sustainable performance. Table 2 shows the correlation matrix of inputs and outputs and clearly indicates that the correlation coefficients for our inputs and outputs were all positive and significant, suggesting that adding inputs would lead to increases in outputs.

DEA framework

China was divided into three areas: the eastern, central, and western areas. The eastern area included 8 coastal provinces such as Shandong, Jiangsu, Zhejiang, and Guangdong and 3 municipalities such as Beijing, Tianjin, and Shanghai. This area also referred to as the coastal area-accounts for nearly two-thirds of GDP, nearly half of energy usage in China. Additionally, the emission quantity of this area is relatively high. The central area included 10 inland provinces such as Heilongjiang, Jilin, and Inner Mongolia. This area has a large population and it is a home base for farming and related industries. The western area covered more than half of China’s entire territory and included 1 municipality (Chongqing) and 9 provinces such as Gansu, Qinghai, Xinjiang, and Sichuan. The western area, with the lowest population density, was the least developed area.

We used the proposed SBM-DEA model to measure the sustainable performance of these 30 regions of China in 2009. The MAXDEA5.0 with LINGO9.0 packages were used to compile the linear programming equation. Figure 1 showed the results for the sustainable performance of China’s industrial sector by region. Beijing, Shanghai, Jiangsu, Tianjin, and Guangdong, located in the eastern area, showed the highest scores (1). Henan and Inner Mongolia, located in the central area, also showed the highest scores (1). Gansu (0.34), located in the western area, showed the worst score. From the regional perspective, the results indicated that the three areas showed different levels of sustainable performance. The

