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Is energy utilization among Chinese provinces sustainable?

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ABSTRACT

With the advent of China's reformation and open policy, its economy and levels of urbanization experienced explosive growth. However, the widely employed "high input, high pollution" style of resource consumption violates the green growth principle, and is imposing increasing pressure on both the energy infrastructure and the environment. Due to the complex relationships between resources, energy, urbanization, and the environment, it is imperative to explore methods that maximize total-factor energy efficiency and reduce environmental pollution, to achieve green growth. The slack-based measure (SBM) of efficiency was used to evaluate the total-factor energy efficiencies of 29 Chinese provinces for specific periods. Further, we leveraged the Malmquist index to explore efficiency trends from 2005 to 2014. The results show that urbanization and energy efficiency are positively correlated, whereas decreasing ratings in some provinces indicate economic recession or severe environmental pollution. Almost two-thirds of the measured provinces are energy inefficient, but have shown slow but clear improvement, indicating the huge potential for growth. Based on the findings, Chinese provinces are allocated to three categories, and policy recommendations and implementation measures are discussed, for improving total-factor energy efficiency nationwide.

1. Introduction

China's economic momentum has spiked aggressively in recent years, and the country continues to play a major role in the process of economic globalization. Following such rapid development, environmental damage has become a severe problem and the availability of natural resources has sharply declined. The Chinese Government has increased investment in energy infrastructure construction and pushed for new technologies to supply power more effectively. Energy resources are materials and natural processes that have the ability to provide widespread power under present socioeconomic conditions. Coal and petroleum are two relevant modern energy resources.

Although production efficiency has greatly improved since the Industrial Revolution, the main resources for developing machine production, such as iron ore, coal and petroleum, are still in short supply. Due to its energy-intensive economy, China has the highest national annual energy consumption (Statistical Review of World Energy, 2015). From 2012 to 2013, China's annual energy consumption increased by 15.4%, to 3.75 billion tons of standard coal equivalent (TCE), of which coal, oil and natural gas accounted for 68%, 19% and 4.4%, respectively (China Statistical Yearbook, 2015). In 2012, China's energy consumption per 10,000 Yuan GDP was 0.76 TCE, a 6% decrease compared with 2010. This is a result of China recently advocating the development of renewable and clean energy while decreasing the use of non-renewable energy. It is important to note that many people continue to use less efficient energy sources, such as coal and oil, both of which provide little energy for pollution they create. Despite this, alternative energies with high efficiency and low environmental impact are also becoming more prevalent, including geothermal and hydropower systems, nuclear power, wind power and natural gas.

China's rapid economic growth and associated high energy-consumption in both imply huge social costs, including water pollution, health and safety problems, poor air quality, and resource shortages on both local and global scales (He et al., 2002). For example, Song et al. (2015a) demonstrated that the economic scale effect significantly explained the increased carbon emissions in the Yangtze River Delta region. Among 500 developed cities in China, fewer than five achieve the World Health Organization standards for air quality. China contains some of the most polluted places in the world. The main reason for these problems is the emission of sulfur dioxide, nitrogen oxides, and smoke from heavy chemical industries, coal plants and the over-exploitation of natural resources.

By seeking to reduce the consumption of resources and energy to ease environmental pressure, efficiency emerges as the most important factor. Improving energy efficiency is key to solving the energy problem and is a major goal that China is pursuing for the sake of current and future economic growth (Dan, 2007). Additionally, efficiency is an important index of energy utilization and the degree of pollution. Enhancing energy efficiency is vital for economic development and urbanization,

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as well as energy safety and environmental protection. Efficiency can also help elucidate the complex relationships between economics, environmental protection, and energy consumption. There is an extensive literature on evaluating energy efficiency, employing different methods and from various perspectives (see Table 1). The two main methods for evaluating energy efficiency are single-factor and total-factor energy efficiency. The single-factor method is a traditional approach that describes energy efficiency as energy consumption per unit GDP. Empirical results show that this method is simple and effective. However, the method is unrealistic without considering other factors such as industrial structure and technical progress. Due to the presence of additional factors that affect energy efficiency, it is necessary to adjust the model accordingly. Total-factor energy efficiency has been studied in both developing countries (Hu and Wang, 2006; Zhang et al., 2011) and developed countries (Honma and Hu, 2013; Wang et al., 2012a, 2012b). In the face of increasingly serious environmental and resource issues, many researchers have combined environmental problems into the total-factor energy evaluation. Previous studies utilized various input and output indicators to evaluate total-factor energy efficiency.

