Total-factor energy productivity growth, technical progress, and efficiency change: An empirical study of China

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ABSTRACT

This article introduces total-factor energy productivity change index (TFEPI) based on the concept of total-factor energy efficiency and the Luenberger productivity index to evaluate the energy productivity change of regions in China with a total-factor framework. Moreover, the TFEPI can be decomposed into change in energy efficiency and shift in the energy use technology. According to the computation results, China's energy productivity was decreasing by 1.4% per year during 2000–2004. The average total-factor energy efficiency improves about 0.6% per year, while total-factor energy technical change declines progressively 2% annually. The factors affecting TFEPI are also examined: (1) The east area has a higher TFEPI than the central and west area; (2) increasing the development status and electricity share of energy consumption will improve the region's TFEPI performance, while increasing the proportion of GDP generated by the secondary industry deteriorates TFEPI of a region.

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1. Introduction

In the course of economic development, energy use provides the embodied and disembodied technical progress and productivity growth [1,2]. In fact, several studies have found positive relationships between energy consumption and economic growth [3,4]. However, energy use is also a major source of greenhouse gas causing environmental problems [5–8]. Under the concern of economic growth and environmental pressure, the study of energy use, such as energy efficiency, energy intensity, and energy productivity, has become a significant research issue over the past several decades.

The energy issue is more important in China, as the economy has grown aggressively in the past two decades, and China is now the second largest energy-consuming economy in the world behind the United States. In 2004, China consumed primary energy over 59 quadrillion Btu, which accounted for 13.3% of the world [9]. Moreover, Crompton and Wu [10] forecast that the total energy consumption in China shall increase at an annual growth rate of 3.8% from 2003 to 2010. Along with this progressive demand for energy, the assessment of energy use should be taken into consideration under China's energy policy. Due to the above concern, the Chinese government has been actively shifting its economic development mode and reforming the economic structure since China's

Agenda 21 was adopted in 1993. The 10th 5-Year Plan carried out in 2001 also emphasizes improving energy efficiency and conservation. For example, energy consumption per 10,000 RMB yuan GDP in 1990 prices should be reduced to 2.2 tons of standard coal; energy conservation should be accumulated to 340 million tons of standard coal; and the annual energy conservation ratio shall reach 4.5% by 2005. Whether or not these energy policies actually improve regional energy efficiency in China remains to be examined by empirical research.

There are two well-known indicators used to study how energy inputs are efficiently used: One is energy intensity which measures the amount of energy consumption for every economic output produced in the economy, and the other is energy efficiency (or energy productivity) defined as economic output divided by energy input [1,11–13]. Notice that each represents identical measures from different perspectives, but we only focus on the application of the later (energy productivity) in this paper. The conventional energy efficiency index is actually the partial-factor energy productivity in which energy is the single input while substitution or complement among energy and other inputs (e.g., labor and capital stock) are neglected. Some researchers suggest that only using partial-factor energy productivity to evaluate energy consumption may obtain a plausible result [12,14]. For example, the energy efficiency index may increase solely when energy is substituted by labor, instead of any underlying improvement in technical energy efficiency [11].

Hu and Wang [14] propose a new indicator, so-called the total-factor energy efficiency (TFEE) index defined as a ratio of the optimal-to-actual energy input, in order to compute the relative

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energy efficiency of each region in China under a multi-factor framework. Meanwhile, they conclude that the commonly used energy efficiency index overestimates the benefit from energy consumption because of significant substitution effects among inputs. Wei et al. [15] later extend the work of Hu and Wang [14] to explain what factors cause the variation in the cross-regional TFEE. Moreover, Hu and Kao [16] and Honma and Hu [17] also apply the concept of TFEE to investigate related issues in APEC economies and Japan's regions, respectively. However, the methodology used by previous studies only focuses on computing relative energy efficiency among objects in each year such that it lacks insights with longitudinal data. Therefore, an innovative method will be proposed in this paper to deal with dynamic energy productivity changes.

The main purpose of this article is to evaluate the energy productivity change of regions in China with a total-factor framework during 2000–2004. In order to study the energy productivity changes, this paper introduces a total-factor energy productivity index (TFEPI) which integrates the concept of the TFEE index with the Luenberger productivity index to measure the change of total-factor energy productivity. Note that the terms, energy efficiency and energy productivity, are used interchangeably in traditional literature, while they are clearly distinguished in this paper. The term energy productivity in this study is similar to the well-known definition as a ratio of the output (GDP) to energy inputs. Nevertheless, energy efficiency is defined as using less energy input to produce the same amount output under a production frontier representing the current technology to use energy.

The Luenberger productivity index introduced by Chambers et al. [18], as a difference of directional distance function, measures whether total-factor productivity changes from the base period to the next period. As shown by Luenberger [19] and Chambers et al. [20], the directional distance function provides a flexible method to calculate both input contractions and output expansions. According to the flexibility of directional distance function, some researchers have considered that the Luenberger productivity index is more appropriate than the well-known Malmquist productivity index [21,22]. Moreover, Chambers et al. [18] illustrates that the Luenberger productivity index can be decomposed into efficiency and technical changes. Hence, our study applies a nonparametric programming method, commonly known as the data envelopment analysis (DEA) approach, to compute the total-factor energy productivity change. Additionally, TFEPI can be decomposed into two components: One is the change in relative energy efficiency, indicating that an object is getting closer to or farther from its annual frontier (catch-up effect or fall-behind effect). The other is shift in the technology level of energy use, showing the shift in the production frontier under the total-factor framework. The improvement of energy technology may be because of many aspects, such as changing energy mix, innovating and diffusing energy-saving technologies, and upgrading production process and equipments [6,23].

Comparing to traditional parametric methods (such as the Cobb–Douglas function and translog production function), the advantage of using the DEA method is that this method avoids model misspecification [21,24]. Moreover, the DEA-Luenberger index can easily compute total-factor productivity change, efficiency change, and technical change. Since the DEA-Luenberger index cannot analyze the change in single factor productivity under total factor concern, the TFEPI is introduced to deal with this issue in this article.

