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Constructing stratifications for regions in China with sustainable development concerns

Wen-Min Lu · Shih-Fang Lo

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Abstract China's economic boom has brought about environmental dark sides, i.e., serious air, water, and solid waste pollutions. As the largest developing countries in the world, China's road toward economic-environmental balance is even complicated since there are various regions of diversified geographical and economic conditions. Using context-dependent-DEA (data envelopment analysis) as performance evaluating technique, this study constructs the regions' benchmark-learning ladders for those inefficient regions to improve progressively; and to identify real benchmark for those efficient regions to rank ascendant by incorporating the stratification DEA method, attractiveness measure, and progress measure. Decision matrix covering attractiveness and progress scores is made to help the regions position themselves. Furthermore, we find that capital/employee ratio plays important role on forming levels of regions, which can be interpreted that advanced technology is one of key factors toward regional sustainable development.

Keywords Data envelopment analysis (DEA) · Attractiveness · Progress · Efficiency · Pollution · Sustainable development

1 Introduction

China's economic boom has several dark sides behind the spectacular growth. The environmental problem is one that is threatening to bite into the country's newly-found prosperity. People in China are suffering from the environmental degradation that takes many forms,

W.-M. Lu (✉)
Department of Financial Management, National Defense University,
No. 70, Section 2, Zhongyang North Road, Beitou, Taipei 112, Taiwan
e-mail: wenmin.lu@gmail.com

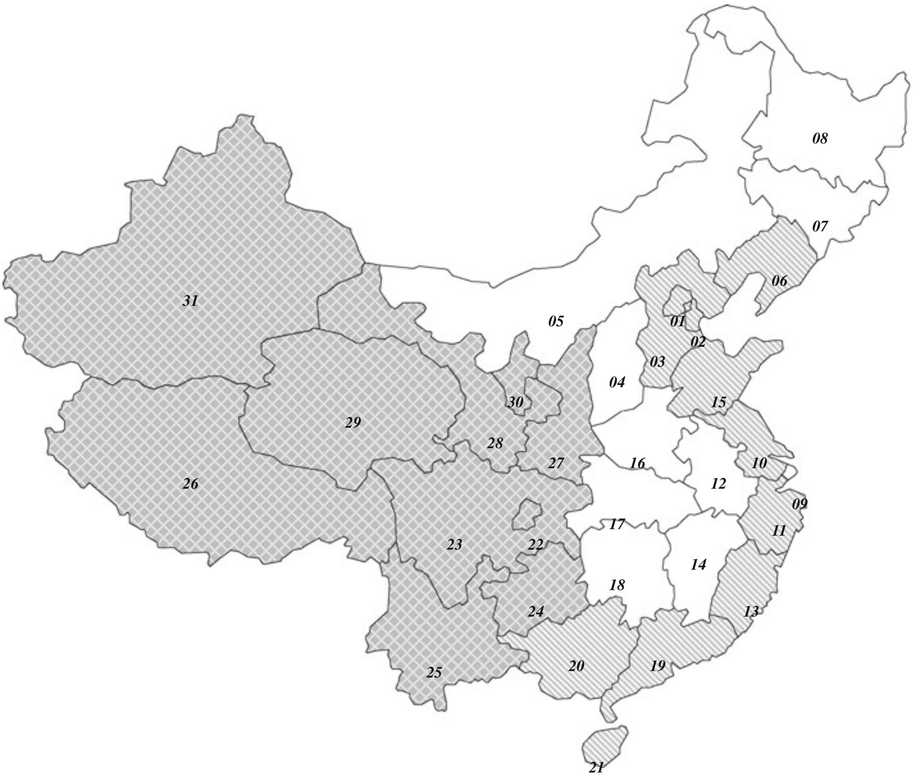
S.-F. Lo
International Division, Chung-Hua Institution for Economic Research,
Rm. 531, 75 Chang-Hsing St., Taipei 106, Taiwan
e-mail: shihfang.lo@gmail.com

including air, water, and solid waste pollution. As for air pollution, China has the world's highest emissions of sulphur dioxide and one fourth of the territory has to endure acid rain (the Economist 2004). Air pollution can lead to the premature death of many thousands of Chinese annually. In the case of water pollution, it is estimated that about 70% of the water that flows through China's urban areas is unsuitable for drinking and fishing (Nankivell 2005). Furthermore, solid waste production in China is expected to more than double over the next decade, which will push China far ahead of other countries as the largest producer in the world. It is estimated that, in each year, only 20% of the solid waste is properly disposed of (the Economist 2004). The environmental pollution and degradation in China, i.e., the damage to crops caused by acid rain, related medical bills, floods, and resource depletion, etc., is estimated to annually account for 8–12% of its GDP (APCSS 2000). This environmental degradation has threatened both the current and future generations and is undermining the sustainability of national long-term growth. Although pollution is an invariable consequence of development based on historical experience, the dilemma between growth and the environment in China is more complicated since there is a diversity of geographical and economic conditions across regions.

Regions in China can be roughly divided into three major areas: the east, the central region, and the west. Per capita GDP is highest in the urban/industrial centers of eastern China, lower in the middle provinces, and lowest in China's western hinterland. The eastern region stretches from the province of Liaoning to Guangxi, including Shandong, Hebei, Jiangsu, Zhejiang, Fujian, Guandong, and Hainan, as well as the municipalities of Beijing, Tianjin, and Shanghai. Of these three major regions, the eastern region has experienced the most rapid economic growth. The central area consists of Heilongjiang, Jilin, Inner Mongolia, Henan, Shaanxi, Anhui, Hubei, Hunan, and Jiangxi. There is not as much foreign investment in this area as in the eastern coastal regions, and existing equipment relatively-speaking lags somewhat behind. The western region covers more than half of China, and includes the provinces of Gansu, Guizhou, Ningxia, Qinghai, Shaanxi, Tibet, Yunnan, Xinjiang, Sichuan, and the municipality of Chongqing. Compared to the other two, this area in general has a low population density and is the least developed (Fig. 1).