Desirable outputs of total-factor energy efficiency can be represented by many indicators. The most common measure of nationwide economic performance is GDP. Recent research has discussed the relationship between GDP and energy consumption. Soytas and Sari (2003) found a stationary linear co-integrating relationship between GDP and energy consumption. Reducing per unit GDP energy consumption is a major goal of China's economic development. However, GDP only presents the sum gross values of all residential and institutional units, and is therefore an absolute figure. The present study introduces urbanization rate (defined as the ratio of urban population to total population) to model how this relates to efficiency. According to China Statistical Yearbook, we use the ratio of urban population to the total population to calculate the urbanization rate. Fig. 1 shows the GDP and urbanization rates of Chinese provinces. Due to intensive energy exploitation and usage, China's urbanization rate is growing much faster than ever before. According to data from the DRCNET Statistical Database System, the rate of urbanization has increased by 1.36% (year on year) since 2000. In 2012, China's annual urbanization rate reached 52.57% as a result of rapid growth of the urban economy, increasing population, building density, and improvements to health care, etc. In other words, China's energy demand is rapidly growing during the current urbanization phase (Lin and Ouyang, 2014). Hence, the 16th and 18th Communist Party of China National Congress proposed introducing new strategies for urbanization to achieve sustainable development. These new strategies emphasize intelligence, intensive management of industry, environmental protection, and low-carbon technologies. The core of this new model of urbanization construction is people, as reflected in labor worker's benefits, infrastructure construction, and quality-of-life improvements. There are several ways by which energy usage can promote urbanization. Firstly, energy use can increase production to provide sufficient products, food, etc. to fulfill the needs of the increasingly urban population, which can also facilitate the transport construction between urban areas and rural areas. Secondly, energy-related construction provides a rural employment and creates the conditions for rural development. Thirdly, increasing energy usage provides better infrastructures, which speeds up the urbanization process. A number of studies have examined the relationship between urbanization and energy consumption. However, there are no widely accepted conclusions at an international level. Most studies have found that the significance of the relationship between urbanization and energy consumption varies across regions according to the level of development. Zhang and Lin (2012) found that the effects of urbanization on energy consumption vary across regions, and observed greater consequences in the western region of China. However, most studies agree that there is positive link between urbanization and energy consumption. Jones (1991) indicated that a 10% increase in the proportion of the population living in cities would increase energy consumption per capita by approximately 4.5% of GDP. Li et al. (2011) found that urbanization is one of the main factors affecting China's energy consumption. Shahbaz et al. (2015) found that urbanization is a major contributor to energy consumption in Malaysia. Al-mulali et al. (2013) used dynamic ordinary least square to validate the long-term bidirectional positive relationship between urbanization and consumption; similar results were found by Wang et al. (2014).

There are many kinds of undesirable outputs. The coal consumption in China accounted for approximately 69.8% of the total energy consumption in 2014 and produces massive amounts of CO_2, SO_2, smoke, and dust. Large proportions of industrial and residential wastewater and solid wastes are caused by energy consumption.

In China, there is a stable long-term relationship between energy consumption, GDP and the urbanization level when energy consumption is the dependent variable (Liu, 2009; Ramanathan, 2006). (Wang et al., 2014) pointed out that the relationships between urbanization, energy consumption, and CO_2 emissions are bidirectional and causal, whereas urbanization and energy consumption maintain a one-way positive relationship. In conclusion, China's economy encountered a resource bottleneck because of the cause-and-effect relationship between environmental and urbanization influences.

Table 1 also summarizes various methods of evaluating total-factor energy efficiency. These can be broadly classified as either parametric or non-parametric, both having specific adaptive conditions and application methods. Parametric methods estimate parameters and calculate efficiency by building a production function, such as stochastic frontier analysis (SFA), which is complicated by the need to estimate unknown parameters. SFA models are usually employed when there is a clear

Table 1
Summary of inputs/outputs and methodology of total-factor energy evaluation.

Study	Inputs	Outputs	Method
Jiang and Lin (2012)	Household energy consumption	Residential CO_2 emissions	Gray model
Shahbaz et al. (2015)	Household energy consumption	Residential CO_2 emissions	STIRPAT model
Al-mulali et al. (2012)	Energy consumption	CO_2 emissions	Fully modified ordinary least squares model
Kasman and Duman (2015)	Energy consumption and trade	CO_2 emissions and economic growth	Panel cointegration methods and panel causality tests
Honma and Hu (2008)	Biomass energy, labor, capital stock, energy consumption and total sown areas of farm crops	GDP	Data envelopment analysis (DEA)
Wang et al. (2012a, 2012b)	Energy consumption, average remaining balance of capital assets and average amount of working force	The gross industrial output	Data envelopment analysis (DEA)
(Li and Hu, 2012)	Total energy consumption, capital stock and labor	CO_2 and SO_2	Slack-based model
Zhang and Xie (2015)	The gross product, labor, capital stock and energy consumption	CO_2	Non-radial efficiency model.
Rao et al. (2012)	Labor, capital stock and energy consumption	GDP,	Slack-based model
Li and Shi (2014)	Capital, labor, energy	GDP, wastes	Super-SBM model and the Tobit regression model.
Zhang and Kim (2014)	Capital, labor, energy, turnover of each company	Gas emission	Sequential slack-based efficiency measure model

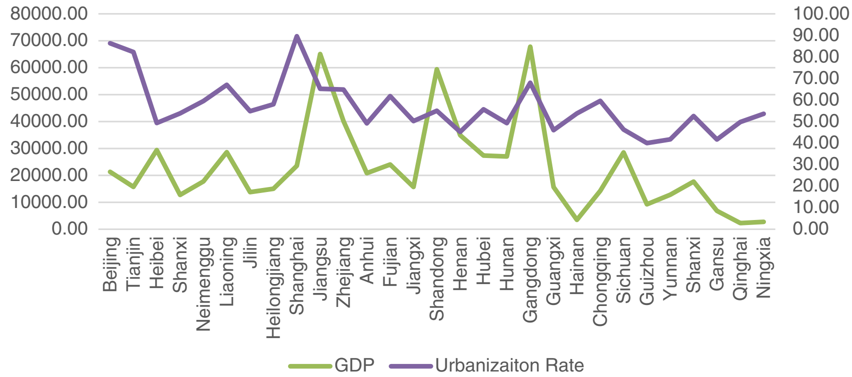

Fig. 1. Average GDP and urbanization rates of Chinese provinces.

relationship between the inputs and outputs. Non-parametric methods treat the production process as a black box, and employ an envelope surface of inputs and outputs to evaluate efficiency. Data envelopment analysis (DEA) is a typical non-parametric method (Charnes et al., 1978) and is widely employed in energy efficiency evaluation (Song et al., 2012). Since Charnes proposed DEA 1977, researchers have further developed the method to create more innovative applications of extended models.

