Evaluation of Urban Resource and Environmental Efficiency in China Based on the DEA Model

ZHANG Xiaoping*, LI Yuanfang and WU Wenjia

College of Resources and Environment, University of Chinese Academy of Sciences, Beijing 100049, China

Abstract: This paper illustrates the spatial variations in urban resource and environmental efficiency (REE) amongst 285 cities in China using a Data Envelopment Analysis (DEA) model, and examines the factors that have had the greatest effect on this spatial pattern by regression models. The results gave an average urban REE of 0.6381, and an average pure technical efficiency (PTE) and scale efficiency (SE) of 0.6964 and 0.9225, respectively. The results support the existence of a U-shaped relationship between REE and income level, which means that an increase in urban GDP does not result in an equivalent increase in environmental efficiency. Economic growth affects REE in three ways: scale effects (population scale and urbanization rate); composition effects; and spatial effects. Improvements in urban resource use and environmental efficiency depend upon both technological innovation and effective governance. Policies designed to achieve these improvements should therefore be implemented at all levels of government and local enterprise.

Key words: resource-environmental efficiency; DEA model; urban economy; China

1 Introduction

China has experienced rapid urbanization since the economic reforms and opening up process began in 1978. By the end of 2010, the urbanization rate of China had exceeded 50 percent and it is expected to increase greatly during the next twenty years. Economic activities in urban areas have contributed a lot to the Chinese economy. In 2010, cities at prefectural level and above had produced 24.6 trillion CNY of GDP (gross domestic production value), a 61.3 percent share of China’s total GDP. However, the aggressive growth of the urban economy has resulted in severe environmental problems, such as acute resource shortages and aggravated pollution. Accordingly, China has been under great pressure to construct a resource-conserving and environment-friendly society. For metropolitan areas, it is thus of great importance to illustrate the significant degree of co-ordination between economic development and ecological protection that is already occurring. Therefore, measuring and improving resource use efficiency in parallel with the consideration of environmental constraints has become very important for municipalities, as they attempt to reduce overall resource consumption and mitigate environment pollution.

Ecological efficiency in regional economies has been a hot topic in both Chinese and international academic circles during the past decade. In the existing literature, research on resource utilization efficiency is embodied in the evaluation and influencing factors of ecological efficiency (Cui et al. 2014). Ecological efficiency is usually measured by operational performance indicators that are based on material and energy consumption balances (Dyckhoff and Allen 2001), however a common practice in ecological efficiency research is to use a single measure to represent the multiple aspects of such indicators. For example, energy intensity, which is defined as the ratio between total energy consumption and GDP in a region, is the most widely applied index used to measure the efficiency of energy utilization. However, as resource consumption intensity fails to indicate the change in technical efficiency of resource utilization in practice, researchers have turned to other indices to better describe the context of “efficiency” in respect of resource consumption (Patterson 1996; Yang and Wang...
composite indicators combining economic, social and environmental dimensions have been widely debated and have already been applied in many empirical studies to evaluate environmental efficiency and sustainability (Krotscheck and Narodoslawsky 1996; Siche et al. 2008). Unfortunately, as most of the empirical analyses in this research field have been developed at national and provincial levels, research based upon urban statistical datasets remains relatively weak.