Sustainable development at the national level should start at the regional level since these sub-national regions serve as key sites for the integration of economic and environmental policy (Gibbs 1998, 2000; Wallner et al. 1996, Dryzek 1997). From the perspective of regional sustainable development, a region's macroeconomic policy should be based on its ability to maximize wealth as well as minimize the environmental impact of its inhabitants. This study thus provides an in-depth analysis of China's sustainable development that covers both economic performance and environmental degradation, including air, water and solid waste pollution at the regional level.

When it comes to measuring the sustainability performance for the above-mentioned 31 regions in China, the actual task of ranking these regions from the highest to the lowest is quite basic. However, a region's 'attractiveness' or 'progress' compared to its peers is another interesting issue that is worth investigating. The performance of regions is influenced by the 'context.' A region may appear attractive against a background formed by other less attractive peers, or else unattractive when compared to other more attractive peers. For example, the relative attractiveness of region X compared to region Y depends on the presence or absence of a third party, say, region Z. Therefore, the context for region X changes with/without the existence of region Z. Against this background (or what we refer to as 'context' in this study), a region's 'attractiveness' can be interpreted, when found to be outperforming its competitors, as being how close it is to its competitors, while a region's 'progress' can, when found to be underperforming when compared with its competitors, be regarded as what it



Eastern Area		*Central Area*		*Western Area*	
01 Beijing*	25,523	***04*** Shanxi	5,460	***22*** Chongqing*	5,654
02 Tianjin*	20,154	***05*** Inner Mongolia	6,463	***23*** Sichuan	5,250
03 Hebei	8,362	***07*** Jilin	7,640	***24*** Guizhou	2,895
06 Liaoning	12,041	***08*** Heilongjiang	9,349	***25*** Yunnan	4,866
09 Shanghai*	37,382	***12*** Anhui	5,221	***26*** Tibet	5,307
10 Jiangsu	12,922	***14*** Jiangxi	5,221	***27*** Shaanxi	5,024
11 Zhejiang	14,655	***16*** Henan	5,924	***28*** Gansu	4,163
13 Fujian	12,362	***17*** Hubei	7,813	***29*** Qinghai	5,735
15 Shandong	10,465	***18*** Hunan	6,054	***30*** Ningxia	5,340
19 Guangdong	13,730			***31*** Xinjiang	7,913
20 Guangxi	4,668				
21 Hainan	7,135				

Fig. 1 Regions of China and average per capita GDP 2001 (RMB)

needs to do to improve its outputs. When faced with the diversity in terms of the economic-environmental conditions for the 31 regions in China, we would like to ask "what is the relative attractiveness or progress of a particular region when compared to its context that varies?" For policy-makers, it should be more important to identify the 'real' benchmark for those underperformers. While a poor performing region may be trying to improve itself by benchmarking the best performing one, it may be very difficult to do so, because of the huge gap between them. It is therefore necessary to provide an attainable benchmark target via a stepwise improvement for those inefficient regions.

The data envelopment analysis (DEA) approach and its extensions have recently been widely applied to regional studies. For example, DEA has been used to measure the efficiency and productivity specialization of Spanish and Turkey regions (Maudos et al. 2000; Armagan et al. 2008), the total factor productivity growth of Spanish regions (Boscá et al. 2004), the growth of factor productivity in Turkish manufacturing industry (Karadağ et al. 2005), and local government spending efficiency in the Lisbon region (Afonso and Fernandes 2006; Uri 2006), etc. By focusing on an application to regional sustainable development in China, this study presents a context-dependent DEA model that measures the relative attractiveness and progress of regions at a specific performance level. DEA, which was first introduced by Charnes et al. (1978), is a methodology used to identify the efficient frontier of a decision making unit (DMU). In referring to the DEA approach, context-dependent DEA evaluates DMUs against a specific context, or a specific performance level (Seiford and Zhu 2003). The basic idea of context-dependent DEA is that DMUs can be divided into different levels of efficient frontiers. Once the original efficient frontier is removed, a new second-level efficient frontier made up of the remaining DMUs will be formed. While the above process keeps operating, a series of frontiers is constructed as a scaling ladder that groups the DMUs into several stratifications. Context-dependent DEA is developed to measure the attractiveness and progress of DMUs with respect to a given evaluation context. The attractiveness measure estimates the competitiveness a DMU possesses, and the progress measure in turn estimates the extent to which a DMU needs to improve. Different strata of efficient frontiers rather than the traditional only-one-first-level efficient frontier are used as evaluation contexts. Due to its generating finer results, the context-dependent DEA is favored in this study, and also enables us to discriminate among the respective performances of the 31 regions in China with their diversified geographical and environmental characteristics.

The remainder of this paper is organized as follows: Following this section, Sect. 2 introduces an estimation methodology including the techniques used to cope with undesirable outputs and context-dependent DEA. Section 3 presents the empirical results. Section 4 concludes the paper.

2 Estimation methodology

This section employs DEA to measure the technical efficiency (TE) of DMUs, or regions in China in this case. We first describe the process for handling the undesirable factors in DEA in Sect. 2.1. In Sect. 2.2, the context-dependent-DEA is introduced to construct the regions' benchmark-learning ladder to enable the inefficient regions to improve progressively, and to identify real benchmarks for the more efficient regions to further improve their rank by incorporating the stratification DEA method, attractiveness measure, and progress measure, etc.

2.1 Undesirable factors in DEA

DEA measures the relative efficiency of DMUs with multiple performance factors that are grouped into outputs and inputs. Once the efficient frontier is determined, the inefficient DMUs can improve their performance to reach the efficient frontier by either increasing their current output levels or decreasing their current input levels. While conducting efficiency analysis, it is often assumed that all outputs are 'good' or 'desirable,' as in the case of GDP for a country. However, such an assumption cannot always be justified in the real world, because outputs may be 'bad.' For example, if inefficiency exists in production processes where final products are manufactured along with waste and pollutants, then the outputs of such waste and pollutants are undesirable (bad) and should hence be reduced to improve performance.

