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Quande Qin
Xin Li
Li Li
Wei Zhen
Yi-Ming Wei

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Center for Energy and Environmental Policy Research
Beijing Institute of Technology
No.5 Zhongguancun South Street, Haidian District
Beijing 100081
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Yi-Ming Wei
Director of Center for Energy and Environmental Policy Research, Beijing Institute of Technology

For more information, please contact the office:

Address:
Director of Center for Energy and Environmental Policy Research
Beijing Institute of Technology
No.5 Zhongguancun South Street
Haidian District, Beijing 100081, P.R. China

Access:
Tel: +86-10-6891-8551
Fax: +86-10-6891-8651
Email: ceeper@vip.163.com
Website: http://ceep.bit.edu.cn/english/index.htm

Air emissions perspective on energy efficiency: An empirical analysis of China's coastal areas

Quande Qin[a,b,c], Xin Li[a], Li Li[a], Wei Zhen[a], Yi-Ming Wei[b,c,d,*]

[a] Department of Management Science, Shenzhen University, Shenzhen 518060, China

[b] Center for Energy & Environmental Policy Research, Beijing Institute of Technology, Beijing 100081, China

[c] School of Management and Economics, Beijing Institute of Technology, Beijing 100081, China

[d] Collaborative Innovation Center of Electric Vehicles in Beijing, Beijing 100081,China

Abstract: Improving energy efficiency has been recognized as the most effective way to reduce the greenhouse effect and achieve sustainable development. From the perspective of air emissions, this paper adopts data envelopment analysis approach to evaluate the energy efficiency in China's coastal areas over the period of 2000-2012. Carbon dioxide, sulfur dioxide and nitrogen oxide are treated as undesirable outputs of energy consumptions. The proposed global Epsilon-based measure is used to estimate the static energy efficiency with an annual cross-section of data. The weights of the three undesirable outputs are determined according to their treatment costs. A global Malmquist-Luenberger productivity index based on directional distance function is employed to dynamically evaluate the energy efficiency. The results indicate the following in China's coastal areas: 1) the level of economic development is positively related to energy efficiency scores; 2) energy efficiency scores decrease when considering undesirable outputs except Beijing and Hainan; 3) the Circum-Bohai Sea Economic Region greatly improved energy efficiency and has great potential of air emission; 4) the annual growth rate of Malmquist-Luenberger productivity index change is overestimated; 5) energy efficiency improvement is mainly driven by technological improvement, and scale efficiency and management level are the main obstacles.

Keywords: Energy efficiency; Data envelopment analysis; China's Coastal areas; Air emissions

Nomenclature

DEA	data envelopment analysis
DMU	decision making unit
DDF	directional distance function
GBT	global benchmark technology
ML	Malmquist-Luenberger
GML	global Malmquist-Luenberger
SBM	slacks-based measure
EBM	epsilon-based measure
VRS	variable return to scale
CRS	constant return to scale
CO_2	carbon dioxide
SO_2	sulfur dioxide
NOx	nitrogen oxides
N	number of DMUs
L	number of inputs
M	number of desirable outputs
I	number of undesirable outputs
x	input vector
y	desirable output vector
b	undesirable output vector
g	director vector
$P\ x$	production set
w_m^y	weights of the desirable output variables
w_k^b	weights of the undesirable output variables

1. Introduction

The threats posed by global climate change, which are mainly caused by the emission of greenhouse gases (GHG), are now widely recognized by the international community. Many countries have paid enormous attention to addressing these issues. Energy consumption is a major source of GHG emissions and air pollutants. In 2009, China became the largest global energy consumer [1]. According to the China Statistical Yearbook 2013, primary energy consumption in China accounted for 21.3% of the global level. Of the alternative ways for reducing energy consumption, improving energy efficiency has been regarded as one of the single most cost-effective ways [2]. It is widely acknowledged that monitoring energy efficiency performance can provide an analytical foundation for assessing the effectiveness of an energy policy.

Due to China’s industrial structure and lifestyle, the coal share of China's total primary energy consumption is 66% in 2014. In China, industries using fossil fuels, such as the thermal power-generation [3,4], iron and steel industry [5,6], cement industries[7,8] and transport sectors [9,10,11], are found to be the major emitters of undesirable outputs, resulting in serious environmental problems, especially air pollutants. In order to explore the effect of these undesirable outputs on energy efficiency in China, this study considers three undesirable outputs in air emissions: carbon dioxide (CO_2), sulfur dioxide (SO_2), and nitrogen oxide (NO_X). The motivation of choosing the three outputs are as follows: 1) global warming, acid rain, and ozone depletion are the three air pollution problems that cause the most concern both regionally and globally, and they are thought to be caused by large quantities of CO_2, SO_2, and NO_X emissions; 2) China has been the largest emitter of CO_2, SO_2, and NO_X around the world, and the Chinese government has included in its emissions reduction targets in the "Twelve Five Plan" specific reductions in CO_2 emissions per GDP of 17%, total reduction in SO_2 emissions by 8%, and total reduction in NO_X emissions by 10%.

Many studies of energy efficiency evaluation in China widely concentrate on the whole country or one specific industry at national level [12,13,14,15,16,17,18]. Due to the uneven levels of regional economic development and energy consumption structures variations in different China's regions, whole-country studies of energy efficiency evaluation may lead to a biased measure in evaluating energy efficiency. In this paper, we focus on the coastal areas, which include nine coastal provinces (Hebei, Liaoning, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Guangxi, and Hainan) and three municipalities (Beijing[1], Tianjin, and Shanghai)[2][19,20]. In China's coastal areas, five provinces (Beijing, Tianjin, Hebei, Liaoning, Shandong) belong to Circum-Bohai Sea Economic Region. Yangtze River Delta Economic Zone includes Jiangsu, Shanghai, and Zhejiang. Four provinces (Fujian,

[1]In this paper, Beijing is included as a coastal city for the following reasons: 1) Beijing is the capital of China and an economically developed city; 2) Beijing is one of the two largest urban energy consumers in China, and its air pollution has received widespread attentions; 3) Beijing is near the sea, and some studies suggested that it is a coastal city [25,26].

[2]For simplicity, we call them China's 12 coastal provinces.