In practice, resource and environmental efficiency is usually measured by comparing environmental performance indicators, and data envelopment analysis (DEA) shows a high potential to support such comparisons. Therefore, DEA has been widely used in recent literature to evaluate the relative environmental efficiencies of different regional entities (Wei 2000; Ke and Li 2005). Halkos and Tzeremes (2009) measured the environmental efficiency of 17 OECD countries and revealed that a Kuznets type relationship between environmental efficiency and income did not exist. Stern (2012) modeled the differences in energy efficiency across 85 countries, and concluded that technological change was the most important factor affecting energy-use and carbon-emissions under conditions of economic growth. In recent years, there has been a rapid increase in the number of studies using DEA in the broad area of urban development performance evaluation. Yang and Xie (2002) evaluated the input-output efficiency of China's 30 main cities, and concluded that the development efficiency of cities in western China was much lower than those in the eastern region. In an empirical study of 75 resource-intensive cities, Gu and Xiao (2009) evaluated the regional differentiation of DEA relative efficiency in China, and revealed that tourism-oriented cities had higher potential for efficiency improvement. Guo et al. (2011) evaluated the comprehensive resource efficiencies of metropolitan areas in China by using DEA and Malmquist Index models. They found that China’s metropolitan population boom and the rapid spread of built-up areas has resulted in significant resource efficiency losses. By employing a DEA model and the Malmquist Productivity Index, Sun et al. (2012) evaluated the efficiencies of 24 typical resources-based cities in China, and concluded that small and medium-sized cities have recorded greater improvements in efficiency than large ones. A common feature of these studies is that their DEA models only used economic indicators (e.g. GDP) as output indicators, and did not include indicators of undesirable environmental impact.

Because any economic production activity is a joint-production process, it utilizes natural resource inputs (e.g. energy, water), and non-natural resource inputs (e.g. capital, labor) to produce desirable output (e.g. products, GDP), along with the emission of by-products which may be undesirable for human beings (e.g. waste water, dust, solid waste, and other pollutants). In this situation it is necessary to develop a multiple-factor model to correctly assess the aggregated efficiency of resource utilization and environmental improvement. In the recent literature there has been some research which has discussed the energy efficiency or environmental efficiency evaluation problem in relation to the use of the DEA model. Zhou and Ang (2008) presented several DEA-type linear programming models within a joint production framework of both desirable and undesirable outputs for measuring economy-wide energy efficiency performance, and have applied these models to the measurement of the energy efficiency performance of 21 OECD countries. Bian and Yang (2010), Wang et al. (2013), and Jia and Liu (2012) extended the DEA model to establish a comprehensive efficiency measure for resource and environment efficiency analysis, and used this to evaluate the relative resource use and environment efficiency of provinces in China. Their empirical results showed that the east area of China has higher energy and environmental efficiency than western China. Li et al. (2005) compared the efficiency of 202 cities in 1990 and 2000, and found that the spatial pattern of urban efficiency was similar to that of China’s economic distribution pattern. Wu et al. (2011) used DEA to assess urban land use efficiency in China, and concluded that the input-output efficiency of urban land use in China was relatively high in smaller cities. By analyzing 23 high-density urban agglomerations as case studies, Fang and Guan (2011) found that the input and output efficiency of urban agglomerations decreased gradually from the eastern region to the central and western regions of China. However, quantitative studies of the main factors affecting urban resource and environmental efficiency have not yet been deeply examined.

There are therefore two fundamental research objectives that this paper seeks to pursue. First, it further explores the regional variation of environmental efficiency among Chinese cities based on the DEA model. Second, it examines the main factors affecting the environmental performance of China’s urban development using regression models. The results are expected to shed new light on China’s metropolitan development and environmental management policies.

2 Data and methodology
2.1 City sampling

In this paper, we selected 285 Chinese cities for evaluation, including: (i) 1 national capital city, Beijing, and 3 municipalities directly under the control of the central government (Tianjin, Shanghai, and Chongqing); (ii) 26 Provincial Capital Cities (Lhasa City in Tibet Autonomous Region has not been included in the analysis because of a lack of data); and (iii) 255 cities at prefectural level and above. Fig. 1 gives their location and size. These cities are diverse, show large differences in population size and level of economic development, and many of them are the key industrial, commercial and cultural centers of a particular region. Urban territorial areas also include two spatial parts:
municipal districts and counties. In this paper, the spatial range of a sample city refers to its municipal districts only, county areas are excluded. The data set was generated from the *China City Statistical Yearbook* and the *China Statistical Yearbook*.