DEA and derived models have many advantages compared with other methods: 1) There are many inputs and outputs of total-factor energy efficiency, rather than a single input or output. There is no clear functional relationship between inputs and outputs of total-factor energy efficiency; 2) DEA models use weightings of input and outputs as variables, which can effectively avoid subjectivity; 3) Rather than utilizing measures of absolute efficiency, DEA models compare the relative efficiencies of regions; and provide slacks for input improvement, which are far more feasible and achievable (Adler et al., 2002). Consequently, such methods can easily identify the reasons for inefficiency, and how to improve and learn from other provinces. The highest efficiency could serve as a benchmark for other units (Andersen and Petersen, 1993). In order to deal with undesirable outputs, Tone (2004) proposed an advanced model named slack-based measure (SBM). Tone also integrated the entropy method and the SBM model to evaluate the environmental efficiency of the power industry in China, thereby reducing errors and improving creditability. For example, Ming and Xiaoping (2011) collected carbon emissions data and employed an SBM model to measure the total-factor energy efficiency of China's different industrial sectors; Song et al. (2015b) used the SBM model to comprehensively evaluate the efficiency of coal enterprises from the perspective of environmental effects. Traditional models cannot deal with undesirable outputs, potentially leading to increased environmental pollution. By taking these undesirable outputs into account, SBM solves this problem. One limitation of SBM is that the results only show the comparisons between provinces. In the present study, the Malmquist index is used to further understand and quantify the rate of progress of each province, and to propose effective strategies according to the results.

It is also very important to take into account the different characteristics among regions when discussing energy efficiency. Significant differences exist between provinces in terms of the impact of urbanization on energy consumption and CO_2 emissions (Wang et al., 2016). For instance, Chang and Hu (2010) found that total-factor energy productivity index (TFEPI) performances are improving and vary widely between different regions. In terms of dealing with undesirable outputs, Wang et al. (2012a, 2012b) investigated methods that are more appropriate for China's regional characteristics. Nevertheless, most previous studies generally neglect environmental considerations.

This paper adopts the SBM and Malmquist index to present a thorough analysis of total-factor energy efficiency. Compared with other researches, we have considered urbanization and economic development as desirable outcomes and environmental pollution as undesirable. The following sections describe the methodology and its applicability of our study in terms of environmental evaluation. We present an empirically derived slack-based measure, and then a comparative analysis of Malmquist indices, followed by discussion. Finally, we provide recommendations for the coordinated development of China's energy infrastructure, and the pursuit of environmental and urbanization goals.

2. Methodology

2.1. DEA model and SBM model

The DEA model provides a way to compare the efficiencies of similar units. Consequently, a producer can reduce resource wastage by improving efficiency. DEA can effectively address complex decision-making problems with multiple inputs and outputs, by evaluating relative effectiveness. The basic DEA model involves a linear programming model to minimize the input–output ratio, which ranges from zero (worst) to 1 (best) when compared with other DMUs (Decision Making Units). This technique has been applied extensively by banks, hospitals, etc. In general, technical efficiency refers to pure technical efficiency multiplied by scale efficiency, where pure technical efficiency is production efficiency as influenced by company scale. Introducing technical efficiency is a comprehensive way to measure a DMU's ability to configure resources and use them effectively. A technical efficiency value of 1 indicates that the input and output of this DMU are comprehensively efficient, i.e., both technical efficiency and scale efficiency are efficient. A pure efficiency value of 1 indicates that the use of input resources is efficient, while the scale is inefficient. Therefore, the critical point of a DMU's reformation is to improve its efficiency of scale.

The DEA method has advantages and disadvantages in both implementation and application. Firstly, because DEA is a non-parametric method, errors have less effect on model parameter estimation. Additionally, while functions are not required for production, cost, and profit, they can be widely used in situations where the relationship between inputs and outputs is unclear. Secondly, DEA applies LP rather than the more familiar method of least squares regression analysis. On the other hand, DEA cannot be applied to situations where the relationship between inputs and outputs is negative.

In accordance with the serious environmental problems faced by today's society, we need to consider the undesirable outputs of our production and operating activities. However, traditional DEA models assume that higher efficiency means more outputs and fewer inputs. In consideration of undesirable outputs, more inputs should be relative to more positive outputs and less negative inputs. Based on the traditional DEA model, Tone (2004) presented a modified a SBM of efficiencies to deal with the problem of undesirable outputs. The basic SBM model, based on the DEA model, is shown as follows:

$$
\begin{aligned}
&\text{Min } \delta = \frac{1-\frac{1}{m}\sum_{i=1}^{m} s_i^- / _{x_{i0}}}{1+\frac{1}{s}\sum_{r=1}^{s} s_r^+ / _{y_{r0}}} \\
&\text{s.t.} \quad x_{i0} = \sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- \qquad i = 1,\dots,m \\
&y_{r0} = \sum_{j=1}^{n} y_{rj}\lambda_j - s_i^+ \qquad r = 1,\dots,s \\
&\lambda_j \geq 0, s_i^- \geq 0, s_r^+ \geq 0 \qquad j = 1,\dots,n; i = 1,\dots,m; r = 1\dots,s
\end{aligned}
\tag{1}
$$

Where s^+ and s^- indicate the input excess and output shortfall respectively, when compared with efficient DMUs. These coefficients are called *slacks*.