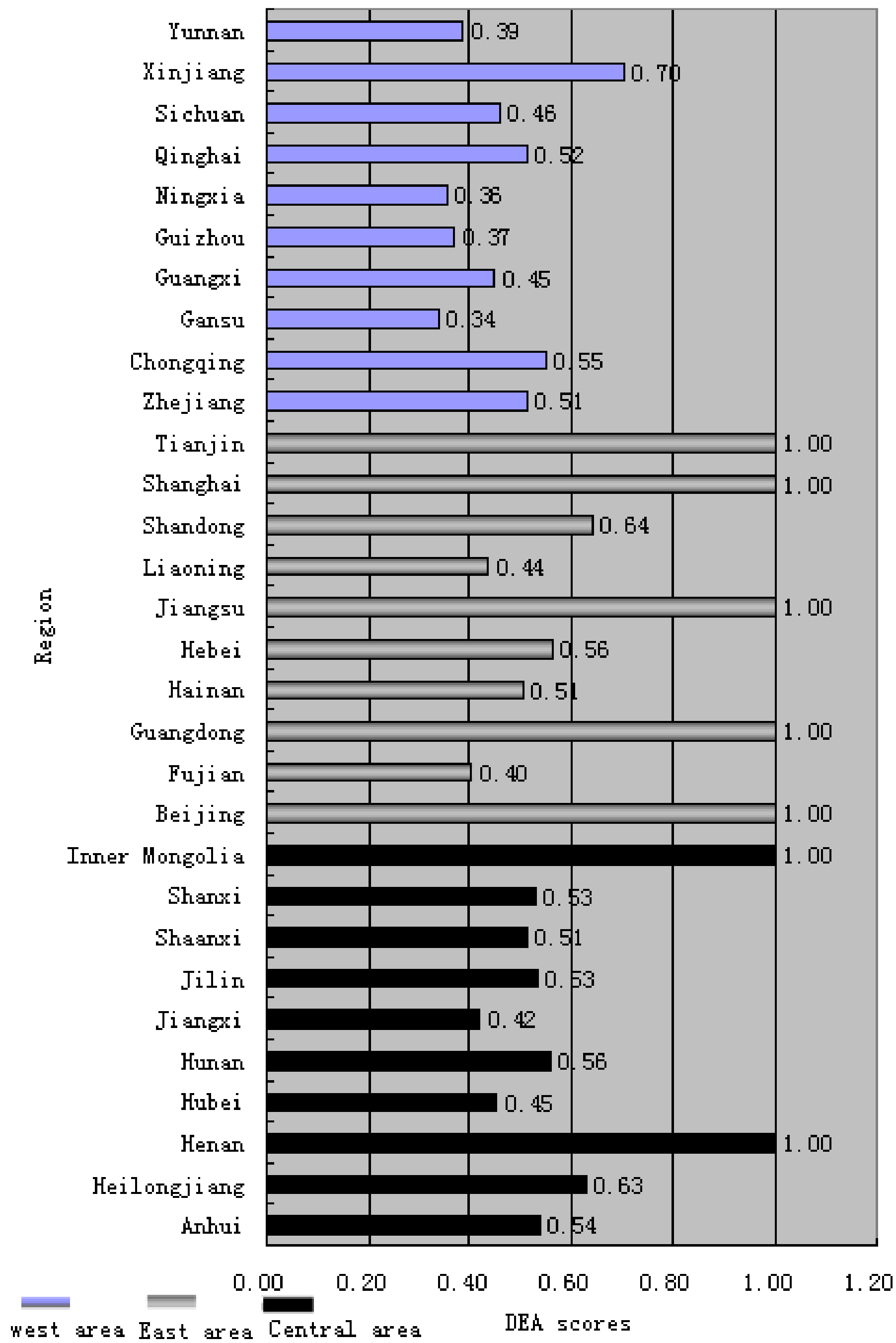

Figure 1. Sustainable performance by region.

eastern area (0.78) had the highest average score, followed by the central area (0.62) and the western area (0.46).

DISCUSSION

Lindmark (2004) argues that because less developed areas with lower income are likely to have fewer industries, they tend to experience less pollution and higher sustainable performance than more developed ones. By contrast, our results suggested that both the income and sustainable performance of the eastern area were higher than those of other areas.

Hu and Wang (2006) find that the central area of China showed the lowest energy management performance (0.494) followed by the western area (0.641) and the eastern area (0.746). Our results, however, indicated that the western area showed the lowest management performance. This difference may be due to the fact that Hu and Wang did not incorporate undesirable outputs into the model.

These results have some important implications. The eastern area is a more developed and economically advanced area, and thus, its industries may be able to attract more capital not only for the area’s rapidly increasing economic performance but also for its environmental management and pollution control, contributing to the sustainable development of the area. Thus, economic growth and environmental governance have been harmonious in the eastern area. If the industries in the eastern area are confronted with the problem of environmental waste, then they may simply transport these parts to other areas, allowing the industries in the eastern area to focus only on green parts of the manufacturing process. The central area, a developing area, has abundant natural resources and a strong industrial base, but its industrial structure is seriously unbalanced. Thus, its economic growth has entailed high energy consumption and heavy environment pollution. That is, its ecological environment has not been able to accommodate the area’s rapid economic development. The western area is well known for its rich natural resources but has lagged far behind the other areas in terms of economic development and income. Its ecological environment is highly vulnerable to economic development because of a lack of infrastructure.

The results also indicated that China has been in a dilemma over how it should address the western area in terms of sustainable development. If the local government overemphasizes environmental protection, the area’s already struggling economy may not improve. However, deregulation to the level of its environmental protection is inconsistent with the spirit of China’s plan for sustainable development nationwide. In this regard, the Chinese government should pursue differentiated policies that can address the unique needs of each area. Such policies should be able to enhance the sustainable performance of not only the western area but also the others. This is because the role of the government is to find and restore the missing link for sustainable development (Choi and Lee, 2009).