### 2.2 DEA methodology

#### 2.2.1 The DEA model

Data Envelopment Analysis (DEA) has been widely used since 1978 to evaluate the relative efficiency of multi-input and multi-output production units (Charnes et al. 1978). The main advantage of DEA is that it does not require any prior assumptions about the underlying functional relationships between inputs and outputs. The original idea behind DEA was to provide a methodology whereby, within a set of comparable decision making units (DMUs), those exhibiting best practice could be identified, and would form an efficiency frontier. Furthermore, the approach allows measurement of the level of efficiency of non-frontier units, and can be used to identify benchmarks against which inefficient units can be compared (Cook and Seiford 2009).

DEA is applied in this paper to measure the resource-environmental efficiency of cities in China. Supposing that there are \( K \) cities to evaluate and each city has \( N \) inputs and \( M \) outputs. Let \( X_{kn} \), the matrix of input variables, represent the \( n \)th input \((n=1, 2, \ldots, N)\) in the \( k \)th city \((k=1, 2, \ldots, K)\), \( Y_{km} \), the matrix of output variables, represent the \( m \)th output in the \( k \)th city, and the Constant Returns to Scale (CRS) DEA model for the \( k \)th cities can be defined as (Equation 1):

\[
\begin{align*}
\min_{\theta} & \quad \theta - \epsilon (\sum_{n=1}^{N} s_n^- + \sum_{m=1}^{M} s_m^+) \\
\text{Subject to} & \quad \sum_{n=1}^{N} x_{kn} \lambda_n = \theta x_{k0} (n=1, 2, \ldots, N) \\
& \quad \sum_{m=1}^{M} y_{km} \lambda_m = y_{k0} (m=1, 2, \ldots, M) \\
& \quad \lambda_n \geq 0, \kappa = 1, 2, \ldots K \\
\end{align*}
\]

where, \( \theta (0<\theta\leq1) \) is the comprehensive resource-environmental efficiency (REE) of the \( k \)th city; \( \lambda_n \) is a \( k \) dimensional weight vector; \( s^- (s^- \geq 0) \) is an input slack variable vector; \( s^+ (s^+ \geq 0) \) is an output residual variable vector; and \( \epsilon \) is a non-Archimedean infinitesimal.

For the \( k \)th city, if \( \text{REE} \) equals 1, that city operates on the production frontier and is DEA efficient, because \( \text{REE} \) reaches 1 only if both slack vectors are equal to zero and none of the input variables of DMU \( k \) are larger than any linear combination of other DMUs (Cook and Seiford 2009). The closer the value of \( \text{REE} \) is to 1, the higher the relative efficiency is, and vice versa.

Equation (1) is referred to as the CCR model, and provides for constant returns to scale (CRS). Banker (1984) extended this model by providing for variable returns to scale (VRS). The VRS model differs from that of the CRS by way of an additional constraint to Equation (1):

\[
\sum_{k=1}^{\infty} \lambda_k = 1
\]

By using a VRS model, the \( \text{REE} \) can be decomposed as the pure technical efficiency (\( \text{PTE} \)) and the scale efficiency (\( \text{SE} \)), that is

\[
\text{REE} = \text{PTE} \times \text{SE}
\]

According to the DEA model, \( \text{REE} \) is the overall measurement of the resource allocation, utilization level and scale effect of a city; while \( \text{PTE} \) is the indicator of efficiency achieved by pure technical improvement in urban resources utilization, and \( \text{SE} \) measures the efficiency gained through metropolitan scale increase. Similarly, if \( \text{PTE} \) or \( \text{SE} \) equals 1, this indicates that the \( k \)th city is relatively efficient in terms of pure technical effect or in scale effect.