There are several alternatives for dealing with undesirable outputs in the DEA framework. The first is simply to ignore the undesirable outputs. The second is either to treat the undesirable outputs in terms of a non-linear DEA model or to treat the undesirable outputs simply as outputs and adjust the distance measurement in order to restrict the expansion of these undesirable outputs (Färe et al. 1989). The third is either to treat the undesirable outputs as inputs or to apply a monotone decreasing transformation (e.g., $1/y^b$, where y^b represents the bad output proposed by Lovell et al. (1995)). However, these methods cannot truly reflect the real production process or else remove the invariance to the data transformation. To overcome the shortcomings mentioned above, Seiford and Zhu (2002) propose a way that deals with undesirable outputs in the DEA framework. This approach can truly reflect the real production process and is invariant to the data transformation within the DEA model. We therefore apply this method to treat the undesirable output factors in this study.

Let y_{rj}^g and y_{rj}^b denote the desirable (good) and undesirable (bad) output, respectively. Obviously, we wish to increase y_{rj}^g and to decrease y_{rj}^b to improve the performance. However, in the output-oriented constant returns to scale (CRS) model (Charnes et al. 1978), both y_{rj}^g and y_{rj}^b are supposed to increase to improve the performance. To increase the desirable outputs and decrease the undesirable outputs, we proceed using the approach outlined in the following paragraphs.

First, we multiply each undesirable output by '−1' and then find a proper value v to let all negative undesirable outputs be positive. That is, $\overline{y}_{rj} = -y_{rj}^b + v > 0$. This can be achieved by $v = \max\left\{y_{rj}^b\right\} + 1$. The TE of the target DMU ($o = 1, \ldots, n$) can be computed as a solution to the following linear programming (LP) problem:

$$
\begin{aligned}
& Max \quad \eta_o \\
& s.t. \sum_{j=1}^{n} \lambda_j x_{ij} \leq x_{io}, \quad i = 1, \ldots, m, \\
& \sum_{j=1}^{n} \lambda_j y_{rj}^g \geq \eta_o y_{ro}^g, \quad r = 1, \ldots, s, \\
& \sum_{j=1}^{n} \lambda_j \overline{y}_{rj} \geq \eta_o \overline{y}_{ro}, \\
& \eta_o, \ \lambda_j \geq 0; \quad \forall\, i \ and \ r; \quad j = 1, \ldots, n,
\end{aligned}
\tag{1}
$$

where n is the number of DMUs; and m and s are the numbers of inputs and outputs, respectively. Let x_{ij} and y_{rj} be the amount of the ith input consumed and the amount of the rth output produced by the DMU j, respectively. The TE of the target DMU is defined as TE $= 1/\eta_o$. By varying the index 'o' over all DMUs, we arrive at the TE in each DMU. If TE = one, then the target DMU is technically efficient. If TE is smaller than one, then the target DMU is technically inefficient. The solution value of λ_j indicates whether the DMU$_j$ serves as a role model or a peer for the target DMU. If $\lambda_j = 0$, then DMU$_j$ is not a peer. However, if $\lambda_j > 0$, say, $\lambda_j = 0.4$, then DMU$_j$ is a peer DMU with a 40% weight placed on deriving the target efficient output and input level for target DMU.

2.2 Context-dependent DEA

The context-dependent DEA (Seiford and Zhu 2003) is introduced to construct the regions' benchmark-learning ladder for those inefficient regions to progressively improve, and to identify real benchmarks for those efficient regions to improve their rank by incorporating the stratification DEA method, attractiveness measure, and progress measure. The stratification DEA method, attractiveness measure and progress measure are now described in what follows.

2.2.1 Stratification DEA method

The basic idea behind the stratification DEA method is that DMUs can be divided into different levels of efficient frontier. Once the original efficient frontier is removed, a new second-level efficient frontier made up of the remaining DMUs will be formed. While the above process keeps operating, a series of frontiers is constructed as a scaling ladder grouping the DMUs into several stratifications. The stratification DEA with undesirable outputs is introduced as follows:

Let $J^1 = \left\{\mathrm{DMU}_j, \quad j = 1, \ldots, n\right\}$ (the set of all n DMUs). Interactively define $J^{l+1} = J^l - E^l$, where $E^l = \left\{\mathrm{DMU}_k \in J^l \left|\phi\left(l, k\right)\right.\right\}$, and $\phi\left(l, k\right)$ is the optimal value for the following LP when DMU_k is under evaluation.

$$\begin{aligned}
&\underset{\lambda_j, \phi(l,k)}{Max}\ \phi\left(l, k\right)\\
&s.t. \sum_{j \in F(J^l)} \lambda_j x_{ij} \le x_{ik},\\
&\sum_{j \in F(J^l)} \lambda_j y^g_{rj} \ge \phi\left(l, k\right) y^g_{rk},\\
&\sum_{j \in F(J^l)} \lambda_j \overline{y}_{rj} \ge \phi\left(l, k\right) \overline{y}_{rk},\\
&\phi\left(l, k\right), \ \lambda_j \ge 0; \quad \forall\ i\ and\ r,\ j \in F\left(J^l\right),
\end{aligned} \tag{2}$$

where $j \in F\left(J^l\right)$ means $\mathrm{DMU}_j \in J^l$, i.e., $F(.)$ represents the correspondence from a DMU set to the corresponding subscript index set. When $l = 1$, Eq. 2 becomes the original output-oriented CRS model, Eq. 1, and E^1 consists of all the frontier DMUs. These DMUs in set E^1 define the first-level best-practice frontier. When $l = 2$, Eq. 2 gives the second-level best-practice frontier after the exclusion of the first-level frontier DMUs, and so on. In this manner, several levels of best-practice frontiers are identified. We call E^l the lth-level best practice frontier. The following algorithm accomplishes the identification of these best-practice frontiers using Eq. 2.