The remainder of this paper is organized as follows. Section 2 introduces the proposed total-factor energy productivity index using the DEA approach. Section 3 interprets data sources and variables' descriptions. Section 4 presents and discusses empirical results in the case of China. Finally, Section 5 concludes this paper.
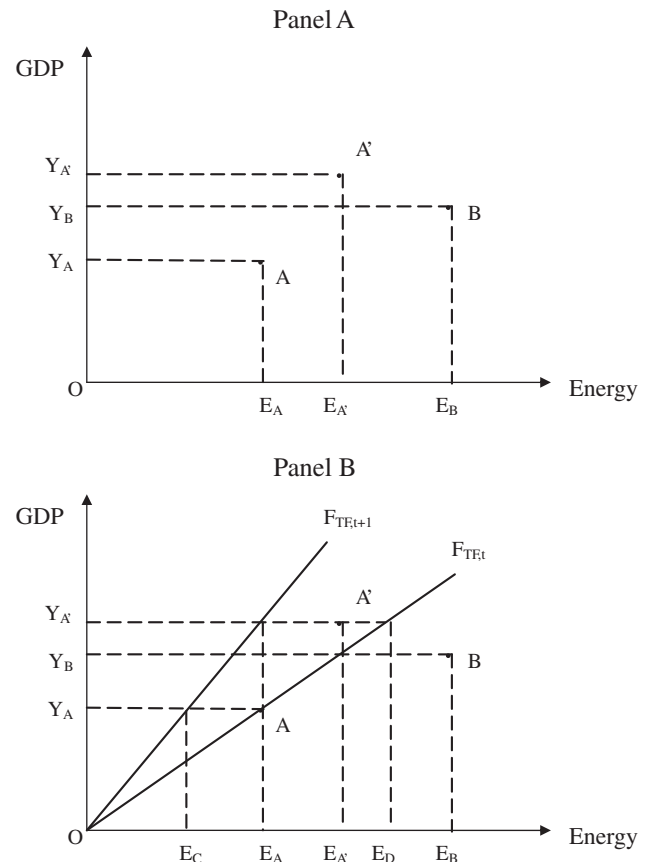

Fig. 1. The graphic conception of traditional productivity, TFEE, and TFEPI.

2. Total-factor energy productivity index

The ratio of GDP to energy consumption is one of the most popular indicators to measure energy efficiency due mainly to its simplicity and intuitive [25]. However, the TFEPI introduced in this study provides two advantages: first, traditional energy efficiency indicator only takes account of energy as single input. This indicator may easily overestimate the real change in energy productivity when energy is substituted for other inputs. Second, traditional indicator disregards the technology level of energy use. In other words, the traditional indicator assumes the technology is always consistent year after year. In fact, the productivity would improve because of technical progress [26]. Hence, this paper uses Fig. 1 to illustrate above-mentioned concerns.

Panel A of Fig. 1 sketches the conception of traditional energy efficiency (or productivity) indicator. If two objects operate at point A and B, their traditional energy productivity would equal to Y_A/E_A and Y_B/E_B, respectively. In this example, the energy productivity of point A is higher than point B. When we consider that one object has increased its energy productivity from 1 year to the next (from point A to point A'), the improvement of energy productivity is equal to $(Y_{A'}E_A–Y_AE_{A'})$[1].

Hu and Wang [14] propose TFEE indicator under total-factor framework to compare the relative energy efficiency among regions in China. We use Panel B of Fig. 1 to demonstrate their ideas and consider a special case assuming the production frontier for

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[1] In this paper, the Luenberger productivity index is used to examine the energy productivity change in China. Therefore, any change here is based on differences rather than more traditional ratios. For more advantages about differences, see Boussemart et al. [21].

energy use is linearity in multi-factor framework. TFEE is a relative index which computes a ratio of minimum (target) input level to actual level for each object at each particular year. The two production frontiers, $F_{TF,t}$ and $F_{TF,t+1}$, refer the best practice using the minimum energy to produce the same amount output under total-factor framework at year t and $t + 1$ so that a technical growth is assumed in this example. According to the definition, the TFEE of point A and B would equal to E_A/E_A (=1) and $E_{A'}/E_B$ (<1), indicating a higher efficiency if an object operate at point A. Unfortunately, TFEE cannot completely depict the productivity improvement due to the technical change. As shown in Panel B of Fig. 1, if one object improves its energy productivity from one year to the next (from point A to point A′), the TFEE framework only computes the total-factor energy efficiency change ($E_A/E_{A'} - 1$) while cannot measure the effect of frontier shift at all.In the case of productivity growth, the Luenberger productivity index is a convenient method to overcome the drawbacks of TFEE: We first assumed that the production technology $\mathbf{F}^t$ models the transformation of multiple inputs, $\mathbf{x}^t \in R_+^M$, into multiple outputs, $\mathbf{y}^t \in R_+^S$, for each time period t, where:

$$\mathbf{F}^t = \{(\mathbf{x}^t, \mathbf{y}^t) : \mathbf{x}^t \text{ can produce } \mathbf{y}^t\}. \tag{1}$$

The computation of the Luenberger productivity index relies on directional distance functions. Following Chambers et al. [20], the directional distance functions could be defined at t as:

$$\vec{D}_{(t)}(\mathbf{x}^t, \mathbf{y}^t; \mathbf{g}_x, \mathbf{g}_y) = \max\{\beta \in \Re : (\mathbf{x}^t - \beta \mathbf{g}_x, \mathbf{y}^t + \beta \mathbf{g}_y) \in \mathbf{F}^t\}. \tag{2}$$

where $(\mathbf{g}_x, \mathbf{g}_y)$ is a nonzero vector in $R_+^M \times R_+^S$. Thus, this function is defined by simultaneously contracting inputs and expanding outputs. One notices that $\vec{D}_{(t)}(\mathbf{x}^t, \mathbf{y}^t; \mathbf{g}_x, \mathbf{g}_y) \geqslant 0$, and $\vec{D}_{(t)}(\mathbf{x}^t, \mathbf{y}^t; \mathbf{g}_x, \mathbf{g}_y) = 0$ if and only if $(\mathbf{x}^t, \mathbf{y}^t)$ is on the production frontier. Therefore, the Luenberger productivity index would be measure as follows:

$$L(\mathbf{x}^{t+1}, \mathbf{y}^{t+1}, \mathbf{x}^t, \mathbf{y}^t) = \frac{1}{2}\left[\left(\vec{D}_{(t)}(\mathbf{x}^t, \mathbf{y}^t) - \vec{D}_{(t)}(\mathbf{x}^{t+1}, \mathbf{y}^{t+1})\right) \right. $$
$$\left. + \left(\vec{D}_{(t+1)}(\mathbf{x}^t, \mathbf{y}^t) - \vec{D}_{(t+1)}(\mathbf{x}^{t+1}, \mathbf{y}^{t+1})\right)\right], \tag{3}$$

if the Luenberger productivity index is less than, equal to, or greater than zero, then it respectively stand for productivity regress, no change, or progress between period t and $t + 1$.Luenberger productivity index is a multi-factor productivity index and can calculate the total-factor productivity change of research objects. However, the commonly used Luenberger productivity index, which assumes a special case with proportional distance function, cannot deal with single factor productivity change, such as energy in this study, under total-factor framework. Therefore, this paper introduces a total-factor energy productivity index (TFEPI) which applies a generalized directional distance function proposed by Färe and Grosskoft [27] and an optimal-to-actual input ratio under total-factor framework (TFEE) to substitute all the components of Luenberger productivity index. Following the work of Färe and Grosskopf [27], we denote $\vec{D}_{E_{(t)}}(\mathbf{x}^t, \mathbf{y}^t)$ as the distance from the frontier for energy using at t, which can be also interpreted as the ratio of the total slack to an energy input. Additionally, because the four components in Eq. (3) consist of two measurements within the same time period and two for intertemporal comparison, those four input-oriented distance functions would be replaced by the ratio of target energy input and actual energy input under technologies in different periods:

$$\text{TFEE}_t^t = \frac{\text{Target energy input under technology in } t}{\text{Actual energy input in } t}$$
$$= 1 - \vec{D}_{E_{(t)}}(\mathbf{x}^t, \mathbf{y}^t),$$
$$\text{TFEE}_t^{t+1} = \frac{\text{Target energy input under technology in } t+1}{\text{Actual energy input in } t}$$
$$= 1 - \vec{D}_{E_{(t+1)}}(\mathbf{x}^t, \mathbf{y}^t),$$

$$\text{TFEE}_{t+1}^{t+1} = \frac{\text{Target energy input under technology in } t+1}{\text{Actual energy input in } t + 1}$$
$$= 1 - \vec{D}_{E_{(t+1)}}(\mathbf{x}^{t+1}, \mathbf{y}^{t+1}),$$
$$\text{TFEE}_{t+1}^t = \frac{\text{Target energy input under technology in } t}{\text{Actual energy input in } t + 1}$$
$$= 1 - \vec{D}_{E_{(t)}}(\mathbf{x}^{t+1}, \mathbf{y}^{t+1}). \tag{4}$$

Therefore,

$$\text{TFEPI} = \left[\text{TFEE}_{t+1}^{t+1} - \text{TFEE}_t^t\right]$$
$$+ \frac{1}{2}\left[(\text{TFEE}_{t+1}^t - \text{TFEE}_{t+1}^{t+1}) + (\text{TFEE}_t^t - \text{TFEE}_t^{t+1})\right]. \tag{5}$$

Note that if the value of TFEPI is less than, equal to, or greater than zero, then it indicates total-factor energy productivity regress, no change, or progress from period t to $t + 1$. These four components of TFEPI in Eq. (4) can be measured by DEA based on linear programming. For more details, see the Appendix A.

However, TFEPI is only an aggregate index which might be oversimplified or over-aggregated. In other words, although TFEPI computes the average of total-factor energy productivity change, it does not indicate the sources of change directly. Thus, a more deeply study in the components of TFEPI is necessary. According to Boussemart et al. [21], TFEPI can be decomposed into two components: total-factor energy efficiency change and total-factor energy technical change. The former component measured the change in relative energy efficiency and the later measured the shift in the technology of energy use. In Eq. (5), the first difference (outside the bracket) represents total-factor energy efficiency changes and the second difference captures total-factor energy technical changes.

Considering the example in Panel B of Fig. 1 again, the total-factor energy productivity change by Eq. (5) from point A to point A′ is equal to

$$\left(\frac{E_A}{E_{A'}} - \frac{E_A}{E_A}\right) + \frac{1}{2}\left[\left(\frac{E_D}{E_{A'}} - \frac{E_A}{E_{A'}}\right) + \left(\frac{E_A}{E_A} - \frac{E_C}{E_A}\right)\right]. \tag{6}$$

Accordingly, the first difference shows a negative total-factor energy efficiency change and the second difference presents a positive total-factor energy technical change.

3. Data and variables' descriptions

This study appends the panel dataset of Hu and Wang [14] and analyzes 29 provincial level data from 2000 to 2004. According to the notion of Dan [28] and *National Western Development Strategy*, the 29 provinces are divided to three major areas: the east (the provinces of Shandong, Hebei, Liaoning, Jiangsu, Zhejiang, Fujiang, Guandong, Guanxi, and Hainan, and the three municipalities of Beijing, Tianjing, and Shanghai), central (the provinces of Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, and Hunan), and west (the provinces of Inner Mongolia, Sichuan, Guizhou, Yunnan, Shaanxi, Ganxu, Qinghai, Ningxia, and Xinjiang). Since the capital stock data of Chongqing are hard to calculate, this municipality is combined with Sichuan province in this research. We also do not take account Tibet, because the energy input data of Tibet are not available for this research.

In our multiple inputs and outputs model, labor, capital stock, energy consumption, and total sown area of farm crops are the four inputs, while real GDP is the single output. Regional energy consumption data are collected from the *China Energy Statistical Yearbook*. The energy datasets include the conventional energy consumption – mainly coal, petroleum, and natural gas. Data of GDP, labor employment, and total sown area of farm crops are all collected from the *China Statistical Yearbook*. This research uses

the total sown area of farm crop data as a proxy of biomass energy, which is one of the main sources for non-commercial energy use in China's rural area [14]. However, data of regional capital stock are not available in any statistical yearbooks of China. Li [29] uses capital formation to construct provincial capital stock datasets for the period 1984–1998. We extend capital stock data calculated by the authors according to the formula [29]:

Capital stock in the current year

$\quad$= Capital stock (previous year)

$\quad\quad$+ Capital formation (current year)

$\quad\quad$− Capital depreciation (current year). $\qquad$ (7)

All monetary inputs and outputs such as the GDP and capital stock are transformed into 2000 prices with GDP deflators.

The units of real GDP, labor, real capital, farm area, and energy consumption are billions of US$, millions of people, billions of US$, 1000 ha, and tons of standard coal equivalent (tce), respectively. Table 1 provides the descriptive statistics of inputs and output variables. The average real GDP of 29 regions in China is 357.3 billion RMB and the standard deviation of GDP is 273.7 billion RMB.

Among 29 regions in this research, Guangdong has the highest GDP output (1.03 trillion RMB), or about 40 times that of Ningxia (29.0 billion RMB). This information reveals a great disparity of economic performance among the regions in China. Other variables appear to have the same pattern with the GDP result. Table 1 also shows a correlation matrix, whereby all inputs have positive correlation coefficients with the output, implying that all inputs satisfy the isotonicity property with output for the DEA model.

4. Results and discussion

4.1. Total-factor energy productivity change in China

Table 2 presents total-factor energy productivity change for regions in China during 2000–2004. China's average total-factor energy productivity change from the period 2000 to 2004 is negative (−0.014), implying that the total-factor energy productivity was decreasing by 1.4% annually since 2000, especially from the period 2001 to 2002 (−3.2%). However, the traditional energy productivity index reveals that China's energy productivity change was only decreasing 0.5% annually during the research period as

Table 1
Summary statistics of input and output variables (2000–2004).

Variables	Mean	SD	Correlation matrix				
Inputs							
Capital stocks (1 billion RMB)	1396.28	1050.96	1.00				
Labor (1 million persons)	22.27	15.47	0.50	1.00			
Energy consumption (tce)	6204.17	3841.46	0.79	0.69	1.00		
Total sown area of farm crops (1000 ha)	5320.23	3624.06	0.27	0.85	0.57	1.00	
Output							
Gross domestic product (1 billion RMB)	357.28	273.74	0.86	0.71	0.83	0.48	1.00

Note: (1) All monetary units are at the 2000 price level. (2) tce: metric tons of standard coal equivalent.

Table 2
Total-factor energy productivity changes by region.