Guangdong, Hainan, and Guangxi) are included in Pan-Pearl River Delta Economic Zone. Generally, the coastal areas in China with the advantages of location are the overall fastest developing economic regions as well those with the highest energy consumption and the greatest population concentration. According to data from the National Bureau of Statistics of China (NBSC), the energy consumption in coastal areas in 2012 accounted for more than 60% of that throughout the country.

Data envelopment analysis (DEA) approach is widely applied in the field of evaluating energy efficiency. Because DEA is a method used to measure the relative efficiency [21], it has a certain practical significance for detailed analysis in the coastal areas and can provide some cues and implications for other regions. Within a joint production framework of desirable and undesirable outputs, in this paper we construct both static and dynamic energy efficiency performance indices for measuring energy efficiency performance based on DEA models. The global benchmark technology (GBT) incorporates the Epsilon-based measure (EBM) [22] and Malmquist-Luenberger (ML) productivity index. We use the modified EBM to estimate the static energy efficiency with annual cross-section data from China's 12 coastal provinces. The static energy efficiency evaluation can offer relative energy efficiency scores and a general change trend, but it fails to give specific factors for the changes. The global Malmquist-Luenberger (GML) productivity index [23] based on DDF is used to measure the changes of productivity efficiency with panel data. Compared with the traditional ML productivity index, GML can evaluate dynamically the total-factor productivity efficiency and consider desirable and undesirable outputs. Moreover, it can overcome the shortcomings of traditional ML productivity index.

The features of this paper can be summarized as follows: 1) this paper presents the evolution of China's coastal areas' energy efficiency during the sample period, and identifies the influencing factors of energy efficiency. 2) from the air emissions perspective, both environmental pollutants (SO_2, NO_X) and greenhouse gas (CO_2) are treated as undesirable outputs in our DEA models. 3) China’s most developed cities are concentrated in its coastal areas, which we choose due to their referential significance to China's inland areas. 4) a modified EBM is proposed to estimate the static energy efficiency. The weights of the three undesirable outputs in the EBM model are calculated in terms of their treatment costs. 5) the GML productivity index based on DDF is used to assess the energy efficiency performance of different regions in China's coastal areas over time.

The remainder of this paper is organized as follows. A literature review is given in Section 2. Section 3 introduces the EBM measure and GML productivity index based on the DDF approach. In Section 4, the paper illustrates the variables and data sources. Section 5 explores the empirical research of China's 12 coastal provinces and presents the results analysis. Section 6 draws the conclusions and provided policy implications.

2. Literature Review

A number of previous studies have contributed to the evaluation of energy efficiency using different analytical techniques. DEA is a nonparametric analytical approach that uses mathematical programming to solve the relative efficiency problem of decision-making units (DMUs) with multi-inputs and multi-outputs [21]. The DEA approach does not have to assume the functional form between inputs and outputs and can avoid manmade subjectivity in parameter weighting for efficiency estimation [24]. This approach has gained popularity in the field of evaluation of energy efficiency. Hu and Wang [25] first used DEA approach to propose a total-factor energy efficiency indicator based on production theory. Thus far, many studies have been proposed using DEA to model energy efficiency performance at different aggregate levels. For instance, Wei et al. [5] investigated energy efficiency of China's iron and steel sector during the period 1994–2003 based on Malmquist Index Decomposition. Wang et al. [26] used meta-frontier DEA approach to measure energy efficiency by considering the "technology gap". In order to avoid evaluation bias, Liu and Wang [27] used the network DEA model, which can characterize the inner structure and associated energy utilization properties of the industry sector, to evaluate the energy efficiency of China's industry sector. Wang and Wei [28] applied a DEA based method to evaluate the regional energy efficiency, emissions efficiencies and the energy saving of the industrial sector of 30 Chinese major cities during 2006–2010. Song et al. [29] utilized a bootstrap-DEA model to measure and calculate the energy efficiency of BRICS. Apergis et al. [30] presented an efficiency assessment of selected OECD countries using a slacks-based measure (SBM) model with undesirable outputs.

The conventional energy efficiency evaluation frameworks contain three key input factors (labor, capital, and energy) and only one economic output factor (GDP) [5,12,31,32]. It was thought that the traditional DEA methods ignored the undesirable outputs. In fact, during the production process, desirable outputs (such as GDP) are usually produced alongside undesirable outputs (pollution). CO_2 emissions are widely treated as undesirable output. Additionally, some papers considered some other undesirable outputs, such as SO_2, Chemical Oxygen Demand (COD), waste water, waste gas and solid waste. A brief summary of DEA model considering undesirable outputs is presented in Table 1, which enumerates the object of study, period, inputs, desirable outputs and undesirable outputs used in the corresponding paper. Researchers have tried to calculate energy efficiency while paying attention to the desirable and undesirable outputs simultaneously and ultimately have proposed several methods for dealing with them. The first treats the undesirable outputs as inputs [44]. The second, the transformation method, treats the reciprocal of undesirable outputs as desirable outputs

[45] or "multiplicative inverse" [46]. Both methods may cause a certain deviation of the results. The third uses direct approaches based on theoretical developments such as directional distance function (DDF), suggested by Chung et al. [47]. A major advantage of DDF is that it is capable of expanding desirable outputs and contracting undesirable outputs simultaneously. Recently, some extended DDF methods have been proposed [48,49].