Compared with the traditional DEA model, the advantages of the SBM model are: 1) the SBM is non-radial and non-oriented to avoid errors from a single angle; 2) input and output slacks directly reflect the inefficiency of activities; 3) SBM will sort the DMUs whose efficiencies are all 1.

To solve undesirable outputs, we assume that there are n MUs, each of which has inputs ($x \in R^m$), desirable outputs ($y^g \in R^{s1}$) and undesirable outputs ($y^b \in R^{s2}$). We also define X, Y^g and Y^b by three matrices: $X = [x_1, x_2, \dots, x_n]$, $Y^g = [y_1^g y_2^g \dots y_n^g]$ and $Y^b = [y_1^b y_2^b \dots y_n^b]$. The production possibility set will be $P = \{(x, y^g, y^b) | x \geq X\lambda, y^g \leq Y^g\lambda, \geq Y^b\lambda, \lambda \geq 0, X \geq 0, Y^g \geq 0, Y^b \geq 0.\}$

In accordance with the definition, the SBM model is shown as follows:

$$
\begin{aligned}
&\text{Min } \delta^* = \frac{1-\frac{1}{m}\sum_{i=1}^{m} s_i^- / _{x_{i0}}}{1+\frac{1}{s_1+s_2}\left(\sum_{r=1}^{s_1} s_r^g / _{y_{r0}^g} + \sum_{r=1}^{s_2} s_r^b / _{y_{r0}^b}\right)} \\
&\text{s.t.} \quad x_{i0} = \sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- \qquad i = 1,\dots,m \\
&y_{r0}^g = \sum_{j=1}^{n} y_{rj}^g\lambda_j - s_r^g \qquad r = 1,\dots,s_1 \\
&y_{r0}^b = \sum_{j=1}^{n} y_{rj}^b\lambda_j - s_r^b \qquad r = 1,\dots,s_2 \\
&\lambda_j \geq 0, s_i^- \geq 0, s_r^g \geq 0, s_r^b \geq 0 \quad j = 1,\dots,n; i = 1,\dots,m; r = 1\dots,s
\end{aligned}
\tag{2}
$$

The objective value δ^* varies from 0 to 1. DMU_0 is efficient ($\delta^* = 1$) only when $s_i^{-*} = 0$, $s_i^{g*} = 0$ and $s_i^{b*} = 0$. If the DMU_0 is inefficient ($0 < \delta^* < 1$), it can be improved by decreasing inputs and negative outputs while increasing positive outputs, which means that wasted resources always exist. The SBM-projection to promote efficiency is as follows:

$$x_0 \longleftarrow x_0 - s^{-*}, y_0^g \longleftarrow y_0^g + s^{g*}, y_0^b \longleftarrow y_0^b - s^{b*} \tag{3}$$

2.2. The Malmquist index

The Malmquist index is used to study the change in tendency of efficiency during different periods. The Malmqusit index is as follows:

$$M_{j0}^{t+1}\left(X_{j0}^{t+1}, Y_{j0}^{t+1}, X_{j0}^{t}, Y_{j0}^{t}\right) = \left[\frac{F_{j0}^{t}\left(X_{j0}^{t+1}, Y_{j0}^{t+1}\right)}{F_{j0}^{t}\left(X_{j0}^{t}, Y_{j0}^{t}\right)} \cdot \frac{F_{j0}^{t+1}\left(X_{j0}^{t+1}, Y_{j0}^{t+1}\right)}{F_{j0}^{t+1}\left(X_{j0}^{t}, Y_{j0}^{t}\right)}\right]^{1/2} \tag{4}$$

Where F_{j0}^t is the SBM efficiency of each province and t is the year. For example, $F_{j0}^t(X_{j0}^{t+1}, Y_{j0}^{t+1})$ is the efficiency in t year based on the data in $t+1$ year. Based on the formula, Fig. 2 introduces the fundamental Malmquist index more intuitively and Eq. (4) shows the result.

$$M_I^{t+1}\left(X^{t+1}, Y^{t+1},, X^t, Y^t\right) = \left[\frac{oc/ob}{oe/od} \cdot \frac{oa/ob}{of/od}\right]^{1/2} \tag{5}$$

The Malmquist index can attribute the changes in efficiencies resulting from two factors: technology and resource allocation. Technology efficiency (TC) is the ratio of actual outputs and maximum outputs with given inputs. Resource allocation efficiency (AC) means better composition of inputs under fixed technology, prices and given outputs.

$$TC_i^{t+1}(y^{t+1}, x^{t+1}, y^t, x^t) = \left[\frac{F_i^t(y^{t+1}, x^{t+1})}{F_i^{t+1}(y^{t+1}, x^{t+1})} \cdot \frac{F_i^t(y^t, x^t)}{F_i^{t+1}(y^t, x^t)}\right]^{1/2} \tag{6}$$

$$AC_i^{t+1}(y^{t+1}, x^{t+1},, y^t, x^t) = \frac{F_i^t(y^{t+1}, x^{t+1})}{F_i^t(y^t, x^t)} \tag{7}$$

3. Empirical study

This paper evaluates twenty-nine provinces of China (excluding Tibet and Xinjiang due to lack of relevant data) from 2005 to 2014, to explore the total-factor energy efficiency and the complicated relationships between environment, economic growth and energy usage.