Because the central and eastern areas show high economies of scale, the government should transfer a reasonable amount of fixed capital investment from the central and eastern areas to the western area for the public compensation on the disharmonized sustainability nationwide and provide environmental infrastructure support. Furthermore, the central government could enact a regional emission trade scheme (ETS) into the market system, setting the diverse maximum levels on emissions for different areas; if the emissions of east area and central area exceed the level, local enterprises should buy these emission permission directly from the western area via local governmental transactions. Through such an emissions trade scheme (ETS), emissions in the eastern area and west area can be further reduced; furthermore, less developed west area can also benefit from this emissions trading system.

Determinants of sustainable performance

The two-stage regression analysis was used to identify the determinants of sustainable performance. For the two-stage approach, a number of previous studies have used the Tobit model. Wang et al. (2010) included GDP per capita, and the proportionate percentage of the service industry, and energy intensity (energy consumption per GDP) in the Tobit model to analyze the determinants of China’s environmental performance. He also employed urban and regional factors in the model. Wei et al. (2009) used the industry structure, energy intensity, and governmental factors as the key factors of energy performance. He suggested the use of FDI and innovation in the model. Chen and Li (2010) emphasized the influence of innovation technology on business management performance. However, as mentioned earlier, these Tobit models have some disadvantages. According to Barros and Assaf (2009) and Panayides et al. (2009), the truncated bootstrap method is more effective than the Tobit model for DEA regression. Therefore, we used the truncated bootstrap method because the sustainable performance of industries in China is related to economic, environmental, and regional factors in many respects.

Based on previous arguments and for the consistency of the data, six categories of variables were selected for the model: 1) the economic income factor—GDP per capita (GPER) (unit: RMB); 2) industry structure factors—the industry share of GDP (IS, unit: %) and the service industry share of GDP (SIS, unit: %); 3) government policy factors—the level of environmental protection facilities (GP, unit: numbers); 4) the energy efficiency factor—energy intensity (EI, unit: tones/RMB 10,000); 5) the technological factor—waste-recycle management technology (WMT) in terms of the value added from the re-use of waste (unit: RMB 10,000); and 6) the dummy variables (D1,D2) for three regional characteristics:

$$DEA_{i,t} = GPER_{i,t} + IS_{i,t} + SIS_{i,t} + GP_{i,t} + EI_{i,t} + WMT_{i,t} + D_1 + D_2 \tag{4}$$

The data for all the variables were drawn from the 2010 Statistical Year Book of China. Table 3 provides the correlations among the explanatory variables. The correlations between GPER and SIS; GPER and D2; IS and SIS; and GP and WMT were relatively high (0.68, 0.70, -0.64, and 0.79, respectively). If a correlation

Table 3. Correlations among explanatory variables.

Explanatory variable	GPER	IS	SIS	GP	EI	WMT	d1	d2
GPER	1.00							
IS	0.00	1.00						
SIS	**0.68**	**-0.64**	1.00					
GP	0.18	0.54	-0.19	1.00				
EI	-0.51	-0.07	-0.24	-0.33	1.00			
WMT	0.14	0.42	-0.22	**0.79**	-0.31	1.00		
D1	-0.26	0.23	-0.32	-0.14	0.00	-0.12	1.00	
D2	**0.70**	-0.02	0.43	0.47	-0.48	0.39	-0.54	1.00

coefficient is larger than 0.8, the strong multicollinearity exists and the model should be changed accordingly. Moreover, Grewal et al. (2004) suggests that the correlation between 0.6 and 0.8 may also lead to substantial multicollinearity problem. To avoid likelihood of this kind multicollinearity, two variables with greater than 0.6 should not be in the same regression model.

Following Simar and Wilson (2007), we used the R package to bootstrap the confidence intervals (2,000 replications to reduce the bootstrap standard error). The results are presented in Table 4. Several models were estimated to avoid multicollinearity issues and for comparison purposes.

The truncated bootstrap regression model provided a good fit to the data. The positive z-statistics imply that all the parameters (except for the IS variable) were significant. The estimation results generally conformed to a priori expectations.