Table 1. A brief summary of DEA model considering undesirable outputs

Authors	Object of study	Period	Inputs	Desirable outputs	Undesirable outputs
Zhang et al. [15]	62 fossil fuel power plants in Korea	2011	Capital input, the fossil fuel input, labor input	Gross electricity generation	CO_2
Bian et al. [16]	Chinese regional industrial systems	2009	Investment of fixed assets, labor and energy consumption	GDP	SO_2, COD, ammonia nitrogen
Wang et al. [17]	28 provinces in China	2001-2007	Capital stock, labor, energy	GDP	CO_2
Wang et al. [18]	30 provinces in China	2001-2010	Capital stock, energy consumption and labor	GDP	waste water, waste gas and solid waste
Wang and Wei [28]	Industrial sector of 30 Chinese major cities	2006-2010	Energy, labor, capital	Industrial value added	CO_2, SO_2
Apergis et al. [30]	20 OECD countries	1985-2011	Productive capital stock, labor, renewable and non-renewable energy consumption	GDP	CO_2
Long et al.[33]	31 provinces in China	1998-2008	Coal consumption, employment, capital stock, human resources stock	Gross regional product	SO_2
Yang and Wang [34]	29 provinces in China	2000-2007	Capital stock, labor, energy	GDP	CO_2
Zhang and Choi [35]	30 provinces in China	2001-2010	Capital, labor, energy	GDP	CO_2, SO_2, COD
Wang et al. [36]	30 provinces in China	2006-2010	Energy consumption, labor, capital stock	GDP	CO_2
Wu et al. [37]	China's industry	2007-2011	Investment in fixed asserts, electricity	Gross regional product	NO_2
Zhang et al. [38]	27 provinces in China	2001-2010	Energy, labor, capital	GDP	SO_2, COD, CO_2
Huang et al.[39]	30 provinces in China	2000-2010	Energy, labor, capital, land input	GDP	Environmental pollutants
Zhang et al. [40]	Chinese provincial transportation industry	2002-2010	Employees, capital stock, energy consumption	GDP	CO_2
Wang et al. [41]	211 prefecture-level or higher cities in Chinese urban system	2008	Energy, labor, capital	GDP	SO_2
Fan et al. [42]	32 industrial sub-sectors in Shanghai (China)	1994-2011	Energy consumption, labor force, capital stock	Gross industrial output	CO_2
Emrouznejad and Yang [43]	Chinese two-digit light manufacturing industries	2004-2012	Labor, assert, energy	Industrial sales output value	CO_2

3. Methodology

3.1 Directional distance function

Chambers, Chung, and Färe [50] introduced the DDF based on Luenberger's benefit function. We assume that the jth decision making unit (DMU) use input factors, $x=(x_{1j},x_{2j},\ldots,x_{Lj})$, to produce both desirable outputs, $y= y_{1j},y_{2j},\ldots,y_{Mj}$, and undesirable outputs, $b= b_{1j},b_{2j},\ldots,b_{Ij}$ According to Chung et al. [47], DDF can be defined as:

$$\vec{D}_0\ x,y,b;g\ =\sup\ \beta:\ x,y+\beta g_y,b-\beta g_b\ \in P\ x \tag{1}$$

where the nonzero vector $g= g_y,g_b$ is the direction vector on which desirable outputs and undesirable outputs are scaled; $P\ x$ represents the production set; the β value implies the maximum multiple of the same proportion in the expansion of desirable outputs and contraction of undesirable outputs.

3.2 Global Epsilon-based measure model with undesirable outputs

In the DEA models, there are two measures of technical efficiency with very different characteristics: radial and non-radial. The CCR model represents the radial measure [21]. The main shortcoming of the radial measure is the neglect of non-radial slacks in reporting the efficiency score [51]. The non-radial measure aims at obtaining maximum rates of reduction in inputs, relaxing the proportionality, and allowing independent changes to associated slacks. The non-radial model is represented by the slacks-based measure model proposed by Tone in 2001 [52]. In the SBM model, the projected DMU may lose proportionality with the original input, which is inappropriate for the analysis. Because radial and non-radial models have merits and shortcomings, Tone and Tsutsui [22] developed a hybrid distance model, Epsilon-based measure (EBM), which combines the merits of both radial and non-radial measures into a unified framework.

We consider there are N DMUs, and each DMU uses L inputs and Q outputs. The output-oriented EBM model can be expressed as follows:

$$
\min \gamma^* = \frac{1}{\varphi + \varepsilon \sum_{r=1}^{Q} \frac{w_r^+ s_r^+}{y_{r0}}}
$$

$$
s.t. \begin{cases} \sum_{j=1}^{N} \lambda_j x_{ij} \le x_{i0} \\ \sum_{j=1}^{N} \lambda_j y_{rj} - \varphi y_{r0} - s_r^+ = 0 \\ \lambda \ge 0,\ s^+ \ge 0 \\ \ j = 1,2,\cdots,N;\ i = 1,2,\cdots,L;\ r = 1,2,\cdots,Q \end{cases} \tag{2}
$$

where w_r^+ denotes the weight of output r and satisfies $\sum_{r=1}^{Q} w_r^+ = 1\,(w_r^+ > 0)$; λ is the intensity vector; s_r^+ represents the non-radial output slack term; the subscript "0" represents the DMU to be evaluated; ε indicates the relative importance of the non-radial slacks over the radial φ. The range of the key parameter ε is [0, 1]. It is equivalent to the radial model when ε is equal to 0 and to the non-radial model when ε is equal to 1. In order to show the trend of energy efficiency with time, GBT is incorporated into the EBM model. When the undesirable outputs are considered, the global EBM model is proposed as follows:

$$
\min\ \gamma^* = \frac{1}{\phi + \varepsilon \times \frac{1}{2}\left(\sum_{t=1}^{T}\sum_{m=1}^{M} \frac{w_m^y s_{my}^t}{y_{m0}^t} + \sum_{t=1}^{T}\sum_{k=1}^{I} \frac{w_k^b s_{kb}^t}{b_{k0}^t} \right)}
$$

$$
s.t. \begin{cases} \sum_{\mathrm{t}=1}^{T}\sum_{j=1}^{N} \lambda_j^t x_{ij}^t \le x_{i0}^t \\ \sum_{\mathrm{t}=1}^{T}\sum_{j=1}^{N} \lambda_j^t y_{mj}^t \text{-} \phi y_{m0}^t \text{-} s_{my}^t = 0 \\ \sum_{\mathrm{t}=1}^{T}\sum_{j=1}^{N} \lambda_j^t b_{kj}^t \text{-} \phi b_{k0}^t + s_{kb}^t = 0 \\ \lambda \ge 0,\ s_k^b \ge 0, s_m^y \ge 0 \\ j = 1,2,\cdots,N;\ i = 1,2,\cdots,L; m = 1,2,\cdots,M; \\ k = 1,2,\cdots,I; t = 1,2,\ldots,T \end{cases} \tag{3}
$$

where w_m^y and w_k^b are the weights of the desirable output and undesirable output variables, respectively, and they satisfy $\sum_{m=1}^{M} w_m^y = 1$, $\sum_{k=1}^{I} w_k^b = 1$ ($w_m^y \ge 0$, $w_k^b \ge 0$); s_{my}^t and s_{kb}^t refer to the slacks of the corresponding desirable output m and undesirable output k, respectively; x_{ij}^t, y_{mj}^t, and b_{kj}^t represent the ith input, mth desirable output and kth undesirable output, respectively, of the jth DMU at time t

3.3 Global Malmquist-Luenberger productivity index

Compared with the traditional ML productivity index, the estimation results of GML are more stable [53, 54]. A GBT is defined as $P^G = P^1 \cup P^2 \cup ... \cup P^T$. GBT established a single reference from panel data containing all the contemporaneous benchmark technologies [23], and has been revealed its advantages in term of efficiency evaluation [42,54].