- Step 1: Set $l = 1$. Evaluate the entire set of DMUs, J^1, using Eq. 2 to obtain the first-level frontier DMUs, set E^1 (the first-level best-practice frontier).
- Step 2: Exclude the frontier DMUs from future DEA runs. $J^{l+1} = J^l - E^l$. (If $J^{l+1} = \varnothing$, then stop).
- Step 3: Evaluate the new subset of 'inefficient' DMUs, J^{l+1}, using Eq. 2 to obtain a new set of efficient DMUs, E^{l+1} (the new best-practice frontier).
- Step 4: Let $l = l + 1$. Go to step 2.
- Stopping rule: $J^{l+1} = \varnothing$, the algorithm stops.

2.2.2 Attractiveness measure

The attractiveness measure is developed to measure the attractiveness of DMUs with respect to a given evaluation context. The attractiveness measure estimates the competitiveness that a DMU possesses. The attractiveness measure with undesirable outputs is introduced as follows. Based upon these evaluation contexts $E^l (l = 1, \ldots, L-1)$, we can obtain the relative attractiveness measure with undesirable outputs by means of the following LP:

$$\begin{aligned}
H_q^*(d) = &\underset{\lambda_j, H_q(d)}{Max}\ H_q(d), \quad d = 1, \ldots, L - l_o,\\
s.t. &\sum_{j \in F\left(E^{l_o+d}\right)} \lambda_j x_{ij} \le x_{iq}, \quad i = 1, \ldots, m,\\
&\sum_{j \in F\left(E^{l_o+d}\right)} \lambda_j y_{rj}^{g} \ge H_q(d) y_{rq}^{g}, \quad r = 1, \ldots, s,\\
&\sum_{j \in F\left(E^{l_o+d}\right)} \lambda_j \overline{y}_{rj} \ge H_q(d) \overline{y}_{rq},\\
&H_q(d),\ \lambda_j \ge 0; \quad \forall\, i \text{ and } r,\ j \in F\left(E^{l_o+d}\right),
\end{aligned} \tag{3}$$

where $\text{DMU}_q = \left(x_{iq}, y_{rq}\right)$ is from a specific level E^{l_o}, $l_o \in \{1, \ldots, L-1\}$. In Eq. 3, each best-practice frontier of E^{l_o+d} represents an evaluation context for measuring the relative attractiveness of DMUs in E^{l_o}. The larger the value of $1/H_q^*(d)$, the more attractive the DMU_q, since it is outstanding within the level compared to others. Because this DMU_q makes itself more distinctive from the evaluation context E^{l_o+d}, we can therefore rank the DMUs in E^{l_o} based on their attractiveness scores and identify the best one in that stratification.

2.2.3 Progress measure

The progress measure is developed to measure the progress of DMUs with respect to a given evaluation context. The progress measure estimates to what extent a DMU needs to improve. The progress measure with undesirable outputs is introduced as follows. To obtain the progress measure with undesirable outputs for a specific $\text{DMU}_q = \left(x_{iq}, y_{rq}\right) \in E^{l_o}$, $l_o \in \{2, \ldots, L\}$, we use the following LP:

$$\begin{aligned}
G_q^*(g) = &\underset{\lambda_j, G_q(g)}{Max}\ G_q(g), \quad g = 1, \ldots, l_o - 1,\\
s.t. &\sum_{j \in F\left(E^{l_o-g}\right)} \lambda_j x_{ij} \le x_{iq}, \quad i = 1, \ldots, m,\\
&\sum_{j \in F\left(E^{l_o-g}\right)} \lambda_j y_{rj}^{g} \ge G_q(g)\, y_{rq}^{g}, \quad r = 1, \ldots, s,\\
&\sum_{j \in F\left(E^{l_o-g}\right)} \lambda_j \overline{y}_{rj} \ge G_q(g)\, \overline{y}_{rq},\\
&G_q(g),\ \lambda_j \ge 0; \quad \forall\, i \text{ and } r,\ j \in F\left(E^{l_o-g}\right).
\end{aligned} \tag{4}$$

In Eq. 4, each efficient frontier, E^{l_o-g}, contains a possible target for a specific DMU in E^{l_o} to improve its performance. The progress measure here is a level-by-level improvement. For

Table 1 Summary statistics of inputs and outputs in 2001

Variables	Mean	Min	Max	Standard deviation
Inputs				
Capital stock (100 million RMB)	15017.5	1235.4	49078	12091.5
Number of employed persons (10,000 persons)	2019.7	124.6	5517	1443.8
Desirable output				
Regional GDP (100 million RMB)	3444.0	137.7	10648	2762.6
Undesirable outputs				
Total volume of industrial sulphur dioxide (SO_2) emissions (tons)	484979.4	734.0	1408716	356230.7
Total volume of waste water discharged (10,000 tons)	65355.0	1114.0	271029	57204.4
Total volume of industrial solid waste produced (10,000 tons)	2865.8	18.0	8847	2271.2

a larger $G_q^*(g)$, more progress is expected for DMU_q. Thus, a smaller value of $G_q^*(g)$ is preferred, which implies that the DMU is closer to an upper level.

2.3 Data selection

A dataset for 31 regions in China (27 provinces and 4 municipalities) is established from the *China Statistical Yearbook* for the year 2001. Two inputs, one desirable output, and three undesirable outputs are considered into our analysis. The two inputs are the capital stock and the number of employed persons. The one desirable output is regional GDP. The values of the monetary units, e.g., GDP and the capital stock, are in current prices. Three undesirable outputs of the emissions are: the total volume of sulfur dioxide emissions (a proxy for air pollution), the total volume of waste water discharged (a proxy for water pollution), and total volume of industrial solid waste produced (a proxy for solid waste). These variables are also reported in the *China Statistical Yearbook*. The data for the capital stock cannot be retrieved directly from the *China Statistical Yearbook*. The regional capital stock is therefore calculated by summing the capital stock in the previous year and capital formation in the current year less depreciation in the current year. We obtain the initial capital stock (the previous year's data or the year 2000) from a study by Li (2003). All the figures are based on 2001 prices. Summary statistics of these inputs and outputs for the regions are shown in Table 1.