#### 2.2.2 Input and output indicators in DEA

Environmental sustainability is a complex concept, which includes environmental quality, economic efficiency, and social equality, and numerous indicators have been considered in its evaluation (Wu and He 2006; Yu and Wen 2010). On the basis of existing theories, for this study cities were considered to be integrated systems of resources, economy, and environments. To apply the DEA model, each city is represented as production decision making unit using inputs to obtain outputs. To simplify, inputs of DMU are defined as capital, labor, land, energy and water; desirable outputs (also called good outputs) are defined as GDP and other pleasant urban environmental indicators; undesirable outputs (also known as bad outputs) are the various
environmental pollutants. Table 1 explains the details of input and output indicators and their quantitative methods in the DEA model used in this study.

To eliminate statistical differences, the indicators in Table 1 should be standardized. For inputs and desirable outputs, the standardizing formula is:

$$\omega_k = \frac{\rho_k - \rho_{\min}}{\rho_{\max} - \rho_{\min}} \times 100 \quad (k = 1, 2, \ldots, 285)$$

For the undesirable outputs, the standardizing formula is:

$$\omega_k = \frac{\rho_{\min} - \rho_k}{\rho_{\max} - \rho_{\min}} \times 100 \quad (k = 1, 2, \ldots, 285)$$

where, $k$ is the number of cities; $\omega_k$ represents the standardized indicator value of the $k$th city, and $0 \leq \omega_k \leq 100$; $\rho_k$ is the initial indicator value of the $k$th city; $\rho_{max}$ is the maximum value of the index; and $\rho_{min}$ is the minimum value of the index.

The undesirable outputs are byproducts generated in the processes of resource utilization and economic development, which have negative impacts on the natural environment and on human health. In this analysis, indicator $y_3$ is calculated as the weighted average of $y_{31}$, $y_{32}$, and $y_{33}$. Accordingly, the 285 cities were analyzed using 8 indicators as five inputs and three outputs.

### 2.3 The regression model

To further understand the spatial variation of urban ecological efficiency, the efficiency scores obtained by this study by using a DEA model were related to the factors influencing urban resource-environmental efficiency using econometric analysis. The DEA-derived relative efficiency of each city is thus determined by factors beyond the input and output indicators. Scale effect, structure effect, and technical effect have been often argued as being main determinants in previous studies (Zhang et al. 2008; Jia and Liu 2012). In this study, four sets of indicators were regressed as explained variables to analyze their correlation with urban environmental efficiency. On the basis of existing theories then, this research expects to provide some insight into the metropolitan dimension of resource-environmental efficiency.

**Income level.** The relationship between economic growth and environmental quality has been an object of research for many years. The common recognition is that there is no simple linear relationship between these two. The well-known Environmental Kuznets Curve (EKC) hypothesis postulates an inverted-U-shaped relationship between different pollutant density and per capita income. This hypothesis argues that as income grows, people achieve a higher standard of living and care more for the quality of environment where they live. As a result the Kuznets Curve has become a vehicle for describing the relationship between measured levels of environmental quality and per capita income (Dinda 2004). This paper tests whether the level of urban environmental efficiency and per capita income follows the same relationship. A quadratic equation between urban efficiency and income level was constructed and its statistical significance was tested.

**Population Scale.** The impact of urban population scale on environmental efficiency is controversial. Some researchers argue that a metropolitan area has higher efficiency than a small city as a result of agglomeration economies and population thresholds. In contrast, most studies have revealed the lower efficiency of large cities (Guo et al. 2011). In this paper, urban population scale is expected to have a negative impact on resource and environmental efficiency. On the one hand, increasing urban population requires more output and thus more natural resources are used up in production process. However, more output also implies more waste and undesirable by-products, which will have negative impacts on urban environmental efficiency.

**Economic structure.** Economic growth can impact environmental quality through a composition effect (Grossman and Krueger 1995). Considering that an economy dominated by secondary industries may consume more natural resources than those that are services and
knowledge-based, or have technology-intensive industries, it is possible to say that the higher the proportion that secondary industry contributes of urban GDP, the lower will be the environmental efficiency of the city in question. In consideration of the possible differences in environmental load within manufacturing sectors, a dummy variable to describe the impact of industrial type on urban resource use and environmental efficiency was introduced. If a city is dominated by resource-intensive sectors, it is expected to have a higher environmental load, and this will tend to degrade its resource and environmental efficiency.