ID	Region		01/00	02/01	03/02	04/03	Average	Cumulative
1	Beijing	E	0.048	0.040	0.007	−0.029	0.016	0.066
2	Tianjin	E	0.022	0.026	0.038	−0.028	0.014	0.057
3	Hebei	E	−0.002	−0.026	−0.026	0.000	−0.013	−0.053
4	Liaoning	E	0.012	0.020	−0.007	−0.034	−0.002	−0.009
5	Shanghai	E	0.000	−0.024	0.000	0.000	−0.006	−0.024
6	Jiangsu	E	0.014	−0.008	0.000	0.000	0.001	0.006
7	Zhejiang	E	0.072	−0.103	0.031	0.009	0.002	0.000
8	Fujian	E	0.000	0.000	0.000	0.000	0.000	0.000
9	Shandong	E	0.150	−0.240	−0.019	0.009	−0.025	−0.135
10	Guangdong	E	−0.020	0.000	−0.007	0.000	−0.007	−0.027
11	Guangxi	E	0.030	−0.074	−0.046	−0.026	−0.029	−0.115
12	Hainan	E	−0.021	−0.075	−0.067	0.001	−0.041	−0.155
13	Shanxi	C	−0.030	−0.015	0.009	0.019	−0.004	−0.018
14	Jilin	C	0.019	−0.046	−0.030	0.012	−0.011	−0.046
15	Heilongjiang	C	0.035	0.032	−0.018	0.013	0.016	0.063
16	Anhui	C	−0.008	0.004	0.021	0.029	0.011	0.046
17	Jiangxi	C	0.091	−0.124	−0.047	0.041	−0.010	−0.051
18	Henan	C	0.005	−0.026	−0.046	−0.025	−0.023	−0.090
19	Hubei	C	0.053	−0.054	−0.071	−0.043	−0.029	−0.115
20	Hunan	C	−0.107	−0.122	−0.234	−0.085	−0.137	−0.450
21	Inner Mongolia	W	−0.032	−0.012	−0.025	−0.034	−0.026	−0.099
22	Sichuan	W	−0.025	0.020	−0.070	−0.018	−0.024	−0.093
23	Guizhou	W	0.001	0.011	−0.031	−0.005	−0.006	−0.024
24	Yunnan	W	0.004	−0.071	−0.013	−0.015	−0.023	−0.092
25	Shaanxi	W	−0.066	−0.036	−0.001	−0.003	−0.026	−0.103
26	Gansu	W	0.026	−0.016	−0.013	0.008	0.001	0.004
27	Qinghai	W	0.006	0.008	0.003	−0.041	−0.006	−0.024
28	Ningxia	W	−0.003	−0.003	−0.055	−0.003	−0.016	−0.063
29	Xinjiang	W	−0.004	−0.011	−0.001	−0.024	−0.010	−0.039
	Average		0.009	−0.032	−0.025	−0.009	−0.014	−0.056

calculated from *China Energy Statistical Yearbook*. The comparative result shows that the traditional energy productivity index might overestimate the energy productivity change if energy is taken as the single input. One possible explanation is that the substitution among inputs to produce the output is significant. For example, the partial labor productivity (GDP-to-labor ratio) in China shows an increase of about 10% annually during 2000–2004. In addition, if the same process is applied to compute the labor productivity under the total-factor framework, then the total-factor labor productivity improves 0.06% annually. Hence, the partial energy productivity would overestimate when other inputs become more productive and substitute energy input.

In regards to the total-factor energy productivity change of regions level, seven of 29 regions (Beijing, Tianjin, Jiangsu, Zhejiang, Heilongjiang, Anhui, and Qinghai) enhance their total-factor energy productivity. Beijing has the highest total-factor energy productivity growth in China, whereby its total-factor energy productivity cumulatively improves about 6.6% since 2000. Heilongjiang, with a 1.6% improvement annually in total-factor energy productivity, is the second best performer among 29 regions. However, six regions see a sharp decline in their total-factor energy

productivity of more than 10% since 2000: Shandong, Guangxi, Hainan, Hubei, Hunan, and Shaanxi. Among them, Hunan presents the worst performance by decreasing 13.7% annually on average during 2000–2004. In the first period (2000–2001), 16 regions have positive total-factor energy productivity growth, especially for Shandong with a 15% improvement. However, the number of regions improving their total-factor energy productivity shows a significant decline in 2001–2003. Only eight and six regions increase their total-factor energy productivity in the second and third periods, respectively.

The TFEPI represents an arresting pattern among the three major areas in China. Fig. 2 shows the TFEPI of three areas in each period and Fig. 3 shows the cumulative total-factor energy productivity change of three areas in each year. As Fig. 2 shows, only the TFEPI of the east and central areas is positive in the first period, implying that all areas almost present negative growth of total-factor energy productivity in the research period. The east area is the best performer among the three areas, especially showing a increasing of the total-factor energy productivity (2.5%) in the first period. The highest TFEPI of the east area is 0.025 and the lowest is −0.036. The east area's average TFEPI is −0.005, illustrating
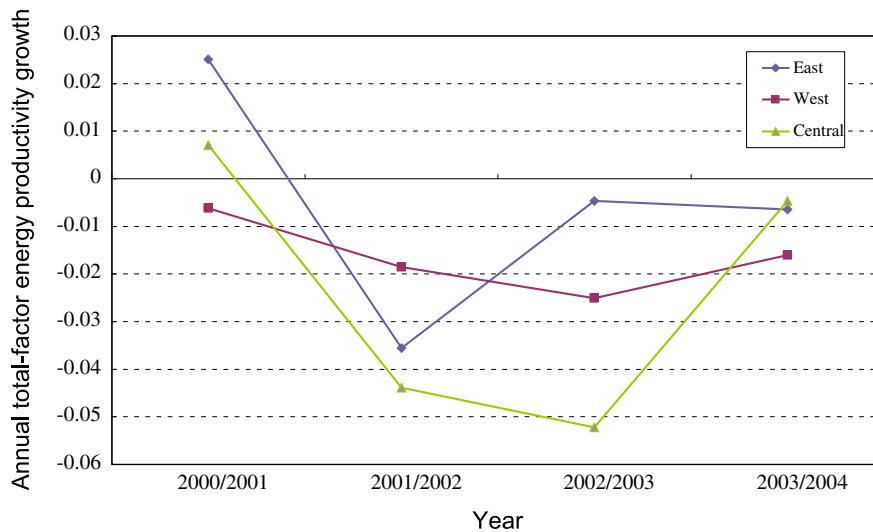