3.1. Descriptive statistics of Chinese regions

The selection of DEA indicators must satisfy the conditions of the model, and at the same time objectively reflect the features of energy use. Additionally, a strong linear relationship between the input indicators and the output indicators should be avoided. Finally, the importance and availability of each indicator should also be considered. Three inputs were selected—two desirable outputs and two undesirable outputs, as listed in Table 2. The three inputs are: working population, energy consumption, and investment for energy construction.

Investment in energy infrastructure is the economic activity of constructing fixed assets in order to further energy-intensive industries and drive urbanization. Investment is an important indicator that affects the scale and speed of development of energy-intensive industries by acting as a measure of healthy financial support. The working population represents the human resources costs associated with social development. Energy consumption is the total consumption of energy from social and economic activities. The data here are sourced from the China Energy Statistical Yearbook (2005–2014). Energy consumption includes coal, oil, and gas, which perfectly reflect China's general energy situation. Gross domestic product (GDP) and urbanization rate are considered as desirable outputs. The urbanization process includes population shift,

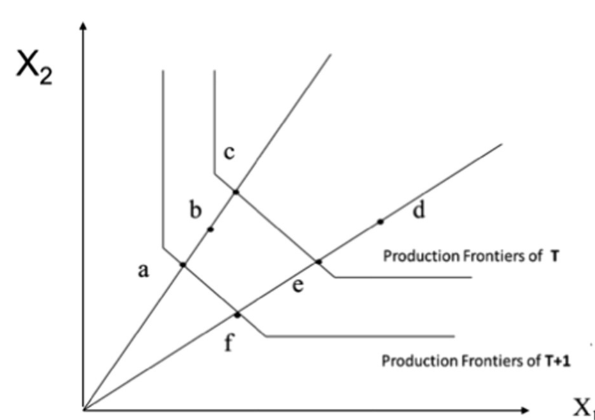

Fig. 2. Malmquist index.

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Table 2
Inputs and outputs indicators.

Variable	Definition	Unit	Mean	Std dev	Minimum	Maximum
Inputs						
EC	Energy consumption	Billion tons of standard coal equivalent (TCE)	12,392.82	1241.55	32,579.60	7615.07
IEC	Investment for energy construction	Billion Yuan	630.17	83.86	1769.97	387.11
Desirable outputs						
GDP	Gross domestic product	Billion Yuan	14,433.49	1332.80	44,105.46	10,740.57
UR	Urbanization rate		51.56	32.46	89.08	13.84
Undesirable outputs						
CO_2	Emission	Million tons	334,827.05	12,751.79	1,022,274.48	239,275.45
CP	Comprehensive pollution index		2.00	0.66	3.72	0.80

transformation of industrial structure, region or space conversion, and so on. The urbanization rate is simplified as the population shift from rural to urban areas.

The presence of undesirable outputs may reduce the accuracy of the SBM results due to the limited number of DMUs. CO_2 is the most common and severe of the negative effects caused by energy consumption, through its effects as a greenhouse gas. No official data are available for regional CO_2 emissions in China. However, emissions can be estimated using both energy consumption data and the net calorific value sourced from the China Energy Statistical Yearbook. The effective CO_2 emission factor for each kind of energy from the 2006 IPCC Guidelines for National Greenhouse Gas Inventories (IPCC, 2006) will also be taken into account. The CO_2 emissions of a region are estimated as:

$$CO_2 \text{ emission} = \sum\nolimits_{j=1}^{n} (\textit{Energy consumption}_j \times \textit{Net calorific value}_j \times \textit{Effective } CO_2 \text{ emission factor}_j) \quad (8)$$

Where j represents different kinds of energies. In terms of harmful gas, water, and solid pollutants, we use the information entropy method to calculate the weighting of SO_2 emissions, smoke and dust, discharged wastewater and industrial solid waste, to derive a comprehensive pollution index (CP).

$$S_I = \sum_{j=1}^{m} W_j \times P_{ij} \; (i = 1, 2, \ldots, n) \quad (9)$$

Here, W_j is the weight (information contribution) of each item and P_{ij} is the ratio of item and the total. The calculated weights indicate the relative value of data: the greater the weight of the undesirable output, the more value and information it provides for the overall evaluation. The values are then added together to calculate the CP. Hence, we only kept these two undesirable outputs in order to evaluate the total-factor energy efficiency more effectively. These two outputs are the concrete embodiment of environmental pollutants.

In order to verify that these data are relevant, the Pearson correlations of the inputs and outputs are examined to verify the applicability of the indicators system and the SBM model. The correlation matrix of inputs and outputs (see Table 3) shows that most correlation indices are high and reasonable, except for CP. The reason for this is that CP is a comprehensive indicator. The high positive correlation coefficients between inputs and desirable outputs indicate that, with increased inputs, desirable outputs will increase. The EC and CP data show the same trend (see Fig. 3). With decreased energy input, the environmental pollution is reduced. In summary, the SBM model is applicable and suitable for assessing the total-factor energy efficiency; the results are reliable and believable.

Table 3
Correlation index of inputs and outputs.

	EC	IEC
EC	1.00	
IEC	0.95	1.00
GDP	0.96	0.99
UR	0.97	1.00
CO_2	0.94	0.92
CP	0.45	0.30

3.2. Calculation of regional total-factor energy efficiency using SBM model

The SBM model is employed to examine the total-factor energy efficiency of 29 provinces in China. Table 4 shows the results of each province from 2005 to 2014, with the undesirable outputs SO_2 and SD.