Urbanization rate. As the urbanization rate increases, the activities of production and consumption will be more concentrated in urban areas. This spatial agglomeration will result in the high development densities and mixed land uses which are advocated as a sustainable form of urban development. To test the influence of spatial concentration on urban environmental efficiency, the proportion of population living in the built-up area to that of the total municipal territory was calculated. It is argued that a city with a higher urbanization rate will improve environmental efficiency through agglomeration economies and external economies of infrastructure spillover.

Based on the above theoretical analyses, the following model was constructed to test the relationship between resource-environmental efficiency and various factors:

$$E_k = \beta_0 + \beta_1 GDP_k + \beta_2 (GDP)^2_k + \beta_3 POPU_k + \beta_4 URBAN_k + \beta_5 INDUS_k + \beta_6 TYPE_k + \epsilon_k$$

where: $k$ is the number of cities; and explained variable $E$ is the efficiency score of each city obtained by the DEA model.

Two models were constructed as Model 1 and Model 2, in which $E$ is defined as $REE$ and $PTE$, respectively, so that different factors between these two efficiencies could be tested. The explanatory variable $GDP$ is the comprehensive economic development level for a given city, which is represented by GDP per capita (measured in ten thousand CNY). The variable $POPU$ represents the amount of urban population, which is the number of the residential population (measured in units of ten thousand persons) in the urban built-up area. The variable $URBAN$ is the urbanization rate, which is the ratio of the residential population in the build-up area to that of the municipality (measured as a percentage). The variable $INDU$ is the urban industrial structure calculated by the proportion of industrial output value in GDP (measured in percentage). $TYPE$ is a dummy variable defined to compare the efficiency differences in cities between those are and are not natural resource-intensive cities, holding other explanatory variables fixed. If a given city has been listed as a natural resource-intensive city in the policy papers issued by China’s National Development and Reform Commission since 2007, $TYPE$ corresponds to 1; otherwise $TYPE=0$. $\beta_0$ is a constant in each model; $\beta_i - \beta_n$ is the regression coefficient of each explained variable, respectively; and $\epsilon_k$ is the error term.

3 Results and analysis

3.1 Results of DEA efficiency

3.1.1 Overall features

The comprehensive resource and environmental efficiencies, pure technical efficiencies and scale efficiencies of our sample cities were calculated by DEAP 2.1. The average $REE$ of 285 Chinese cities is 0.6381 and the decomposition results showed that average $PTE$ and the $SE$ are 0.6964 and 0.9225, respectively. According to the DEA model, 30 cities in the sample are DEA efficient, because their $REE$ equals 1. Fig. 2 provides detailed information about these cities. In line with expectation, tourist cities such as Haikou, Sanya in Hainan Province, Heihe in Heilongjiang Province, and Maoming in Guandong Province, are in the list of DEA efficient cities. Also expected was the finding that because of high pollutant emissions, resource-intensive cities bring heavy environmental loads and have relatively lower efficiency scores.

Are large cities more efficient than small cities? From the perspective of urban population size in relation to $REE$, Table 2 presents a detailed description of the results that relate to efficiency. Cities were divided into five groups according to their population scale. Cities with populations of less than 500 thousand in municipal districts have a relatively higher efficiency of 0.7543. A possible explanation is that their economic and social activities are concentrated geographically, making it relatively easier to manage these activities. In contrast, mega-metropolises with populations of more than 5 million have an average efficiency of 0.6644. From a comparison of the results, it
can be seen that mega-metropolises have no advantage in \( SE \), but their advantages in \( PTE \) are significant.