Fig. 2. Annual total-factor energy productivity growth among three major areas.
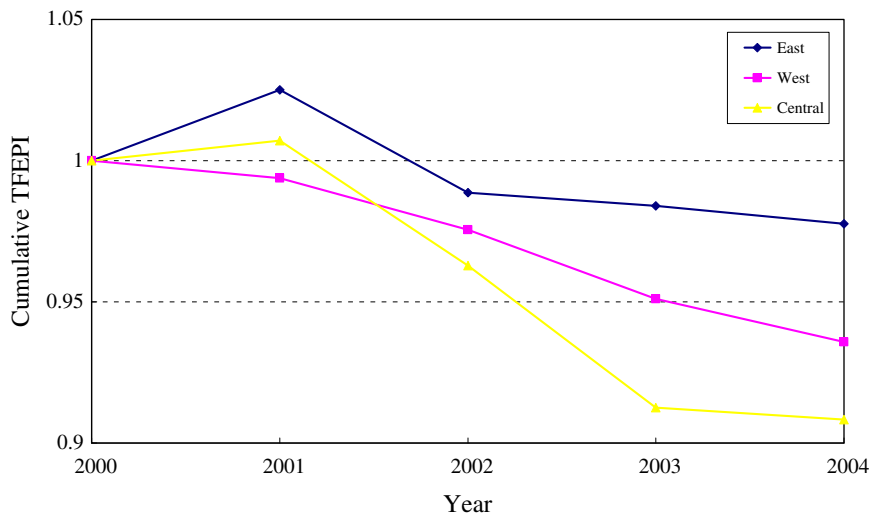

Fig. 3. Cumulated total-factor energy productivity change among three major areas.

that the total-factor energy productivity of the east area decreases by 0.5% annually during the period 2000–2004. However, the central area has the lowest average TFEPI at −0.023, although the TFEPI of central area improves 0.7% in 2001–2002. Moreover, the TFEPI of the west area reveals a similar pattern to the central area, presenting a deep drop in TFEPI from 2002 to 2003.

Fig. 3 depicts the cumulative change of total-factor energy productivity of the three major areas (we assume initial total-factor energy productivity equals to unity in 2000). The result is consistent with Fig. 2 that total-factor energy productivity of all areas provides a progressive decline trend during the research period. The east area's total-factor energy productivity slightly decreased about 2.2% since 2000, while the total-factor energy productivity of central and west areas dramatically decreased over 9.1% and 6.4%, respectively. It is noteworthy that the east area has the highest level of per capita income and the highest level of energy productivity growth. As opposed to the east area, the west has the lowest level of per capita income and energy productivity growth. The results do not represent the convergence of energy productivity in China, suggesting that areas with relatively low economic growth cannot catch up to advanced areas.

These TFEPI results for regions and areas in China are consistent with the arguments of Lin [30] who finds different local emphases in implementing energy policy for Agenda 21. For instance, the richer coastal regions emphasize reforming traditional production and consumption patterns and adopting environmental friendly energy technologies, while the poorer inland regions emphasize efficient use and conservation of energy [30].

4.2. Components of total-factor energy productivity growth

In order to examine what happens to the total-factor productivity of regions in China, we first decompose the TFEPI into its two components – total-factor energy efficiency change and technical change by Eq. (5). Total-factor energy efficiency (TFEE) change

Table 3
Annual total-factor energy efficiency changes by region.

ID	Region		01/00	02/01	03/02	04/03	Average
1	Beijing	E	0.062	0.067	0.022	−0.026	0.031
2	Tianjin	E	0.037	0.054	0.056	−0.022	0.031
3	Hebei	E	0.010	−0.003	−0.004	0.021	0.006
4	Liaoning	E	0.022	0.042	0.016	−0.014	0.016
5	Shanghai	E	0.000	0.000	0.000	0.000	0.000
6	Jiangsu	E	0.025	0.000	0.000	0.000	0.006
7	Zhejiang	E	0.092	−0.070	0.050	0.022	0.024
8	Fujian	E	0.000	0.000	0.000	0.000	0.000
9	Shandong	E	0.171	−0.209	0.013	0.039	0.003
10	Guangdong	E	0.000	0.000	0.000	0.000	0.000
11	Guangxi	E	0.048	−0.040	−0.013	0.003	−0.001
12	Hainan	E	0.000	−0.031	−0.025	0.039	−0.004
13	Shanxi	C	−0.025	−0.005	0.019	0.029	0.004
14	Jilin	C	0.030	−0.025	−0.010	0.032	0.007
15	Heilongjiang	C	0.048	0.060	0.011	0.039	0.039
16	Anhui	C	0.006	0.033	0.052	0.059	0.037
17	Jiangxi	C	0.111	−0.087	−0.012	0.075	0.022
18	Henan	C	0.020	0.003	−0.018	0.000	0.001
19	Hubei	C	0.070	−0.022	−0.041	−0.018	−0.003
20	Hunan	C	0.000	0.000	−0.198	−0.056	−0.063
21	Inner Mongolia	W	−0.023	0.004	−0.009	−0.021	−0.012
22	Sichuan	W	−0.012	0.049	−0.043	0.005	0.000
23	Guizhou	W	0.007	0.022	−0.020	0.005	0.003
24	Yunnan	W	0.017	−0.047	0.011	0.006	−0.003
25	Shaanxi	W	−0.053	−0.012	0.024	0.020	−0.006
26	Gansu	W	0.034	0.000	0.003	0.023	0.015
27	Qinghai	W	0.014	0.023	0.019	−0.028	0.007
28	Ningxia	W	0.002	0.008	−0.046	0.004	−0.008
29	Xinjiang	W	0.005	0.008	0.018	−0.007	0.006
	Average		0.025	−0.006	−0.004	0.008	0.006

indicates the change of relative efficiency for consuming the energy input among 29 regions. Table 3 lists the calculation results of total-factor energy efficiency change. The results of Table 3 show that the whole country's average total-factor energy efficiency change is 0.006 during 2000–2004. This reveals that the total-factor energy efficiency of China improves about 0.6% per year and presents a slight catch-up effect such that the gap between all regions in China has progressively diminished since 2000. However, there is a downward plunge of total-factor energy efficiency during the period 2001–2003. The yearly total-factor energy efficiency change is about −0.6% in the period 2001–2002.

Table 3 also presents the results of total-factor energy efficiency change for regions level. The total-factor energy efficiency changes in three regions (Shanghai, Fujian, and Guangdong) are equal to zero in each period, meaning that these regions' capacities for using energy to generate economic output are the best performer all the time. Stated another way, these regions still perform on the production frontier throughout the periods. However, the catch-up effect does not exist for all regions. Over half of 29 regions possess relative energy efficiency improvement – that is, their energy consumption efficiency catches up to the production frontier. The total-factor energy efficiency of Beijing, Tianjin, Heilongjiang, and Anhui rapidly increases to more than 3% annually on average, especially that of Heilongjiang (3.9%). There are also two regions (i.e., Inner Mongolia, Hunan) confronting a marked efficiency decline with over 1% annual change, especially for Hunan (−6.3%). It is worth noting that the above results only focus on the change of TFEE. We simultaneously consider the regions' TFEE and TFEE change for further analysis. For example, in 2004, although Heilongjiang has the fastest growth rate of TFEE, its TFEE score (0.674) is lower than the score of Hunan (0.746) whose growth rate is the worst among 29 regions. Additionally, there are four regions (i.e., Guizhou, Gansu, Qinghai, and Xinjiang) in the west area that improved their TFEE, but the TFEE of all of them are still below the country's average TFEE in 2004. This indicates that some regions try to catch up to the frontier, while the inequality of total-factor energy efficiency exists in China.