The GML productivity index based on GBT set can overcome the deficiencies that exist in the traditional ML productivity index [23,55]. It is defined as:

$$GML_t^{t+1} = \frac{1 + \vec{D}_0^G \; x^t, y^t, b^t; y^t, -b^t}{1 + \vec{D}_0^G \; x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1}} \tag{4}$$

where x^t, y^t and b^t denote the inputs, desirable outputs, and undesirable outputs of a province in the sample period t; $\vec{D}_c^G$ represents the solution of DDF under the global benchmark technology set P^G and is obtained by solving the model (4). GML index can be divided into two components: technological change (GTCH) and efficiency change (GECH). Färe et al. [56] further divided GECH into pure efficiency change (GPEC) and scale efficiency change (GSEC):

$$\begin{aligned} GML_t^{t+1} = & \left[\frac{1+\vec{D}_c^G\left(x^t, y^t, b^t; y^t, -b^t\right)}{1+\vec{D}_c^t\left(x^t, y^t, b^t; y^t, -b^t\right)} \times \frac{1+\vec{D}_c^{t+1}\left(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1}\right)}{1+\vec{D}_c^G\left(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1}\right)} \right] \times \frac{1+\vec{D}_v^t\left(x^t, y^t, b^t; y^t, -b^t\right)}{1+\vec{D}_v^{t+1}\left(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1}\right)} \\ & \times \left[\frac{1+\vec{D}_c^t\left(x^t, y^t, b^t; y^t, -b^t\right)}{1+\vec{D}_c^{t+1}\left(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1}\right)} \times \frac{1+\vec{D}_v^{t+1}\left(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1}\right)}{1+\vec{D}_v^t\left(x^t, y^t, b^t; y^t, -b^t\right)} \right] \\ = & \; GTCH_t^{t+1} \times GPEC_t^{t+1} \times GSEC_t^{t+1} \end{aligned} \tag{5}$$

where $\vec{D}_c$ and $\vec{D}_v$ represent the DDF under the conditions of constant return to scale (CRS) and variable return to scale (VRS). When GML is greater than 1, it implies productivity growth, whereas less than one indicates regress. If GTCH is greater than, equal to, or less than 1, it respectively means the technological practice is improving, unchanged, or deteriorating, respectively. The improvement of pure efficiency change (aka, management level) is indicated by GPEC is greater than 1, and less than 1 indicates a pure efficiency decrease. The GSEC represents the change of scale efficiency and reflects whether the DMUs are operating on the most appropriate investment scale. When GSEC is greater than, equal to, or less than 1, it indicates that the scale is increasing, stable, or declining respectively.

4. Data

4.1 Data collection

Labor, capital stock, and energy consumption are used as inputs and GDP as a desirable output. CO_2, SO_2, and NO_X emissions are treated as undesirable outputs. The panel data of 12 provinces from the period of 2001-2012 is collected. The data source for each variable is described as follows:

(1) Labor. It is taken from the statistical yearbook 2001-2013 in various provinces and municipalities. The calculation of labor uses the average value between the beginning and end of an employment year.

(2) Capital stock. Capital stock is taken from Zhang [57] who estimated the capital stock of China using the perpetual inventory method. This study puts the year 2000 as the base period and calculates capital stock with the formula: $K_{i,t} = I_{i,t} + (1-\delta)K_{i,t-1}$, where $K_{i,t}$ and $K_{i,t-1}$ denote the capital stock of province i at time t and $t-1$, respectively; $I_{i,t}$ is the investment in fixed assets of region i at time t; δ represents the depreciation rate.

(3) Energy Consumption. Annual energy utilization of each province is used to express the energy consumption, mainly including coal, oil, and natural gas. These data are obtained from China Energy Statistical Yearbook (2001-2013).

(4) GDP. GDP is expressed in Year 2000 price consistent with capital stock and the data are from China Statistical Yearbook (2001-2013).

(5) CO_2 emission. CO_2 emission is estimated following the "2006 IPCC guidelines for national greenhouse gas inventories." The method is the product of carbon dioxide emission coefficient for the specific energy and the specific energy consumption. The related data used to calculate CO_2 emission are taken from China Energy Statistical Yearbook (2001-2013).

(6) SO_2 emission. SO_2 emission is extracted from China Statistical Yearbook (NBSC, 2001-2013).

(7) NO_X emission. NO_X emission data began to be announced in the China Statistical Yearbook since 2010. For unobserved data, NO_X emission is estimated with various types of energy consumption and emission factors in accordance with Ref. [58]. The calculation of NO_X emissions is described as follows: $Q=(1-P)\sum F_i \times K_i$, where i represents the fuel type, and F_i, K_i represent the consumption and NO_X emission factors of energy i, respectively; for selection of NO_X emission factors, please refer to Kato and Akimoto [59]; P represents the removal rate of NO_X under the average pollution control level. Based on the hypothesis of Hao et al. [60], this paper establishes the NO_X removal rate at 10%, 15%, 30% for 2000, 2005 and 2010, respectively.

4.2 Descriptive statistics

Table 2 shows the description statistics of inputs, desirable outputs, and undesirable outputs for China's coastal provinces. The average growth rates of the three undesirable outputs in 2000-2012 are given in Table 3.