3.1.2 Spatial variations

Fig. 2 reports on the geographical variations of urban \( REE \). The overall spatial distribution map shows that cities located in the eastern regions of China have higher efficiency ratings than those of other regions, which coincides with most previous studies. At the provincial level, cities in Hebei, Shanxi, Henan, and Anhui provinces displayed markedly lower resource-environmental efficiency ratings, but in general cities in western China have relatively higher efficiency than those in the central regions. This conclusion is consistent with the result of Wu et al. (2011), but differs from that of Fang and Guan (2011).

With regard to the DEA efficiency frontier, the summary of resource input slacks in the input-oriented model describe those resources that can potentially be saved in the existing outputs of each city. Table 3 presents the details. A careful analysis of the resource input patterns of different cities showed that slacks of urban construction land and fixed asset investments in the cities of central China has resulted in a decline in their resource efficiency.

By analyzing the input and output efficiency of DMUs at the DEA frontier, scale returns analysis under DEA can distinguish between three types: increasing, decreasing and constant returns to scale. When a city is at the stage of decreasing returns to scale, this means that increasing input elements will not bring about an improvement of urban \( REE \), due to mismatching of input to output. Accordingly, emphasis should be put on reducing input slacks instead of scale expansion. As shown in Fig. 3, there are 169 cities which are at the stage of decreasing returns to scale, approximately 59.3% of the total of evaluated cities. The numbers corresponding to cities in the stage of increasing and constant returns to scale are 71 and 45, accounting for

<table>
<thead>
<tr>
<th>Group division</th>
<th>Population scale</th>
<th>Observations</th>
<th>REE</th>
<th>PTE</th>
<th>SE</th>
</tr>
</thead>
<tbody>
<tr>
<td>City average</td>
<td></td>
<td>285</td>
<td>0.6381</td>
<td>0.6964</td>
<td>0.9225</td>
</tr>
<tr>
<td>Group 1</td>
<td>&gt;5 million</td>
<td>11</td>
<td>0.6644</td>
<td>0.8717</td>
<td>0.7617</td>
</tr>
<tr>
<td>Group 2</td>
<td>2–5 million</td>
<td>31</td>
<td>0.6404</td>
<td>0.7512</td>
<td>0.8619</td>
</tr>
<tr>
<td>Group 3</td>
<td>1–2 million</td>
<td>82</td>
<td>0.6059</td>
<td>0.6461</td>
<td>0.9392</td>
</tr>
<tr>
<td>Group 4</td>
<td>500–1000 thousand</td>
<td>108</td>
<td>0.6022</td>
<td>0.6443</td>
<td>0.9397</td>
</tr>
<tr>
<td>Group 5</td>
<td>&lt;500 thousand</td>
<td>53</td>
<td>0.7543</td>
<td>0.8120</td>
<td>0.9307</td>
</tr>
</tbody>
</table>

Table 3 Contrast of input slacks by subgroups in three regions of China.

<table>
<thead>
<tr>
<th>Observations</th>
<th>Eastern</th>
<th>Central</th>
<th>Western</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Labor (10^4 person)</td>
<td>114</td>
<td>110</td>
<td>61</td>
<td>285</td>
</tr>
<tr>
<td>Average</td>
<td>208.08</td>
<td>111.98</td>
<td>44.22</td>
<td>364.29</td>
</tr>
<tr>
<td>Capital (10^5 CNY)</td>
<td>5348.85</td>
<td>3698.33</td>
<td>2378.29</td>
<td>1142.54</td>
</tr>
<tr>
<td>Average</td>
<td>46.92</td>
<td>33.62</td>
<td>38.98</td>
<td></td>
</tr>
<tr>
<td>Land (km^2)</td>
<td>501.56</td>
<td>463.56</td>
<td>287.12</td>
<td>1252.25</td>
</tr>
<tr>
<td>Average</td>
<td>4.39</td>
<td>4.21</td>
<td>4.71</td>
<td></td>
</tr>
<tr>
<td>Energy (10^5 kWh)</td>
<td>409.95</td>
<td>290.96</td>
<td>85.78</td>
<td>786.68</td>
</tr>
<tr>
<td>Average</td>
<td>3.59</td>
<td>2.65</td>
<td>1.41</td>
<td></td>
</tr>
<tr>
<td>Water (10^4 t)</td>
<td>60828.69</td>
<td>47777.39</td>
<td>66352.37</td>
<td>174958.45</td>
</tr>
<tr>
<td>Average</td>
<td>533.59</td>
<td>434.34</td>
<td>1087.74</td>
<td></td>
</tr>
</tbody>
</table>