Most developed places, such as Shanghai, Beijing, and Hainan, are energy-efficient and maintain stable development as a result of energy conservation, environmental protection, high-tech industries, and high-quality workers. However, we cannot ignore that the SBM efficiency in developed cites could obscure the fact that environmental pollution is due to its outstanding advantage of desirable output (such as urbanization rate). From Fig. 4, it is surprising that three out of four direct-controlled provinces are inefficient, since they enjoy advantages of being municipalities. The relevant departments should pay close attention and make great efforts toward achieving smarter energy consumption, environmental protection, and the urbanization of these provinces. In contrast, the energy-efficiencies of two-thirds of the areas have not reached 0.8. In other words, China's economy still reflects a "high input, high output" production pattern and requires continuous societal and governmental efforts in order to achieve reform. Table 4 also suggests marked differences in performance between Chinese provinces, and a widening gap associated with economic and social development. The comparison of total-factor energy efficiencies has illuminated the realistic development circumstances of each province, which is useful for suggesting comprehensive, integrated, and sustainable development of the provinces and defining their future development strategies.

The total-factor energy efficiencies of most provinces show the same direction of change (Fig. 5), which suggests that the development of every province still relies on the Chinese or global macro-economy environment. In accordance with macro-economic environmental trends, this also suggests that it is essential to establish national-scale policy support and strategy guidance in order to increase total-factor energy efficiencies. From 2005 to 2007, both the Chinese economy and society entered a period of rapid development when environmental pollution was less serious than in previous years. Thus, the total-factor energy efficiencies of all provinces gradually increased. However, influenced by the global financial crisis in 2008, China's entity economy faced unprecedented impacts and declined at that time, with the result that energy efficiencies dropped down to their lowest points. To restore the economy as rapidly as possible, the Chinese Government increased investment in infrastructure construction and energy consumption. At the same time, the Chinese Government and society attached great importance to environmental protection. This explains how Chinese energy efficiency has significantly improved along with economic development

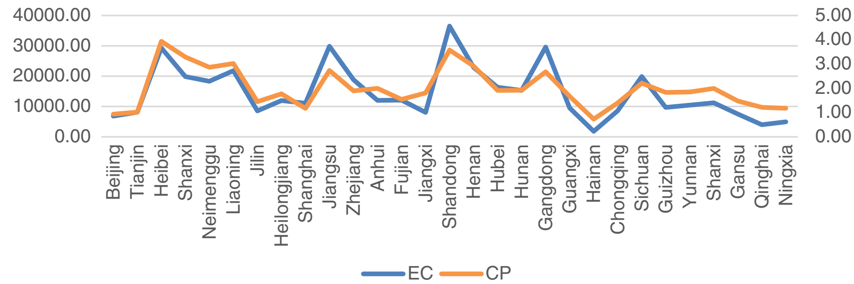

Fig. 3. Trends of EC and CP among provinces.

in recent years. It can be inferred from Fig. 5 that some provinces are experiencing a deep recession, with data for 2014 showing deterioration of their environments and efficiencies.

3.3. Comparative Malmquist index

The SBM analysis compared the total-factor energy efficiencies among different Chinese provinces, giving the relative efficiency of each province. However, because the natural resources, economic environment, and policies differ between provinces, the differences in efficiency enable provinces with low efficiency to learn from those with high efficiency, but the findings are not helpful for comparison of a province's own performance in order to make improvements. The data thereby reveal the realistic developing circumstances of each province, and predict which provinces will develop better and faster through improved efficiency.

To better understand and study the energy efficiency trends of the 29 provinces, we use an average Malmquist index to compare the different tendencies among provinces from 2005 to 2014 (see Table 5).

The Malmquist indices of most provinces are >1 (except Shanghai, Jiangsu, Zhejiang, and Qinghai), from which we conclude that Chinese regional total-factor energy efficiency is increasing and the overall situation in China is improving. This conclusion is further supported by the finding that Fujian and Heilongjiang provinces are ranked bottom. Generally, these provinces have experienced multiple difficult situations. The failure of Shanghai and other provinces is primarily in low technological efficiency, since its resource allocation efficiency is slightly >1. These provinces should focus more on the introduction of new technologies such as energy-saving and environmental technologies. The comparison demonstrates that it is important to use technology appropriately, and to develop specialized and novel technologies for the long term. Combining with the MI trends, we find that the MI of these provinces has dropped significantly in recent years and that energy consumption and environmental pollution have increased greatly. It is crucial to find reasonable energy industries structures that make full use of the available energy.

Meanwhile, there is little change in the MI growth rate. China has not achieved satisfactory and effective coordination of energy and economic and environmental factors during developing. Compared with the large fluctuations in the growth rates of Shandong and Hebei, the provinces of Zhejiang and Jiangsu have entered into a relatively steady phase. It can be concluded that in low-ranking provinces, some unstable factors such as energy consumption, environmental protection and urbanization have emerged, which will result in substantial changes in the growth rate of MI.

The findings show that, from 2005 to 2006, almost all the provinces had an average MI >1, which suggests that the total-factor energy efficiencies of Chinese provinces are continuing to improve. Furthermore, the MI trends of the five top-ranked provinces clearly indicate that:

1) The general trends of MI in each province are almost the same, and mostly rely on the overall context of China.
2) In recent years, MI has shown substantial fluctuation, indicating that the content of the policies is change substantially. The relevant authority should pay greater attention to ensure that they respond appropriately to policy changes.