Table 2. Description statistics of variables for China's coastal provinces in 2000-2012

Variables	Mean	Std. dev.	Medium	Maximum	Minimum
Labor (millions)	26.82	18.13	25.56	65.20	3.31
Capital stock (hundred billion RMB in 2000 constant price)	13.81	8.44	12.35	34.60	1.28
Energy consumption (million tons of coal equivalent)	120.56	88.28	97.39	388.99	4.80
GDP (hundred billion RMB in 2000 constant price)	10.99	8.74	8.57	42.48	0.53

CO_2 emission (million tons)	281.76	222.15	217.49	987.86	8.30
SO_2 emission (million tons)	0.76	0.53	0.77	2.00	0.02
NOx emission (million tons)	0.67	0.48	0.54	2.01	0.04

Table 3. Average growth rate (%) of CO_2, SO_2 and NO_X emissions in 2000-2012

	CO2 emission (million tons)			SO2 emission (million tons)			NO_X emission (million tons)		
	2000	2012	GR(%)	2000	2012	GR(%)	2000	2012	GR(%)
Beijing	83.36	110.33	2.58%	0.22	0.09	-6.78%	0.22	0.18	-1.19%
Tianjin	70.54	183.01	8.59%	0.33	0.22	-2.74%	0.22	0.33	6.22%
Hebei	263.45	765.27	9.79%	1.32	1.34	0.35%	0.77	1.76	8.95%
Liaoning	249.17	589.91	9.26%	0.93	1.06	1.88%	0.61	1.04	4.79%
Shanghai	135.82	228.36	4.52%	0.46	0.23	-5.11%	0.46	0.40	-0.41%
Jiangsu	225.08	732.00	11.13%	1.20	0.99	-1.42%	0.74	1.48	7.01%
Zhejiang	137.60	408.95	9.98%	0.59	0.63	0.72%	0.46	0.81	5.30%
Fujian	61.00	246.92	13.06%	0.22	0.37	5.86%	0.22	0.47	8.17%
Shandong	213.36	987.86	14.90%	1.80	1.75	0.06%	0.54	1.74	12.68%
Guangdong	209.15	559.07	8.87%	0.90	0.80	-0.65%	0.74	1.30	5.40%
Guangxi	57.06	199.83	11.69%	0.83	0.50	-2.62%	0.22	0.50	9.14%
Hainan	8.30	41.60	14.85%	0.02	0.03	4.90%	0.04	0.10	13.38%
Average	142.82	421.09	9.93%	0.74	0.67	-0.46%	0.44	0.84	6.62%

5. Results and discussions

5.1 Energy efficiency of global EBM model

When using the EBM model, the values of w_m^y, w_k^b, and ε should be determined in advance. In this paper, the parameter, ε, is calculated according to the affinity index developed by Tone and Tsutsui [22]. In the classical EBM model, the ratio of desirable outputs and undesirable outputs is set to 1:1 by default. To determine the weight of undesirable outputs, we use treatment cost. The government reports that the treatment costs of SO_2 and NO_X have increased to 10 RMB per kilogram, namely 10,000 RMB per ton[3]. The average transaction price of CO_2 in China's seven-carbon emission trading market is 28.26 RMB per ton[4]. The weight of undesirable outputs is obtained based on their total treatment cost. In other words, we take into account both the treatment cost

[3] This is the new standard of Beijing according to the cost of pollution control, which is five times the original standard, the highest level in the nation (http://www.caepi.org.cn/p/1211/350494.html).

[4] For details please refer to http://www.tanjiaoyi.com/article-14433-1.html

and the emission quantity. For example, the emission quantity of CO_2, SO_2, and NO_X in 2012 is 421.09, 0.67, and 0.84 million tons, respectively. The weight of CO_2, SO_2 and NO_X is therefore expressed as $w_c : w_s : w_n$ = 0.4387:0.2483:0.3130.

In this paper, the related data for 13 years in 12 provinces have been converted into constant 2000 prices. The details of the empirical results are described in Table 4. From Table 4 we can observe that Beijing, Tianjin, Liaoning, Shanghai, and Guangdong have achieved a score of "1" in 2012. This means that the DMUs of the five provinces in 2012 forming the efficiency frontier in China's coastal areas during the sample period. Among the remaining seven provinces, energy efficiencies also demonstrate growth to varying degrees. Hebei has the lowest energy efficiency with 0.66 in 2012. This is possibly because Hebei is known for its iron and steel industry, which consumes large amounts of energy. Substantial energy consumptions lead to more pollutant discharge. In general, the energy efficiency of China's coastal areas shows a marked ascending trend, increasing from 0.63 (mean value) on 2000 to 0.89 in 2012. The level of economic development is positively related to energy efficiency.

Table 4. The energy efficiency of EBM model for China's coastal areas in 2000-2012

Provinces	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
Beijing	0.62	0.63	0.66	0.67	0.68	0.71	0.75	0.77	0.84	0.87	0.90	0.96	1
Tianjin	0.53	0.56	0.58	0.61	0.62	0.65	0.70	0.73	0.77	0.80	0.84	0.91	1
Hebei	0.52	0.51	0.51	0.52	0.52	0.55	0.56	0.58	0.61	0.63	0.63	0.64	0.66
Liaoning	0.55	0.56	0.58	0.59	0.60	0.64	0.64	0.67	0.70	0.73	0.76	0.78	1
Shanghai	0.62	0.64	0.66	0.68	0.70	0.73	0.76	0.78	0.80	0.85	0.88	0.94	1
Jiangsu	0.64	0.66	0.67	0.67	0.65	0.66	0.69	0.72	0.74	0.78	0.79	0.80	0.84
Zhejiang	0.67	0.67	0.68	0.69	0.67	0.70	0.71	0.74	0.76	0.78	0.80	0.82	0.86
Fujian	0.72	0.76	0.72	0.72	0.69	0.70	0.75	0.78	0.81	0.84	0.85	0.86	0.92
Shandong	0.63	0.64	0.61	0.60	0.57	0.59	0.63	0.66	0.69	0.71	0.72	0.73	0.76
Guangdong	0.71	0.72	0.73	0.74	0.73	0.76	0.79	0.81	0.83	0.87	0.90	0.94	1
Guangxi	0.62	0.63	0.64	0.63	0.60	0.62	0.67	0.69	0.71	0.74	0.74	0.76	0.79
Hainan	0.72	0.73	0.71	0.70	0.72	0.74	0.74	0.75	0.79	0.80	0.79	0.79	0.81
coastal areas	0.63	0.64	0.65	0.65	0.64	0.67	0.70	0.72	0.75	0.78	0.80	0.83	0.89