The second component of TFEPI is total-factor energy technical change, representing the shift in the technology of energy use during one period. As shown in Table 4, the whole country's average total-factor energy technical change is −0.020, indicating that the technology of using energy in China regresses significantly by 2.0% per year during the research period 2000–2004. A possible reason for the result may be the proportion of low-efficiency source of energy (such as coal) continues to increase in China during the 2000–2004 periods [23]. None of the four yearly periods shows a positive technical growth, while a rapid drop occurs in 2001–2002 of up to −2.6%. Considering Tables 2–4, we derive a conclusion: The total-factor energy productivity of China has dropped 5.6%, decreasing by 1.4% annually on average since 2000. However, this energy productivity decline is mainly attributable to negative technical growth and not relative efficiency change.

Table 4 also reports regional total-factor energy technical change in each period. Accordingly, only one region (Fujian) has a non-negative total-factor energy technical change over the entire period, showing that the total-factor energy technical change of Fujian is unchanged during the period 2000–2003. This also illustrates no shift in the frontier of energy usage technology in China over the research periods. Conversely, the total-factor energy technical changes of Hainan, Jiangxi, and Hunan decrease most rapidly to more than 3% annually. Moreover, Heilongjiang, one of China's old industrial bases, has an average total-factor energy technical change with −2.4%. The total-factor energy technical change of the other two old industrial base regions, Liaoning and Jilin, are −1.8% and −1.8% annually on average, respectively. It reveals that

Table 4
Annual total-factor energy technical changes by region.

ID	Region		00/01	01/02	02/03	03/04	Average
1	Beijing	E	−0.014	−0.027	−0.015	−0.003	−0.015
2	Tianjin	E	−0.015	−0.029	−0.018	−0.007	−0.017
3	Hebei	E	−0.012	−0.023	−0.023	−0.020	−0.019
4	Liaoning	E	−0.010	−0.021	−0.023	−0.019	−0.018
5	Shanghai	E	0.000	−0.024	0.000	0.000	−0.006
6	Jiangsu	E	−0.011	−0.008	0.000	0.000	−0.005
7	Zhejiang	E	−0.020	−0.033	−0.019	−0.014	−0.022
8	Fujian	E	0.000	0.000	0.000	0.000	0.000
9	Shandong	E	−0.021	−0.031	−0.032	−0.029	−0.028
10	Guangdong	E	−0.020	0.000	−0.007	0.000	−0.007
11	Guangxi	E	−0.018	−0.034	−0.033	−0.029	−0.029
12	Hainan	E	−0.021	−0.044	−0.042	−0.038	−0.036
13	Shanxi	C	−0.005	−0.009	−0.010	−0.010	−0.009
14	Jilin	C	−0.012	−0.022	−0.021	−0.019	−0.018
15	Heilongjiang	C	−0.013	−0.028	−0.028	−0.026	−0.024
16	Anhui	C	−0.014	−0.029	−0.031	−0.029	−0.026
17	Jiangxi	C	−0.020	−0.036	−0.035	−0.034	−0.031
18	Henan	C	−0.015	−0.030	−0.029	−0.025	−0.024
19	Hubei	C	−0.017	−0.032	−0.030	−0.025	−0.026
20	Hunan	C	−0.107	−0.122	−0.036	−0.029	−0.074
21	Inner Mongolia	W	−0.008	−0.017	−0.016	−0.013	−0.013
22	Sichuan	W	−0.014	−0.029	−0.027	−0.024	−0.023
23	Guizhou	W	−0.005	−0.012	−0.011	−0.009	−0.009
24	Yunnan	W	−0.013	−0.023	−0.024	−0.021	−0.020
25	Shaanxi	W	−0.012	−0.024	−0.025	−0.022	−0.021
26	Gansu	W	−0.008	−0.016	−0.016	−0.015	−0.014
27	Qinghai	W	−0.007	−0.015	−0.016	−0.013	−0.013
28	Ningxia	W	−0.005	−0.010	−0.008	−0.007	−0.008
29	Xinjiang	W	−0.009	−0.019	−0.019	−0.016	−0.016
	Average		−0.015	−0.026	−0.020	−0.017	−0.020

Table 5
Estimation results of effects of regional characteristics on TFEPI.

	Dependent variable: TFEPI	
	Model 1	Model 2
Constant	0.012 (0.009)	0.023 (0.024)
West	−0.011* (0.006)	−0.003 (0.014)
Central	−0.018 (0.020)	−0.011 (0.021)
Time trend	−0.005** (0.002)	−0.013* (0.007)
Lagged GDP per capita		0.213** (0.089)
Lagged FDI		−0.002 (0.002)
Lagged human capital		0.052 (0.071)
Growth of primary industry		−0.020 (0.107)
Growth of secondary industry		−0.108* (0.060)
Growth of tertiary industry		−0.311 (0.231)
Growth of coal share		0.001 (0.001)
Growth of oil share		0.001 (0.001)
Growth of natural gas share		0.002 (0.002)
Growth of electricity share		0.065*** (0.017)
Number of observations	116	116
Adjusted R-square	0.035	0.559

Note: (1) Numbers in parentheses are standard errors.
(2) *, **, and *** represent significance at the 10%, 5%, and 1% level, respectively.
(3) Model 1: F test (p-value = 0.16); LM test (p-value = 0.36); Hausman test (p-value = 0.99).
(4) Model 2: F test (p-value < 0.01); LM test (p-value < 0.01); Hausman test (p-value = 0.88).

the major problem of China's old industrial bases is technology regression and not being under efficient energy usage.

4.3. Determinants of TFEPI

As mentioned above, the total-factor energy productivity of China presents a negative growth trend in which only seven regions enhance their total-factor energy productivity among 29 regions in the period 2000–2004. Therefore, three sets of factors affecting the regional TFEPI scores are explored: The first set contains state variables, including area, the ratio of FDI to GDP, human capital, and GDP per capita. Yang [31] considers that China's regional development strategies since the reforms directly drive the widening spatial development gap. The east area consisting of coastal regions and special economic zones has received preferential resource allocations and attracted foreign direct investment since early 1980. This region-biased policy may cause technology, skilled labor, and investment inequality among the regions. FDI is a possible factor affecting regional energy productivity growth. Fisher-Vanden et al. [32] consider that technological innovation can imported from abroad, especially for developing country such as China. The energy productivity may increase due to the human capital accumulation which helps input more skilled labor into the production process. Here the ratio of annual university graduates to population is used as an index of human capital, according to Fleisher and Chen [33]. GDP per capita would measure the region's development status. This factor can also analyze cross-region convergence of total-factor energy productivity and examine whether the advantage of backwardness exists.

The second set is region's industry structural change. Wei et al. [15] and Fisher-Vanden et al. [34] mention that industry structural change can cause a great influence on energy efficiency. For example, a shift from an energy-intensive sector, such as a secondary industry to a tertiary industry, increases energy efficiency. We adopt the proportion change of GDP contributed by primary, sec-

ondary, and tertiary industries to characterize a region's industry structure.