According to both the MI and SBM analyses, the 29 analyzed provinces can be grouped into three classes. Those provinces in the first class (Jiangsu, Shanghai, Zhejiang, etc.) are characterized by high total-factor energy efficiencies, and will take the lead in modern Chinese urbanization. Additionally, they have demonstrated effects on other provinces as people increasingly crowd into large cities. However, developed cities have more environmental and energy problems than other cities, such as atmospheric pollution, water shortages and light pollution. These provinces should solve the contradiction of urbanization and environment by using their own advantages, such as importing advanced technologies, establishing relevant policies, and taking effective measures. The second class includes provinces (Hebei, Shanxi, Ningxia, etc.) with low total-factor energy efficiencies and high MI. These provinces are making gradual progress with enormous potential for improvement. The provincial government should therefore establish a series of more stringent energy usage measures to promote urbanization and economic development (Song and Guan, 2015). Even though environmental conditions in these provinces have improved, environmental protection, environmental protection still needs to be a major topic of attention and discussion. The third class is the provinces

Table 4
SBM results with undesirable outputs for regions of China.

Province	Efficiency	Slack value					
		EC	IEC	GDP	UR	CO_2	CP
Beijing	1.00	0	0	0	0	0	0
Tianjin	0.82	2278.8	284.1	0.0	0.0	136115	0.0
Hebei	0.57	11,258.5	531.5	0.0	39.5	510299	1.5
Shanxi	0.69	10,838.3	1482.0	0.0	0.0	571450	1.9
Neimenggu	0.68	8518.3	1803.5	0.0	8.4	543276	1.4
Liaoning	0.64	8034.0	396.1	0.0	31.0	451201	1.1
Jilin	0.72	2969.7	423.7	0.0	0.8	193992	0.6
Heilongjiang	0.71	5049.1	462.0	0.0	2.0	259131	0.8
Shanghai	1.00	0.0	0.0	0.0	0.0	0	0.0
Jiangsu	0.63	3594.4	17.3	0.0	70.3	338869	0.0
Zhejiang	0.61	3654.0	241.8	0.0	59.9	258017	0.1
Anhui	0.64	3423.6	232.3	0.0	22.6	252158	0.7
Fujian	0.68	3014.6	447.7	0.0	24.3	188056	0.3
Jiangxi	0.68	2067.5	121.7	0.0	9.2	141871	0.8
Shandong	0.46	8112.2	615.9	0.0	86.1	583127	0.4
Henan	0.53	6180.3	180.1	0.0	50.8	327805	0.7
Hubei	0.63	4778.0	113.0	0.0	34.9	222633	0.4
Hunan	0.61	4061.3	272.5	0.0	36.7	181106	0.4
Guangdong	1.00	0.0	0.0	0.0	0.0	0	0.0
Guangxi	0.67	3031.4	249.3	0.0	11.8	154151	0.7
Hainan	1.00	0.0	0.0	0.0	0.0	0	0.0
Chongqing	0.73	2920.1	366.7	0.0	0.0	106168	0.5
Sichuan	0.58	6236.9	713.5	0.0	40.2	205844	0.6
Guizhou	0.70	4676.1	323.7	0.0	0.0	198558	1.0
Yunnan	0.68	4297.5	621.1	0.0	6.9	156010	0.9
Shanxi	0.67	3733.0	982.0	0.0	12.8	325052	0.8
Gansu	0.72	3666.4	728.8	0.0	0.0	138866	0.7
Qinghai	0.41	21.9	114.6	4087.7	0.0	19689	0.3
Ningxia	0.75	2336.4	327.9	551.3	0.0	109765	0.2

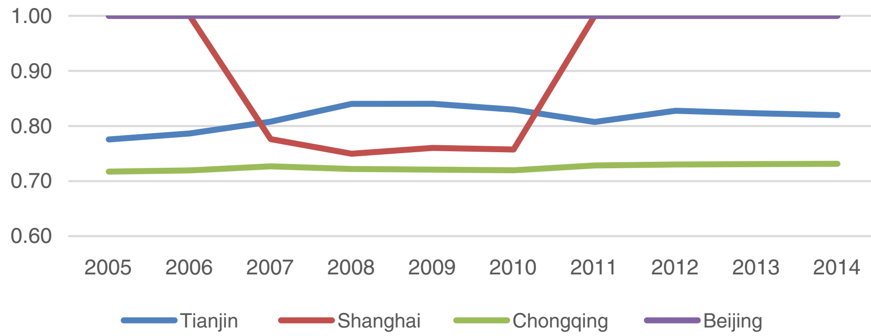

Fig. 4. Tendency toward lower efficiency among direct-controlled municipalities.

(Heilongjiang, Qinghai, etc.) with low total-factor energy efficiencies and low MIs. These provinces should place energy conservation, environmental protection, and low-carbon urbanization in a strategic position to foster competitiveness.

4. Conclusion

To coordinate the new models of economic development and urbanization, it is vital to explore the total-factor energy efficiency of each region of China in order to strike a balance between energy usage and the control of environmental pollution. This study employs indicators of inputs and outputs through the entropy method and empirical study. The innovation of selecting indicators stems from our consideration of previous work concerning total-factor energy efficiencies, combined with realistic circumstances for provincial development, and the introduction of an increased urbanization rate as a desirable output, all of which make the results more objective and comprehensive. Pearson correlation analyses were performed to further investigate the applicability of the SBM model. Positive correlations were observed between inputs and desirable outputs, while there were negative correlations between inputs and undesirable outputs. Subsequently, the SBM model and Malmquist index method were used to analyze total-factor energy efficiency performance at the provincial level from 2005 to 2014. The SBM model provides the relative efficiencies of every province, but does not show how individual provinces change over time. Additionally, the Malmquist exponent was examined to obtain the relative annual rates of improvement for each province. The advantage of this approach is that it reveals aspects that might otherwise be neglected. For example, some cities have higher relative efficiency, but decreasing Malmquist exponent each year, which indicates that the city does not have the capability to achieve sustainable and green development. The results showed that only one-fifth of China's 29 provinces are total-factor energy efficient while others are much weaker. Developed provinces such as Beijing and Guangdong have maintained stable and relatively high levels of efficiency. One explanation could be that developed cities always place greater emphasis on environmental protection with their inherent developmental advantages of economic growth and urbanization. It is recognized that a large gap exists between provinces, because the indicators have different impacts on the total-energy efficiency of different provinces. The data show that the relative efficiency of most provinces starts to deteriorate from 2011.