3 Empirical results and analysis

In this section the results of context-dependent DEA for evaluating regional sustainable development in China are presented by incorporating stratification DEA, as well as the attractiveness measure and progress measure. Section 3.1 introduces previous studies related to the identification of a bunch of efficient DMUs and the process for constructing stratifications with context-dependent DEA. Section 3.2 then reports the results of estimating the attractiveness/progress measures for the 31 regions in China, respectively. More detailed discussions from the perspectives of regional position and national resource distribution problems that correspond to the results are also provided.

3.1 Constructing stratifications for regions

After identifying the efficient DMU, the role it plays in being benchmarked by other inefficient DMUs is also important. Previously, various efforts have been devoted to developing methods without *a priori* information to identify the benchmarks in DEA. One way of accomplishing such a task is to count the number of times a particular efficient DMU acts as a reference DMU (Smith and Mayston 1987). Andersen and Petersen (1993) presented a procedure referred to as the super-efficiency CCR model for ranking efficient units. Their basic idea is to compare the DMU under evaluation with all other DMUs in the sample, i.e., the DMU itself is excluded. Seiford and Zhu (1999) offered a super-efficiency BCC model in which increasing, constant, and decreasing returns to scale are allowed. The model is based on a reference technology constructed from all other DMUs.

Li and Reeves (1999) proposed a multiple criteria approach that is referred to as Multiple Criteria DEA and which focuses on solving two key problems associated with a lack of discrimination and inappropriate weighting schemes. Tone (2002) described a super-efficiency model that used the slacks-based measure of efficiency. To summarize the above previous studies, the benchmarks derived from the proposed methods above can possibly become inimitable or unattainable goals for the inefficient DMUs, at least immediately. A series of step-by-step learning benchmarks for an inefficient DMU to learn and gradually improve its operating efficiency seem to be more realistic and reasonable. Context-dependent DEA just seems to fit this research interest.

By using the stratification DEA model as shown in Eq. 2, the five levels of efficient frontiers are constructed as shown in Table 2. Shanghai, Hunan, Guangdong, and Tibet are revealed to be efficient while running the 1st-Stratification DEA, and these four regions are marked as ‘level 1’ regions. After eliminating the level 1 regions, we run the DEA again, and select 6 regions (Beijing, Tianjin, Hebei, Fujian, Guangxi, and Qinghai), revealing the TE of 1 as level 2 regions. This process continues until we get to the level 5 regions. Frontiers with five levels are therefore constructed. Based on Morita et al. (2005) suggestion, the benchmark targets of the inefficient level 5 regions should take the level 4 regions as initial targets to improve efficiency in the first stage. In the second stage, after the level 5 regions achieve the fourth-level efficient frontier, those at level 5 can use the third-level efficient frontier as a secondary benchmark for improvement and so on in order to proceed stage by stage. We refer to this composition of learning tracks for regions at different levels as ‘benchmark-learning contours,’ where it is recommended that underperforming regions set their current learning target as those who are one-step higher than their own stratification.

3.2 Attractiveness and progress measures for regions

We now turn to the attractiveness and progress measures (Eqs. 3 and 4) for the 31 regions when different efficient frontiers are chosen as evaluation contexts. Table 3 gives the results. The number to the right of each score indicates the ranking position based on the attractiveness measure and the progress measure. For instance, the symbol ‘①’ represents the top-ranked position with distinguished performance in the case of the attractiveness measure. In regard to the progress measure, the symbol ‘①’ indicates that the DMU is the closest to the uppermost frontier within the same level.

The attractiveness measure for each region from level 1 to level 4 is the italics data. The attractiveness measure can be used to identify DMUs that have outstanding performance and can differentiate the performances of efficient DMUs at certain frontier levels. Each region is measured based on levels that are worse than where it is located. In other words, regions