Fig. 1 shows the average energy efficiency values for three regions, Circum-Bohai Sea, Yangtze River Delta and Pan-Pearl River Delta Economic Zone, over time. The energy efficiency values of the Pan-Pearl River Delta Economic Zone are higher than the other two regions from 2000 to 2009. However, Yangtze River Delta Economic Zone is slightly higher than the Pan-Pearl River Delta Economic Zone from 2010 to 2012. A substantial gap in energy efficiency before 2010 can be observed between the Circum-Bohai Sea Economic Region and the other two regions. Until 2012, the energy efficiency values for all three regions were approximately 0.9. These results indicate that the Circum-Bohai Sea Economic Region has obtained a great energy efficiency improvement compared to the other two regions during the sample period.

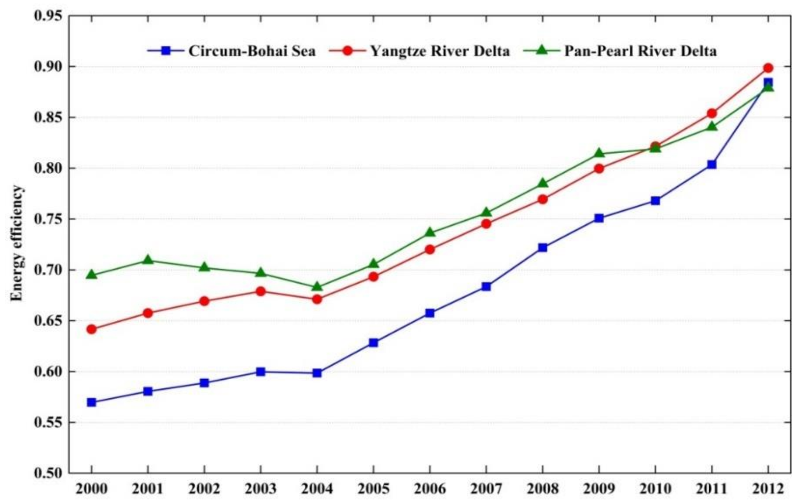
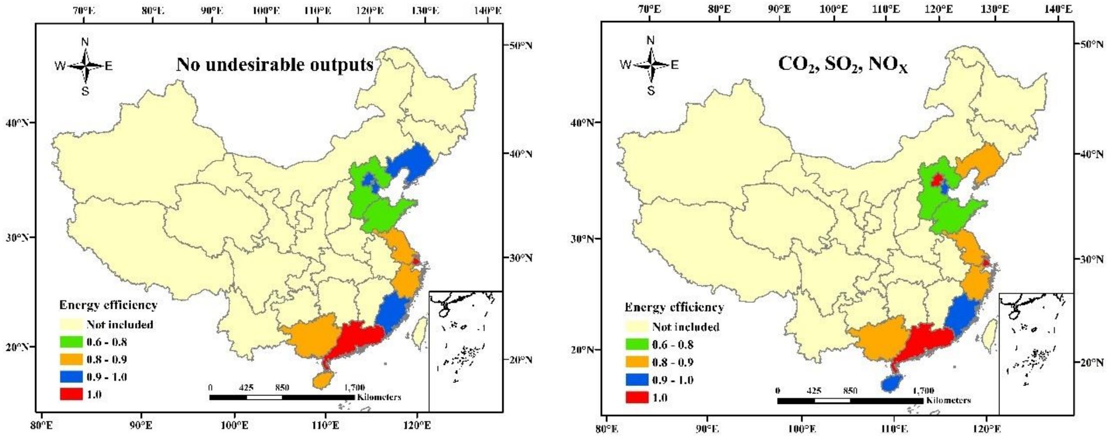


Fig. 1. Average energy efficiency values of different regions in 2000-2012

In order to determine the impacts of undesirable outputs on the energy efficiency frontier, this paper compares two situations, which are considering the three undesirable outputs and no considering undesirable output, using the cross-section data for each year in China's coastal areas. The average energy efficiency values obtained in the two situations are shown in Fig.2. Taken together, we can see that Shanghai, and Guangdong are both in the efficiency frontier. Beijing is efficient when considering undesirable outputs. The main reason for this phenomenon may be that Beijing and Shanghai, as municipalities directly under the central government, must implement national policies and use the latest energy technologies to improve energy efficiency. Guangdong may benefit from the reform and introduction of advanced energy equipment and management experience. When considering undesirable outputs, the energy efficiency of Liaoning decreased. Hainan is the converse of Liaoning. Hainan consumes less coal, which leads to relatively lower air emissions in Hainan and higher energy efficiency of Hainan in the case of undesirable outputs. The rest almost remains unchanged in the two situations.



a) Not considering undesirable outputs b) Considering the three undesirable outputs

Fig. 2. Average energy efficiency under two situations in 2000-2012.