To gain insights into the changing tendency of total-energy efficiency, we introduced the Malmquist index to measure dynamic efficiencies. The resulting Malmquist index showed an improving trend for total-factor energy efficiencies in most provinces except Jiangsu, Zhejiang, Shanghai, and Qinghai. Meanwhile, allocation resource efficiency showed better performance than technology efficiencies. Technology has not yet caught up with energy consumption. Additionally, some serious problems exist in energy resource allocation in China: low-efficiency energy application and irrational distribution of energy resources are two examples. Moreover, the overall MI growth rate is changing slowly, which implies that China is going through a bottleneck period in energy consumption, urbanization, and environmental protection. We also found that the wide-ranging fluctuations of most provinces are random, and mostly depend on each province's own social development, technical innovations, government policies, and so on.

From the above empirical results, we can see that the availability of resources and environmental considerations have seriously impacted and constrained the economic development and urbanization of

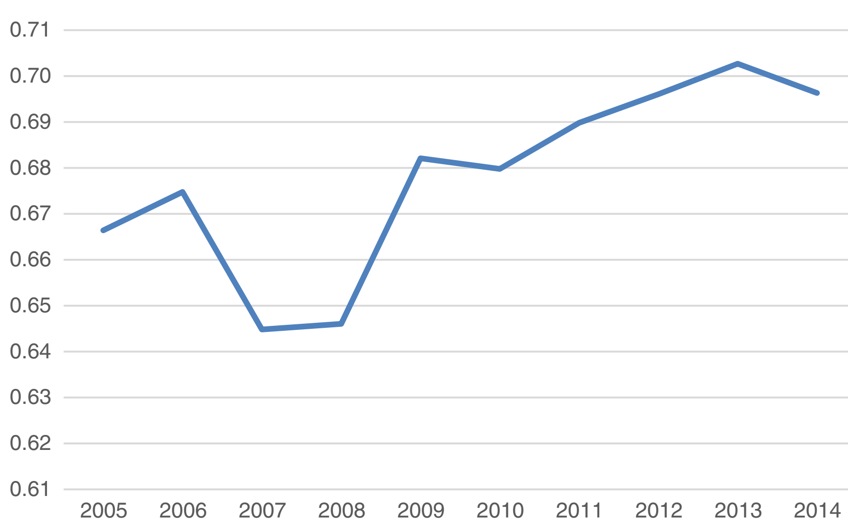

Fig. 5. Trends in average efficiency.

Table 5
Average Malmquist index, TC and AC.

Province	Ranking	MI	TC	AC
Tianjin	21	1.01	1.00	1.01
Hebei	3	1.05	1.03	1.03
Shanxi	2	1.06	1.04	1.02
Neimenggu	8	1.04	1.03	1.00
Liaoning	6	1.04	1.04	1.00
Jilin	20	1.01	1.01	1.00
Heilongjiang	18	1.01	1.01	1.00
Shanghai	26	0.80	0.80	1.01
Jiangsu	23	0.97	0.94	1.03
Zhejiang	25	0.92	0.92	1.01
Anhui	9	1.04	1.03	1.01
Fujian	16	1.02	1.02	1.00
Jiangxi	13	1.03	1.02	1.00
Shandong	10	1.04	1.03	1.01
Henan	7	1.04	1.02	1.02
Hubei	12	1.03	1.03	1.00
Hunan	5	1.04	1.04	1.01
Guangxi	14	1.03	1.02	1.01
Chongqing	19	1.01	1.01	1.00
Sichuan	4	1.05	1.04	1.01
Guizhou	17	1.02	1.01	1.01
Yunnan	11	1.03	1.03	1.01
Shanxi	15	1.02	1.02	1.00
Gansu	22	1.01	1.01	1.00
Qinghai	24	0.95	0.94	1.05
Ningxia	1	1.08	0.98	1.11

China. Going further, these difficulties challenge the social sustainable development of the human being. The central government should introduce additional policies and measures and sustainable development, environmental protection, and resource conservation, in order to support and strengthen China's sustainable developmental path. The most important task is to develop the economy in a comprehensive, coordinated, and consistent way, and to establish appropriate development strategies with the purpose of achieving sustainable growth.

Our research is expected to foster the green growth principle by attempting to identify a balance between the environment, urbanization, and energy consumption that is appropriate to China's unique situation. We also aim to further modernize and streamline development strategies, by evaluating total-factor energy efficiency on the basis of past and present situations. The limitation of this study is that the SBM and Malmquist Index methods do not consider the native environmental factors of each province, with the result that the comparative results are neither objective nor fair. On one hand, hard data are not available. On the other hand, the developmental basis, natural conditions, physical resources, regional benefits, and policy-related advantages contribute to the total-factor energy efficiency, not all kind of which can be isolated or decoupled in the analysis.

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