GDP pre capita (GPER) had a significant positive correlation with sustainable performance ($p<0.000$). This demonstrates the importance of the economies of scale in sustainable performance. That is, regions with higher income were more likely to show higher sustainable performance. The service industry share of GDP (SIS) also had a significant positive correlation with sustainable performance ($p<0.000$), suggesting that the promotion of the service industry to improve industry governance can strengthen management performance. Further, the governance policy factors—the level of environmental protection facilities (GP) had a significant positive correlation with sustainable performance, indicating that public investment in environmental protection is likely to enhance sustainable performance. Waste reuse management technology (WMT) had a significant positive correlation with DEA scores ($p<0.00$), implying that if an area's innovation capability to process waste is high, its technologies for sustainable performance may be more advanced. Energy intensity (EI) had significant negative effects on DEA scores, suggesting that energy efficiency is critical to sustainable performance. The parameter associated with the industry structure factors—the industry share of GDP (IS) —was not significant in all the models, indicating that adding the manufacturing industry share may contribute to economic growth but not to sustainable performance. The regional dummies were all significant; implying that our estimation results obtained using these dummies remained unbiased.

Based on the results of the regression, we suggest that quantitative promotion for manufacturing industry can no longer contribute to sustainable development. Instead, the qualitative measures such as expansion of the service industry, public investment in environmental protection infrastructure, and the promotion of effective waste disposal may enhance the sustainable performance.

Conclusion

This study contributes to the current body of relevant literature by the proposed two-stage DEA model. In the first stage, the sustainability DEA framework is employed with the slacks-based measure (SBM). It gives more practical implications such as detailed ranks of the performance because of fewer constraints in the model. Moreover, since the result of the first stage just tells the performance like many previous studies, in the second stage, the truncated bootstrap regression is used to identify the determinants of performance scores. It gives more practical implications and suggestions due to the systematic decomposition of the performance.

The eastern area had the highest sustainable performance score (0.78), as well as the highest level of economic development. The central area ranked second (0.62). The western area had the lowest sustainable performance score (0.46) as well as the lowest level of economic development. These results are inconsistent with the findings of previous studies and indicate that China has been in a dilemma over how it should address the western area in terms of sustainable development. If the local government overemphasizes environmental protection, the area's already struggling economy may not improve. However, deregulation to the level of environmental protection is inconsistent with the spirit of China's plan for sustainable development nationwide. In this regard, the Chinese government should pursue a more region-specific or field-oriented policy to improve the

Table 4. Estimates from the truncated bootstrap regression.

Variable	Model 1	Model 2	Model 3	Model 4
GPER	1.21e-05*** (5.93)		1.09E-0.5*** (6.30)	
IS	0.507(1.57)		0.71 (1.55)	
SIS		1.176*** (4.51)		1.231*** (3.21)
GP	2.06E-06*** (3.33)			8.13E-6** (2.01)
EI	-0.011* (1.81)	-0.0098* (1.76)	-0.0183* (1.82)	-0.014*(1.72)
WMT		2.50E-0.8** (2.15)	5.03e-06*** (4.94)	
D1	0.10* (1.72)	0.19** (2.16)	0.08** (2.21)	0.16* (1.85)
D2		0.18* (1.68)		0(1.88)

The values in parentheses indicate z-scores. *, **, and *** denote significance at the 10, 5 and 1% levels, respectively.

sustainable performance of underdeveloped regions. This is because the role of the government is to find and restore the missing link for sustainable development while preventing any dichotomy in the economic structure.

For the determinants of sustainable performance, GDP per capita, the service industry share, government support, energy efficiency, and the level of waste disposal technology had significant positive effects on sustainable performance. The relationship between the industrial share and sustainable performance, however, was not significant, suggesting that whereas the manufacturing industry can no longer contribute to sustainable development, other policies such as the expansion of the service industry, public investment in environmental protection infrastructure, and the promotion of effective waste disposal may enhance sustainable performance.

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