The third set is the change in energy mix. Miketa and Mulder [6] point out that the change in energy mix is an important source of energy productivity growth. Moreover, natural gas and electricity are more efficient and energy-saving sources than coal and oil. Hence, the change in share of coal, oil, natural gas, and electricity is used to characterize a region's energy mix.

In this analysis, polling OLS and random-effects regression is used to estimate the determinants of TFEPI in Model 1 and Model 2, respectively. As the note of Table 5 explains, the F, LM, and Hausman tests reveal that the random-effects regression is more appropriate for the comprehensive model (Model 2). Table 5 offers the estimation results. According to the results of regression, this paper has the following findings: First, the east area has a better TFEPI and the west area has a significantly lower TFEPI. Second, regions with a higher previous GDP per capita that represent that higher development have better TFEPI performances. These two findings indicate that the total-factor energy productivity among regions in China is diverse from 2000 to 2004. Third, FDI ratio and human capital reveal slight positive effects on energy productivity growth as they are solely considered, while the effects disappear if these factors are taken with others in Model 2. It indicates that FDI investment and human capital do not have directly effect on energy productivity growth. Four, the result also shows that increasing the proportion of GDP generated by the secondary industry deteriorates the total-factor energy productivity of the region. Finally, the result shows that the energy mix has significant effect on TFEPI, which is similar to the work of Miketa and Mulder [6]. Actually, the total-factor energy productivity would increase substantially as raising the share of electricity use. We conclude that advancing the technology of energy consumption and adjusting industry structure and energy mix are vital matters for the regions in China to raise their energy productivity.

5. Conclusions

Conventional energy indices, such as energy efficiency and energy intensity, can be used to evaluate how energy inputs are efficiently utilized. However, these indicators neglect the substitution

among energy consumption and other factors so that the results obtained from conventional energy indicators overestimate or underestimate the actual state. This paper proposes the total-factor energy productivity index (TFEPI) to assess energy productivity growth for regions in China. TFEPI constructs a multiple-input framework that avoids single-input bias since energy is not the only input to produce economic output. The DEA approach based on the Luenberger index and relative TFEE is applied to conduct a total-factor energy productivity index in this study. The TFEPI proposed in this paper is a dynamic indictor to measure the total-factor energy productivity growth by getting rid of the substitution and complement effects among all inputs. It helps provide more insights about efficiency changes as well as technology changes in energy use.

This paper reports the results of an empirical study of regional productivity growth in China. Accordingly, China's average total-factor energy productivity was decreasing by 1.4% per year during 2000–2004, especially in the period 2001–2002 (−3.2%). However, the traditional energy productivity index reveals that China's energy productivity change was only decreasing 0.5% annually during the research period. This comparative result shows that the traditional energy productivity index overestimates the energy productivity change if energy is taken as the single input. At the regional level, seven of 29 regions enhance their total-factor energy productivity. The TFEPI not only evaluates total-factor energy productivity change, but also appraises change in relative energy efficiency (catching up effect) and shift in the technology of energy use (innovation effect) by decomposing TFEPI. The finding from a change in relative energy efficiency shows that the whole country's average total-factor energy efficiency improves about 0.6% per year and two periods (2001–2003) present negative growth. This indicates that the relative energy efficiency gap between all regions has gradually condensed since 2000. Nevertheless, the results of total-factor energy technical change illustrate that the technology of use energy declines progressively at 2.0% per year during 2000–2004. Over the 5 years, none of all regions in China shows a positive total-factor energy technical change. We conclude that energy productivity decline in China is attributable to negative technical growth and not relative efficiency change.

What causes regional total-factor productivity inequality and decline in China are important issues in future work. In the present study we only examine the effect of a region's development status, economic structure, and energy mix on total-factor energy productivity change, but these effects cannot completely explain the situation of energy productivity in China. Some research studies based on cross-country or cross-region studies suggest that relative energy price may be the key determinants of energy productivity growth [6,34]. For example, the oil price shows a discrepancy between regions in China, because local governments still have some authority to set the selling price. Hence, the difference in pricing among regions could result in some regions with higher prices (such as Shanghai) having an incentive to improve energy productivity. It recommends that additional research focus on the components of the total-factor energy productivity index to draw more precise conclusions about specific effects on energy productivity growth among regions in China. Moreover, it may be of interest for future studies to discuss the contribution of each input variables toward total-factor productivity growth. Hence, additional research would usefully extend the present TFEPI to investigate how the productivity of other input variables change.

Acknowledgements

Appendix A. The four directional distance functions of TFEPI

The proposed total-factor energy productivity index (TFEPI) combines the features of Luenberger productivity index with total-factor energy efficiency. For the ideas of calculating TFEPI, the first step is to compute the efficient level of energy input. In other words, it is important to find out the actual slack of energy input of each region. This paper derives the actual slack of energy input from directional distance function, a flexible tool to account for both efficient inputs and outputs when measuring efficiency. However, most literature considers a special case, assuming the directional vector $(\mathbf{g}_x, \mathbf{g}_y)$ is equal to $(\mathbf{x}, \mathbf{y})$, to contract input and expand output variables by an equal scale [18,20,21]. It is a convenient approach but cannot obtain exact input or output slacks. Fortunately, Färe and Grosskopf [27] introduce a generalized directional distance function and use linear programming method to acquire how many excess inputs have been employed and how many too few outputs have been produced. We illustrate the approach of Färe and Grosskopf [27] and the relationship with the ideas of TFEE as the following:

We first define some mathematical notations. Assume there are M inputs and S outputs for each of N objects in each time period of T. The ith input and rth output variable of the jth object is represented by x_{ij}^t and y_{rj}^t in time t, respectively. Moreover, Färe and Grosskopf [27] propose the vectors

$$e_l = (0, \dots, 0, 1, 0, \dots, 0), l = 1, \dots, m+s. \tag{A1}$$

where the 1 is in the lth place of the vector. Therefore, the generalized directional distance functions for the observation o in time t can be state as following linear programming problems

$$\max \beta_1 + \cdots + \beta_M + \gamma_1 + \cdots + \gamma_S$$

$$\text{s.t.} \quad \sum_{j=1}^{N} \lambda_j x_{ij}^t \leqslant x_{io}^t - \beta_i e_i, i = 1, \dots, M,$$

$$\sum_{j=1}^{N} \lambda_j y_{rj}^t \geqslant y_{ro}^t + \gamma_r e_r, r = 1, \dots, S, \tag{A2}$$

$$\lambda_j \geqslant 0, \beta_i \geqslant, \gamma_r \geqslant 0,$$

$$j = 1, \dots, N; i = 1, \dots, M; r = 1, \dots S.$$

where λ_j is the intensity variable that serves to form a convex combination of observed inputs and outputs. As shown in Eq. (A2), the products $\beta_i e_i$ and $\gamma_r e_r$ can be interpreted as the input and output slacks, respectively. It is noteworthy that the true slacks are based on the constant return to scale assumption, indicating the efficient level of inputs and outputs for achieving the overall technical efficiency.