Fig. 3 Spatial variation of scale returns to urban \( REE \).
24.9% and 15.7% of the total sample, respectively.

3.2 Regression results

The designed models were run in SPSS 19.0. Table 4 presents the estimated coefficients of the explanatory variables. The results show that the influences of all explanatory variables in Model 1 were statistically significant. While the estimated coefficient of GDP squared is positive, statistically speaking it exhibited a U-shaped relationship between urban resource and environmental efficiency commensurate with income level. This result is similar to the classical empirical results within the environmental economics domain. Following the results obtained, the linear GDP term in the estimated econometric equations has a negative coefficient, which means that increasing environmental efficiency is not associated with increased GDP.

The estimated results produced by Model 1 show that the efficiency level in an urban economy does not only depend on income level. Apparently, economic composition is also very important, because an economy with a larger industrial production base is likely to produce a higher environmental burden. This hypothesis is supported by the negative correlation of the variable INDUS at a significance level of 0.01. In other words, between two cities with same income level, the higher the proportion of secondary industrial output in GDP, the lower is the urban resource-environmental efficiency. The higher significance level of the variable TYPE in Model 1 shows that a resource-intensive city has a strong negative effect on urban resource-environmental efficiency when other factors are held constant, which confirms the hypothesis on the role of policy intervention.

The negative correlation between POPU and urban resource-environmental efficiency suggests that larger cities tend to have lower resource-environmental efficiencies compared with cities with smaller populations, when other factors are held constant. It is no surprise that increasing urban populations require more output, and more natural resource consumption. Therefore, severe environmental problems are more often reported as a characteristic of mega-cities.

The rate of urbanization has a positive correlation with environmental efficiency, which coincides with our expectation. That is, holding other factors constant, a greater spatial agglomeration of urban activities is expected to improve relative resource and environmental efficiency within the municipal area. This result is consistent with the idea of the “compact city” developed in recent years, which recommends intensive urbanization instead of low-density spreading (Clark 2013).

The similar patterns revealed by Model 2, which concerned factors impacting on PTE, show that all explanatory variables except POPU demonstrate statistically highly significant relationships. The sign of each variable in Model 2 compared with Model 1 indicated another U-shaped relationship between urban pure technical efficiency and income level. That is, for both the western cities with lower income and the eastern cities with highly developed economies, pure technical efficiencies are relatively high. According to the DEA theory, the REE can be decomposed as PTE and SE, which means that PTE can be understood as the contribution made by technical progress to the REE. Specifically, for the eastern region in China, the high level of its economic development is mainly dependent on advanced production technology and developed tertiary industry, and does not simply rely on resources and consuming the environment. Thus their higher level of technology leads to a larger value of PTE. However, for the relatively backward western region, improvements in production technology are of great importance and contribute significantly to REE. A statistically significant negative impact of INDUS and TYPE on PTE demonstrates the importance of industrial upgrading on urban efficiency improvement.