Table 2 Results of stratification DEA

1st-Stratification DEA		2nd-Stratification DEA		3rd-Stratification DEA		4th-Stratification DEA		5th-Stratification DEA		Level	
DMU	TE	DMU	TE	DMU	TE	DMU	TE	DMU	TE	DMU	
Beijing	1.170	Shanghai	Level 1	Shanghai	Level 1	Shanghai	Level 1	Shanghai	Level 1	Shanghai	Level 1
Tianjin	1.024	Hunan	Level 1	Hunan	Level 1	Hunan	Level 1	Hunan	Level 1	Hunan	Level 1
Hebei	1.118	Guangdong	Level 1	Guangdong	Level 1	Guangdong	Level 1	Guangdong	Level 1	Guangdong	Level 1
Shaanxi	1.693	Tibet	Level 1	Tibet	Level 1	Tibet	Level 1	Tibet	Level 1	Tibet	Level 1
Inner Mongolia	1.400	Beijing	1.000	Beijing	Level 2	Beijing	Level 2	Beijing	Level 2	Beijing	Level 2
Liaoning	1.764	Tianjin	1.000	Tianjin	Level 2	Tianjin	Level 2	Tianjin	Level 2	Tianjin	Level 2
Jilin	1.245	Hebei	1.000	Hebei	Level 2	Hebei	Level 2	Hebei	Level 2	Hebei	Level 2
Heilongjiang	1.131	Shaanxi	1.515	Fujian	Level 2	Fujian	Level 2	Fujian	Level 2	Fujian	Level 2
Shanghai	1.000	Inner Mongolia	1.249	Guangxi	Level 2	Guangxi	Level 2	Guangxi	Level 2	Guangxi	Level 2
Jiangsu	1.195	Liaoning	1.588	Qinghai	Level 2	Qinghai	Level 2	Qinghai	Level 2	Qinghai	Level 2
Zhejiang	1.196	Jilin	1.109	Shaanxi	1.450	Liaoning	Level 3	Liaoning	Level 3	Liaoning	Level 3
Anhui	1.287	Heilongjiang	1.022	Inner Mongolia	1.193	Heilongjiang	Level 3	Heilongjiang	Level 3	Heilongjiang	Level 3
Fujian	1.046	Jiangsu	1.092	Liaoning	1.000	Jiangsu	Level 3	Jiangsu	Level 3	Jiangsu	Level 3
Jiangxi	1.279	Zhejiang	1.108	Jilin	1.049	Zhejiang	Level 3	Zhejiang	Level 3	Zhejiang	Level 3
Shandong	1.283	Anhui	1.139	Heilongjiang	1.000	Hainan	Level 3	Hainan	Level 3	Hainan	Level 3
Henan	1.344	Fujian	1.000	Jiangsu	1.000	Sichuan	Level 3	Sichuan	Level 3	Sichuan	Level 3
Hubei	1.256	Jiangxi	1.146	Zhejiang	1.000	Ningxia	Level 3	Ningxia	Level 3	Ningxia	Level 3
Hunan	1.000	Shandong	1.128	Anhui	1.076	Xinjiang	Level 3	Xinjiang	Level 3	Xinjiang	Level 3
Guangdong	1.000	Henan	1.175	Jiangxi	1.092	Shaanxi	1.302	Inner Mongolia	Level 4	Inner Mongolia	Level 4
Guangxi	1.112	Hubei	1.119	Shandong	1.071	Inner Mongolia	1.000	Jilin	Level 4	Jilin	Level 4
Hainan	1.268	Guangxi	1.000	Henan	1.123	Jilin	1.000	Anhui	Level 4	Anhui	Level 4

Table 2 continued

1st-Stratification DEA		2nd-Stratification DEA		3rd-Stratification DEA		4th-Stratification DEA		5th-Stratification DEA		Level	
DMU	TE	DMU	TE	DMU	TE	DMU	TE	DMU	TE	DMU	
Chongqing	2.165	Hainan	1.057	Hubei	1.079	Anhui	1.000	Shandong	Level 4	Shandong	Level 4
Sichuan	1.196	Chongqing	1.890	Hainan	1.000	Jiangxi	1.021	Hubei	Level 4	Hubei	Level 4
Guizhou	1.313	Sichuan	1.038	Chongqing	1.829	Shandong	1.000	Guizhou	Level 4	Guizhou	Level 4
Yunnan	1.246	Guizhou	1.155	Sichuan	1.000	Henan	1.022	Yunnan	Level 4	Yunnan	Level 4
Tibet	1.000	Yunnan	1.105	Guizhou	1.061	Hubei	1.000	Gansu	Level 4	Gansu	Level 4
Shaanxi	1.812	Shaanxi	1.618	Yunnan	1.024	Chongqing	1.504	Shaanxi	1.000	Shanxi	Level 5
Gansu	1.543	Gansu	1.356	Shaanxi	1.542	Guizhou	1.000	Jiangxi	1.000	Jiangxi	Level 5
Qinghai	1.178	Qinghai	1.000	Gansu	1.265	Yunnan	1.000	Henan	1.000	Henan	Level 5
Ningxia	1.287	Ningxia	1.080	Ningxia	1.000	Shaanxi	1.422	Chongqing	1.000	Chongqing	Level 5
Xinjiang	1.250	Xinjiang	1.137	Xinjiang	1.000	Gansu	1.000	Shaanxi	1.000	Shaanxi	Level 5

Table 3 Attractiveness and progress scores for the regions at the different evaluation contexts

Level	Region	Background (efficient frontier)			
		Second-level 1st-degree[a]	Third-level 2nd-degree[a]	Fourth-level 3rd-degree[a]	Fifth-level 4th-degree[a]
Level 1	Shanghai	*1.582* ②	*2.752* ①	*3.551* ②	*5.038* ②
	Hunan	*1.158* ③	*1.230* ③	*1.332* ③	*1.401* ④
	Guangdong	*1.140* ④	*1.219* ④	*1.331* ④	*1.893* ③
	Tibet	*2.008* ①	*2.534* ②	*9.974* ①	*18.241* ①
	Region	First-level 1st-degree[b]	Third-level 1st-degree[a]	Fourth-level 2nd-degree[a]	Fifth-level 3rd-degree[a]
Level 2	Beijing	1.170 ⑤	*1.831* ②	*2.253* ③	*3.478* ③
	Tianjin	1.024 ①	*1.946* ①	*2.837* ②	*4.955* ②
	Hebei	1.118 ④	*1.064* ⑥	*1.153* ⑥	*1.232* ⑥
	Fujian	1.046 ②	*1.121* ④	*1.260* ④	*1.786* ④
	Guangxi	1.112 ③	*1.108* ⑤	*1.166* ⑤	*1.510* ⑤
	Qinghai	1.178 ⑥	*1.292* ③	*4.967* ①	*9.203* ①
	Region	First-level 1st-degree[b]	Second-level 2nd-degree[b]	Fourth-level 1st-degree[a]	Fifth-level 2nd-degree[a]
Level 3	Liaoning	1.764 ⑦	1.588 ⑧	*1.362* ④	*1.934* ④
	Heilongjiang	1.131 ①	1.022 ①	*1.112* ⑦	*1.538* ⑦
	Jiangsu	1.195 ②	1.092 ⑤	*1.322* ⑤	*1.880* ⑤
	Zhejiang	1.196 ③	1.108 ⑥	*1.208* ⑥	*1.715* ⑥
	Hainan	1.268 ⑤	1.057 ③	*3.635* ②	*6.623* ②
	Sichuan	1.196 ③	1.038 ②	*1.108* ⑧	*1.137* ⑧
	Ningxia	1.287 ⑥	1.080 ④	*4.306* ①	*7.471* ①
	Xinjiang	1.250 ④	1.137⑦	*1.656* ③	*2.944* ③
	Region	First-level 1st-degree[b]	Second-level 2nd-degree[b]	Third-level 3rd-degree[b]	Fifth-level 1st-degree[a]
Level 4	Inner Mongolia	1.400 ⑦	1.249 ⑦	1.193 ⑦	*1.785* ④
	Jilin	1.245 ①	1.109 ②	1.049 ②	*1.887* ③
	Anhui	1.287 ⑤	1.139 ⑤	1.076 ⑤	*1.056* ⑧
	Shandong	1.283 ④	1.128 ④	1.071 ④	*1.424* ⑤
	Hubei	1.256 ③	1.119 ③	1.079 ⑥	*1.340* ⑥
	Guizhou	1.313 ⑥	1.155 ⑥	1.061 ③	*2.243* ①
	Yunnan	1.246 ②	1.105 ①	1.024 ①	*1.311* ⑦
	Gansu	1.543 ⑧	1.356 ⑧	1.265 ⑧	*2.217* ②
	Region	First-level 1st-degree[b]	Second-level 2nd-degree[b]	Third-level 3rd-degree[b]	Fourth-level 4th-degree[b]
Level 5	Shaanxi	1.693 ③	1.515 ③	1.450 ③	1.302 ③
	Jiangxi	1.279 ①	1.146 ①	1.092 ①	1.021 ①
	Henan	1.344 ②	1.175 ②	1.123 ②	1.022 ②