Although this advanced approach would easily obtain the actual slacks of each type of input and output variables, it has difficulty applying this generalized directional distance function to derive the Luenberger productivity index. Since the e_l has a value of one for each input and output, implying that e_l plays the role of the units of data, β_i (γ_r) would be the number of units of each type of input (output) that can be contracted (expanded). Concerning the widespread variation of each input and output among regions, the Luenberger productivity index would present a meaningless and incomparable result if we directly use the 'number' of slacks.

For dealing with the above-mentioned problem, the concept of TFEE, an optimal-to-actual ratio under total-factor framework, is applied in this study. Then we define $\vec{D}_{E_{(t)}}(\mathbf{x}^t, \mathbf{y}^t)$ as the ratio of slack to original energy input, indicating the distance from the frontier for energy using at t. Accordingly, $TFEE_t^t$ is equal to

$(1 - \overrightarrow{D}_{E_{(t)}}(\mathbf{x}^t, \mathbf{y}^t))$ as shown in the first line of Eq. (4). Other three distance functions can be substituted by TFEE in the same consideration. The computation of $\overrightarrow{D}_{E_{(t+1)}}(\mathbf{x}^{t+1}, \mathbf{y}^{t+1})$ is exactly like Eq. (A2), where $t + 1$ is substituted for t. However, there would confront an infeasible linear programming problem when computing the two intertemporal directional distance function, i.e., $\overrightarrow{D}_{E_{(t)}}(\mathbf{x}^{t+1}, \mathbf{y}^{t+1})$ and $\overrightarrow{D}_{E_{(t+1)}}(\mathbf{x}^t, \mathbf{y}^t)$. It is because that the production possibilities frontier constructed from observations in period t may not contain an observation from period $t + 1$ (and vice versa). Therefore, we employ 3 year windows data following the approach of Färe et al. [35] to calculate two intertemporal directional distance function. Finally, the index of energy productivity change under total-factor framework, TFEPI, will be completely constructed by Eqs. (4) and (5).

References

[1] Berndt ER. Energy use, technical progress and productivity growth: a survey of economic issues. J Prod Anal 1990;2:67–83.
[2] Narayan PK, Wong P. A panel data analysis of the determinants of oil consumption: the case of Australia. Appl. Energy 2009;86:2771–5.
[3] Abosedra S, Dah A, Ghosh S. Electricity consumption and economic growth, the case of Lebanon. Appl. Energy 2009;86:429–32.
[4] Narayan PK, Narayan S, Popp S. A note on the long-run elasticities from the energy consumption–GDP relationship. Appl. Energy 2010;87:1054–7.
[5] Herring H. Does energy efficiency save energy? The debate and its consequences. Appl. Energy 1999;63:209–26.
[6] Miketa A, Mulder P. Energy productivity across developed and developing countries in 10 manufacturing sectors: patterns of growth and convergence. Energy Econ. 2005;27:429–53.
[7] Jinke L, Hualing S, Dianming G. Causality relationship between coal consumption and GDP: difference of major OECD and non-OECD countries. Appl. Energy 2008;85:421–9.
[8] Sari R, Soytas U. Are global warming and economic growth compatible? Evidence from five OPEC countries? Appl. Energy 2009;86:1887–93.
[9] Energy Information Administration (EIA), Annual Energy Outlook, US Department of Energy, Washington, DC, 2006.
[10] Crompton P, Wu Y. Energy consumption in China: past trends and future directions. Energy Econ. 2005;27:195–208.
[11] Patterson MG. What is energy efficiency? Concepts, indicators, and methodological issues. Energy Policy 1996;24:377–90.
[12] Han ZY, Fan Y, Jiao JL, Yan JS, Wei YM. Energy structure, marginal efficiency and substitution rate: an empirical study of China. Energy 2007;32:935–42.
[13] Nel WP, van Zyl G. Defining limits: energy constrained economic growth. Appl. Energy 2010;87:168–77.
[14] Hu JL, Wang SC. Total-factor energy efficiency of regions in China. Energy Policy 2006;34:3206–17.
[15] Wei C, Ni J, Shen M. Empirical analysis of provincial energy efficiency in China. China World Econ. 2009;17:88–103.
[16] Hu JL, Kao CH. Efficient energy-saving targets for APEC economies. Energy Policy 2007;35:373–82.
[17] Honma S, Hu JL. Total-factor energy efficiency of regions in Japan. Energy Policy 2008;36:821–33.
[18] Chambers RG, Färe R, Grosskopf S. Productivity growth in APEC countries. Pac. Econ. Rev. 1996;1:181–90.
[19] Luenberger DG. New optimality principles for economic efficiency and equilibrium. J. Optim. Theory Appl. 1992;75:221–64.
[20] Chambers RG, Chung Y, Färe R. Profit, directional distance functions, and Nerlovian efficiency. J. Optim. Theory Appl. 1998;98:351–64.
[21] Boussemart JP, Briec W, Kerstens K, Poutineau JC. Luenberger and Malmquist productivity indices: theoretical comparisons and empirical illustration. Bull. Econ. Res. 2003;55:391–405.
[22] Managi S. Luenberger and Malmquist productivity indices in Japan, 1955–1995. Appl. Econ. Lett. 2003;10:581–4.
[23] Ni W, Johansson TB. Energy for sustainable development in China. Energy Policy 2004;32:1225–9.
[24] Wei YM, Jiao H, Fan Y. An empirical analysis of energy efficiency in China's iron and steel sector. Energy 2007;32:2262–70.
[25] Ang BW. Monitoring changes in economy-wide energy efficiency: from energy–GDP ratio to composite efficiency index. Energy Policy 2006;34:574–82.
[26] Coelli T, Rao DSP, Battese GE. An introduction to efficiency and productivity analysis. London: Kluwer Academic Publishers; 1998.
[27] Färe R, Grosskopf S. Directional distance functions and slacks-based measures of efficiency. Eur. J. Oper. Res. 2010;200:320–2.
[28] Dan S. Regional differences in China's energy efficiency and conservation potentials. China World Econ. 2007;15:96–115.
[29] Li KW, China's capital and productivity measurement using financial resources, Center Discussion Paper No. 851, Economic Growth Center, Yale University, 2003.
[30] Lin G. Implementing China's Agenda 21: from national strategy to local action. Impact Assess. Proj. Apprais. 1998;16:277–87.
[31] Yang DT. What has caused regional inequality in China? China Econ. Rev. 2002;13:331–4.
[32] Fisher-Vanden K, Jefferson GH, Ma J, Xu J. Technology development and energy productivity in China. Energy Econ. 2006;28:690–705.
[33] Fleisher BM, Chen J. The coast–noncoast income gap, productivity, and regional economic policy in China. J. Comp. Econ. 1997;25:220–36.
[34] Fisher-Vanden K, Jefferson GH, Liu H, Tao Q. What is driving China's decline in energy intensity? Resour. Energy Econ. 2004;26:77–97.
[35] Färe R, Grosskopf S, Pasurka Jr CA. Accounting for air pollution emissions in measures of state manufacturing productivity growth. J. Reg. Sci. 2001;41:381–409.