4 Conclusion and discussion

This paper has reported on the aggregated efficiency of resource and environment in 285 Chinese cities, based on the DEA model. The scores obtained by using the DEA model were shown through econometric analysis to be related to a range of factors that influence urban resource and environmental efficiency. The study also re-examined the hypothesis of the Environmental Kuznets Curve in Chinese urban development using regression analysis. The results showed a U-shaped relationship between urban resource and environmental efficiency and income level, which means that an increase in environmental efficiency is not associated with increased GDP. However, these two results are not completely contradictory, and can perfectly go together if understood properly. Both models show how economic growth affects environmental efficiency in three other channels: scale effects (population scale and urbanization rate); composition effects; and spatial effects,

Table 4 Estimated coefficients of the explanatory variables.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Model 1</th>
<th>Model 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>86.673*** (17.788)</td>
<td>91.452*** (17.654)</td>
</tr>
<tr>
<td>GDP</td>
<td>–3.582*** (–2.610)</td>
<td>–2.772* (–1.900)</td>
</tr>
<tr>
<td>(GDP)^2</td>
<td>0.460*** (4.251)</td>
<td>0.442*** (3.843)</td>
</tr>
<tr>
<td>POPU</td>
<td>–0.024*** (–3.368)</td>
<td>–0.005 (–0.701)</td>
</tr>
<tr>
<td>INDUS</td>
<td>–0.401*** (–4.058)</td>
<td>–0.470*** (–4.475)</td>
</tr>
<tr>
<td>URBAN</td>
<td>0.186*** (3.784)</td>
<td>0.166*** (3.177)</td>
</tr>
<tr>
<td>R^2</td>
<td>0.227</td>
<td>0.249</td>
</tr>
<tr>
<td>Observations</td>
<td>285</td>
<td>285</td>
</tr>
<tr>
<td>F</td>
<td>13.851***</td>
<td>15.371***</td>
</tr>
</tbody>
</table>

Where *, **, *** represent significance levels of 0.10, 0.05 and 0.01, respectively; figures in brackets are t-values.
and both show that the path that growth takes is more important than growth itself. As each city has different economic level and development policies, their levels of resource and environmental efficiency differ greatly. As a result, to provide higher standards of living without exceeding regional carrying capacity, a transition to a new steady and sustainable development model is often needed. Despite the fact that sustainable forms of development are possible, they will however not automatically be adopted. Economic incentive policies by governments can be used to manage the transition from current practices to new and more efficient forms of development. For less developed cities, it is necessary to adopt effective clean energy policies, to use recycled and low-pollution energy, and to encourage low-emission industries. Additionally, institutional re-orientation toward technological innovation and incentives are of great importance in the improvement of urban resource use patterns and environmental efficiency. Although the DEA model has been widely used in efficiency evaluation, there are inherent limitations in this form of analysis when it is extended to ecological variables. In the DEA model, efficiency is evaluated by comparing a DUM with recommended or preference units. However, a city is a complex system of natural, human, social and economic elements, and thus each city may have a different optimal path for development. The evaluation in this paper has in this sense only provided a relative performance evaluation of Chinese cities in terms of their resource and environmental efficiency. Further research should aim at addressing categorial datasets and constructing models with more comprehensive factor bases.

References
基于DEA模型的中国城市资源环境效率评价

张晓平，李媛芳，吴文佳

中国科学院大学 资源与环境学院，北京 100049

摘 要：本研究以全国地级以上城市为实证数据，试图刻画我国城市资源—环境效率的空间差异并分析影响这一空间格局的主要因素。研究中采用数据包络分析法（DEA），对全国285个城市的资源—环境效率进行了评价。结果表明，城市平均资源—环境效率指数为0.6381，该指数的分解结果表明城市的纯技术效率指数为0.6964，低于规模效率指数0.9225。对城市资源—环境效率影响因素的回归分析结果表明，城市资源—环境效率与城市收入水平呈U形关系。经济增长可以通过三个渠道影响城市的资源—环境效率：规模效应（包括人口规模和城市化水平）、经济结构效应以及空间效应。城市资源—环境效率的提高并不是自然发生的，而需依赖于技术创新和有效管治等手段。因此各级政府、企业和组织必须实施一系列应对措施才能确保城市的高效发展。

关键词：资源—环境效率；DEA模型；城市经济；中国