5.2 Reduction potentials of undesirable outputs

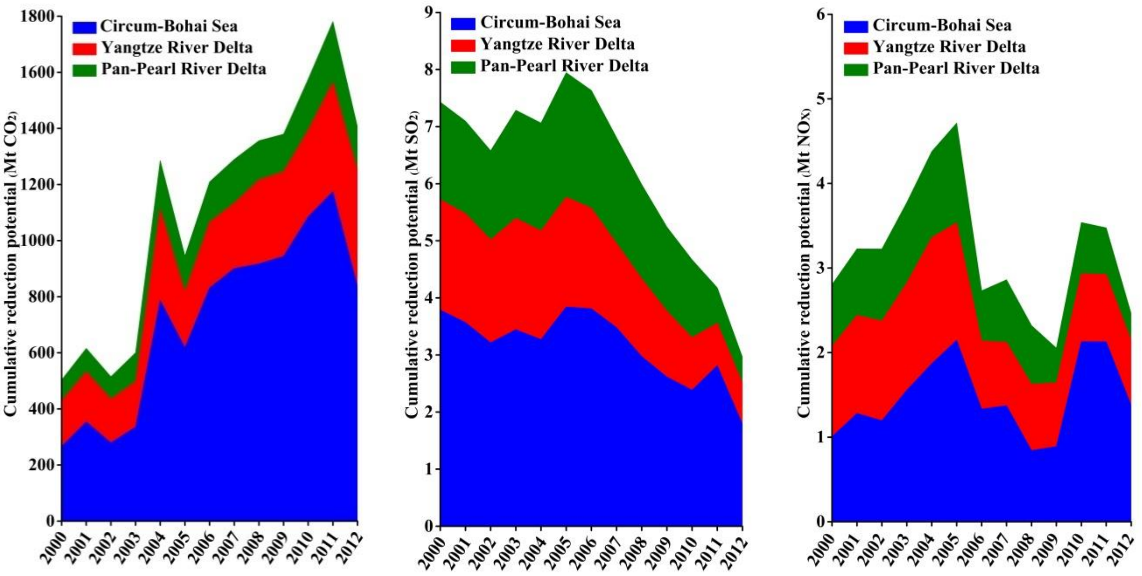
According to the global EBM model, the undesirable outputs in specific inefficient regions can reach the benchmark by adjusting for potential improvements. Therefore, we can further indicate the CO_2, SO_2 and NO_X emissions reduction potential for each of China's coastal provinces. From Table 5 we see that five provinces have reached environmental efficiency. They are Beijing, Tianjin, Liaoning, Shanghai, and Guangdong, all of which attained zero CO_2, SO_2 and NO_X emissions reduction potential in 2012. Individually, CO_2 emissions reduction potentials for four provinces are more than 100 million tons in 2012, with Shandong province showing the largest CO_2 emissions reduction potential, followed by Hebei, Jiangsu, and Zhejiang. In terms of SO_2 emissions reduction potential, the provinces show reduction potential similar to CO_2 emissions, with Guangxi showing the largest reduction potential rate. Similarly, we also note that Hainan has the second lowest NO_X emissions reduction potential, but its potential rate is more than 50%, second only to Hebei among the inefficient provinces. This indicates that even the total SO_2 and NO_X emissions of Guangxi and Hainan are not very large, and the two provinces have great improvement potential if they focus on NO_X emissions reduction.

In addition, Hebei has the largest undesirable outputs reduction potential with all three undesirable rates at more than 50%, followed by Guangxi and Shandong. In general, we found a great emission reduction potential rate for CO_2, SO_2 and NO_X in almost all of the inefficient provinces. The results show that compared to the five provinces that reached the efficiency frontier, the other provinces need to pay more attention to their CO_2, SO_2 and NO_X emissions in order to improve their efficiency and match the reduction potential of the benchmark five provinces.

Table 5. The undesirable outputs reduction potentials of China's coastal areas in 2012

2012	CO_2 emissions reduction potential	CO_2 reduction potential rate	SO_2 emissions reduction potential	SO_2 reduction potential rate	NOx emissions reduction potential	NOx reduction potential rate
Beijing	0	0	0	0	0	0
Tianjin	0	0	0	0	0	0
Hebei	414.33	54.14%	0.84	62.60%	0.94	53.54%
Liaoning	0	0	0	0	0	0
Shanghai	0	0	0	0	0	0
Jiangsu	276.53	37.78%	0.41	41.62%	0.51	34.30%
Zhejiang	138.02	33.75%	0.31	49.06%	0.26	32.47%
Fujian	56.65	22.94%	0.11	30.35%	0.04	8.62%
Shandong	421.30	42.65%	0.95	54.73%	0.43	24.90%
Guangdong	0	0	0	0	0	0%
Guangxi	80.78	40.42%	0.33	66.24%	0.22	44.30%
Hainan	16.53	39.72%	0.01	13.27%	0.05	51.03%

Fig. 3 illustrates the cumulative reduction potentials of three undesirable outputs reduction in three regions in China's coastal areas based on 2012 data. From Fig.3, we can see that the total CO_2 emissions reduction potential in the three regions is continuously increasing, especially in the Circum-Bohai Sea Economic Region. In 2012, CO_2 emissions reduction potential of Circum-Bohai Sea Economic Region nearly increases by three times compare to Year 2000. As for SO_2 emissions, its reduction potential in China's coastal areas is declining, mainly due to Yangtze River Delta and Pearl River Delta Economic Zone. The reduction potential of NO_X emissions in the three regions fluctuates throughout the study period. Until recent years, NO_x emissions significantly decreased in both Yangtze River Delta and Pearl River Delta Economic Zone. Overall, the Circum-Bohai Sea Economic Region has the largest CO_2 emissions reduction potential during the study period, as well as the largest SO_2 and NO_X emissions reduction potentials, and the Pearl River Delta Economic Zone has the smallest. Hebei and Shandong become the main force to complete the task of air emission reduction in Circum-Bohai Sea Economic Region. The main reason is that coal consumption accounts for more than 73% of energy consumption in Hebei and Shandong.



a) CO_2 b) SO_2 c) NO_x

Fig. 3. The three undesirable outputs reduction potential in different regions

5.3 Energy efficiency of GML productivity index

Table 6 shows the results of the GML productivity index based on DDF in China's 12 coastal provinces. Overall, the average GML productivity index change of observed periods in China's coastal regions is 1.0233, which means the average growth rate is 2.33%. The average increase in GTCH has reached 2.52%. It indicates that technological progress is an important factor to increase the energy efficiency. Tianjin and Liaoning are the only two provinces that increased the total-factor energy efficiency through the improvement of three aspects (technological change, pure efficiency change, and scale efficiency change). For the rest of the provinces, production scale and management level have been the main obstacles. This may be caused by a large amount of excessive investment in many industries. From Table 6, it can also be seen that technological progress is the biggest contributor for the improvement of energy efficiency in Circum-Bohai Sea, Yangtze River Delta and Pan-Pearl River Delta Economic Zone. Note that the extent of technological progress of the improvement of energy efficiency in the three regions is different.