Table 3 Continued

Region	First-level 1st-degree[b]	Second-level 2nd-degree[b]	Third-level 3rd-degree[b]	Fourth-level 4th-degree[b]
Chongqing	2.165 ⑤	1.890 ⑤	1.829 ⑤	1.504 ⑤
Shaanxi	1.812 ④	1.618 ④	1.542 ④	1.422 ④

Ranks are given in the circle on the right
[a] This represents the attractiveness measure
[b] This represents the progress measure

are evaluated several times as the background to which they refer is changed. For example, when the second level is chosen as the relevant evaluation context, Tibet at level 1 is the best region owing to its receiving the greatest attractiveness score of 2.008. The regions at level 1 are ranked in the order of Tibet, Shanghai, Hunan, and Guangdong. This implies that Tibet performs the best in terms of handling economic growth and environmental awareness. Furthermore, we find that Tibet also ranks consistently in first position under different evaluation contexts, except that it ranks in second position at the third-level. The results also show that Shanghai at the first level is one of four municipalities, indicating that this city is more competitive than the other municipalities in terms of balancing economic and environmental development. When the third level is chosen as the evaluation context, Shanghai is the best region of all other regions, followed by Tibet. This result also reinforces the view that the performance of regions is dependent on their respective evaluation backgrounds (Zhu 2003).

The progress measures for each region from level 2 to level 5 are presented in the cells that are not italics in Table 3. A region's 'progress' is regarded in terms of how substantially it needs to improve its outputs, compared to an upper ladder frontier. For an inefficient DMU, the larger the value of the progress measure that is evaluated, the more effort is needed for it to improve. In regard to the progress measure, when the first level is chosen as the evaluation context, Chongqing performs the worst among the regions in level 5 because it has the largest progress score of 2.165. The regions at the fifth level can be ranked using such a progress measure. When the second level is chosen as the evaluation context, Chongqing is still the worst region at the fifth level. Chongqing consistently ranks the worst, regardless of the evaluation context chosen. This implies that Chongqing urgently needs to improve its performance both in terms of economic development and environmental healthiness among the 31 regions in China.

3.3 Regional position in stratification

According to Seiford and Zhu (2003), for regions that are not located on the first or last level of an efficient frontier, we can characterize their performances based on their attractiveness and progress scores by means of a decision matrix that is used pervasively in management studies. By taking the regions listed at the second level, for example, each region is classified into a zone consisting of a 2×2 matrix by examining (1) whether the attractiveness score is greater than or less than 1.50, and (2) whether the progress score is greater than or smaller than 1.10. The cutting edge is quite arbitrary, but the goal is to group regions into zones of equal numbers as shown in Fig. 2. Within the same stratification, a good performer exhibits relatively high attractiveness and low progress, and an underperforming one shows relatively low attractiveness and high progress. High progress indicates that the region needs to improve its outputs substantially, and high attractiveness indicates that the region has more

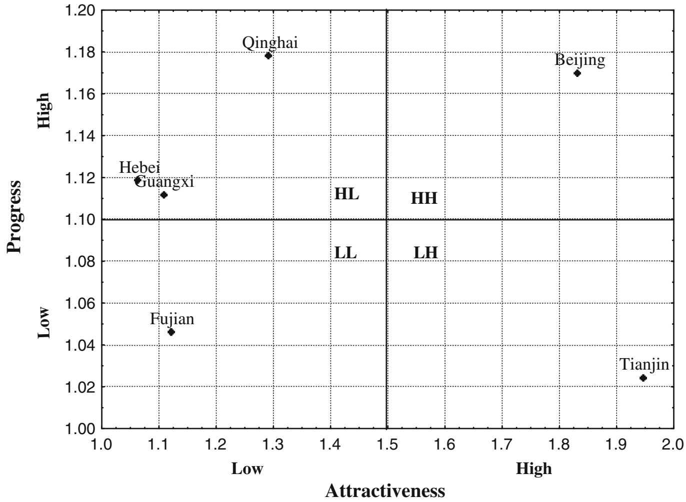


Fig. 2 Attractiveness/progress scores for the regions at 'Level 2'

of a competitive advantage than the other regions. Regions are split into four groups plotted respectively in the zones HH, HL, LL, and LH. The regions in each zone are summarized as follows:

Zone LH (Low-Progress/High-Attractiveness): The Tianjin region enjoys low progress and high attractiveness scores. The findings show that the Tianjin region located in Zone LH has more of a competitive advantage than the other ones at the second level. In regard to sustainable development, Tianjin has attained a better position in this stratification.

Zone HH (High-Progress/High-Attractiveness): The region here experiences higher progress and attractiveness scores, which is the region why the Beijing region is included. This implies that Beijing is now competitive in terms of balancing economic and environmental development. However, this region still needs to place more emphasis on activities that are geared toward improving its outputs substantially.

Zone LL (Low-Progress/Low-Attractiveness): Fujian has lower progress and lower attractiveness scores. This suggests that Fujian does well in terms of allocating its resources toward sustainable development. However, this region still needs to formulate a short-term or middle-term plan to enhance its competitive advantage in order to move up to Zone LH.

Zone HL (High-Progress/Low-Attractiveness): The regions here have experienced higher progress scores but lower attractiveness scores, for which the Qinghai, Hebei, and Guangxi regions are included. It is suggested that the Qinghai, Hebei and Guangxi regions should step up their efforts to upgrade their learning capabilities for effective outcomes such as enhancing the activities of operational management and relocating the resources between inputs and outputs. Furthermore, these regions need to draw up a short-term or middle-term plan to enhance their competitive advantage.

3.4 Relating stratifications to the K/L ratio

After constructing various levels for regional sustainable development in China, one may feel curious about the extent to which the stratification reflects the capital/employment ratio

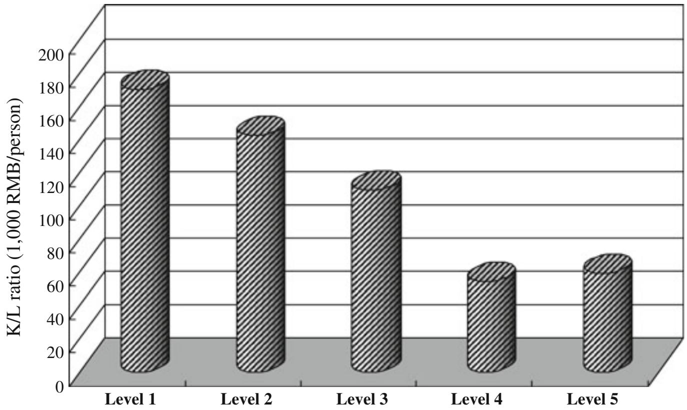


Fig. 3 Average K/L ratios with level of regions

of each region, since the capital stock per worker plays a major role in increasing GDP as well as pollution. The capital/employment ratio (abbreviated as the K/L ratio hereafter) is computed by dividing the total capital stock by the total number of employed persons. We find an obvious relationship between the K/L ratio with various levels of regions as shown in Fig. 3. For regions in level 1, the average K/L ratio is the highest among the five. Those regions in level 4 and 5 have the smallest K/L ratios, implying their straitened circumstances in terms of achieving sustainable development.

The empirical results shown above reflect one of the important issues for the disparities in China, namely, the unequally distributed capital across regions, and the gap increases around three times from the largest to the smallest. The K/L ratio, to some extent, can be deemed to be a proxy for technological development. While regions classified in level 1 are those that create wealth with less pollution by using advanced technology and equipment, those regions in levels 4 and 5 cannot afford to engage in production with cleaner techniques. The pollution that these regions emit thus increases at a faster rate than GDP growth. However, a system that allocates the costs to the polluter will be hard to introduce and enforce in those regions with a low K/L ratio.

4 Conclusions

As the largest developing country in the world, China has been sacrificing its environment to develop its economy. People in China are suffering from various forms of environmental degradation, including air, water, and solid waste pollution. China's economy is also affected by such environmental pollution and degradation. A balance between sustainable development and all-out economic growth has to be continuously achieved. However, the dilemma in terms of striking a balance between economic growth and the environment in China is more complicated since there is a diversity of geographical and economic conditions among its regions. This study thus attempts to provide an in-depth analysis of China's sustainable development that covers economic performance as well as environmental degradation, including air, water and solid waste, from a regional perspective.

This study presents a context-dependent DEA model which measures the relative attractiveness and progress of China's various regions with applications to regional sustainable development. The attractiveness measure estimates the competitiveness a region possesses, while the progress measure estimates to what extent a region needs to improve. Thirty-one regions in China are stratified into different levels of efficient frontiers. Our main conclusions may be summarized as follows. First, five levels of efficient frontiers are constructed by means of a DEA context-dependent technique. The series ladders formed by the regions are referred to as 'benchmark-learning contours,' where it is recommended that underperforming regions set their current learning target at a level that is one step higher than their own stratification. Secondly, the attractiveness measures and progress measures for each region are computed for different stratifications. Each region's performance changes depending on the evaluation context considered. Thirdly, the decision matrix covering the attractiveness and progress scores is constructed to help the regions position themselves at the same level. Fourthly, we find an obvious relationship between the K/L ratio with various levels of regions. For regions in level 1, the average K/L ratio is the highest among the five. Those regions in levels 4 and 5 have the smallest K/L ratios. This is interpreted as meaning that regions with a higher K/L ratio are generating wealth with less pollution by using advanced technology and equipment. However, regions with a lower K/L ratio cannot afford to engage in production with a cleaner technique.

In investigating the causes of the differences between the stratifications constructed by this study, we have pointed out one reason, which is that the amount of capital per worker matters. Other reasons may have to do with the economic or geographical conditions, such as industry background, the distance to major markets, transportation costs, domestic and international assistance in financing, local environmental policy reforms, and education, etc. We leave these interesting issues to future studies. In regard to its development over the longer term, China indeed needs to 'grow and be green,' especially at the regional level. The context-dependent DEA used in this research can provide new direction while evaluating a region's performance in other cases by focusing on the changes in performance as the reference context varies.

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