Table 6. GML productivity index and its components in China's coastal areas in 2000-2012

	GML	GTCH	GECH	GPEC	GSEC
Beijing	1.0317	1.0317	1	1	1
Tianjin	1.0410	1.0275	1.0133	1.0023	1.0110
Hebei	1.0108	1.0239	0.9881	0.9872	1.0009
Liaoning	1.0431	1.0358	1.0070	1.0040	1.0030
Shandong	1.0120	1.0264	0.9871	0.9853	1.0030
Shanghai	1.0332	1.0332	1	1	1
Jiangsu	1.0225	1.0213	1.0017	1.0098	0.9924
Zhejiang	1.0173	1.0208	0.9979	0.9979	1.0006
Fujian	1.0161	1.0187	0.9978	1.0002	0.9976
Guangdong	1.0219	1.0219	1	1	1
Guangxi	1.0239	1.0236	1.0008	0.9970	1.0038
Hainan	1.0066	1.0174	0.9898	1	0.9898
Circum-Bohai Sea	1.0277	1.0291	0.9991	0.9958	1.0036
Yangtze River Delta	1.0243	1.0251	0.9999	1.0026	0.9977
Pan-Pearl River Delta	1.0063	1.0037	0.9981	0.9986	0.9978
Coastal Areas	1.0233	1.0252	0.9986	0.9986	1.0002

The annual average values of the ML and GML productivity index are presented in

Fig.4 and Fig.5, respectively. It can be inferred from Fig.5 that the yearly change in the GML productivity index first decreased from 2000-2004, increased rapidly in the next year, and then remained stable at approximately 1.03. The trend of yearly ML productivity index change is broadly consistent with GML. However, we can see clearly from the charts that the annual growth rate of ML is significantly more than GML and roughly stable at 5%. The results show that the ML productivity index is overestimated. The yearly GML productivity index change in China's coastal areas is almost always greater than 1 during the sample period except 2004. This implies that the total-factor energy efficiency of China's coastal areas is continuously increasing. A growth rate of almost 2% has been maintained since 2004.

In contrast with Fig. 4 and Fig. 5, the growth trend of the technological progress is similar between the ML and GML productivity index change. The index reveals that technological progress is the greatest driver of energy efficiency growth in China's coastal areas. It also can be seen from Eq. (5) that the pure efficiency change and the scale efficiency change of GML remain the same regarding ML, which indicates that ML is mainly overestimated in technological progress. Before 2005 and from 2009 to 2010, the annual slight growth of scale efficiency compensated for the lack of management level. Otherwise, management level improved from 2005 to 2008 and after 2010. This implies that we need to change the investment-oriented economic mode and introduce advanced management experience from abroad.

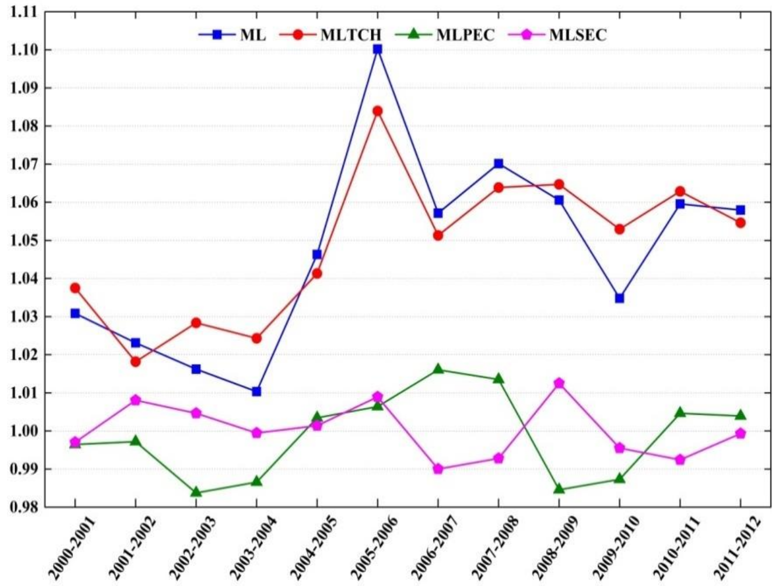


Fig. 4.Annual ML productivity index and its components in China's coastal areas in 2000-2012

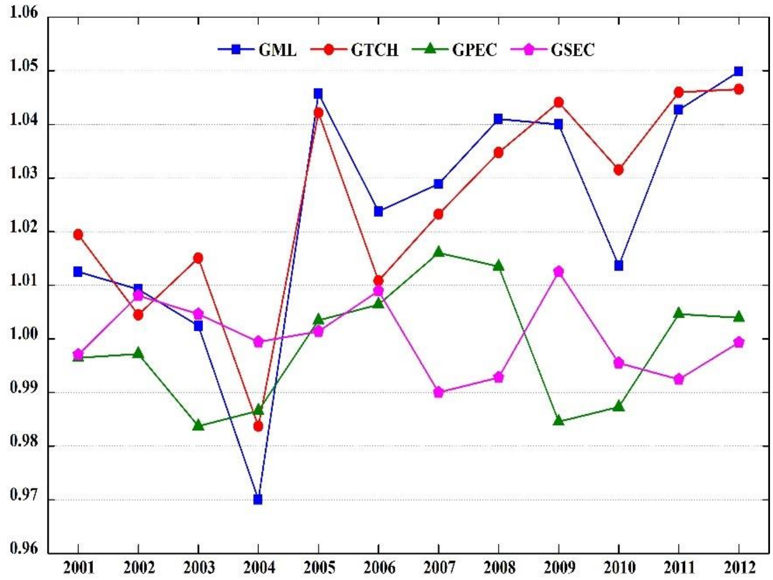


Fig. 5.Annual GML productivity index and its components in China's coastal areas in 2000-2012

6. Conclusions and policy implications

In this paper, we utilize the modified EBM model to evaluate the energy efficiency of China's coastal areas in 2000 to 2012. In addition, the GML productivity index is employed to estimate the total-factor energy efficiency and to find the key factor contributing to the change in the energy efficiency from the standpoint of technological progress, scale efficiency, and management level. In these DEA model, environmental pollutants (SO_2, NO_X) and greenhouse gas (CO_2) are treated as undesirable outputs of energy consumptions. We analyze the CO_2, SO_2, and NO_X emission reduction potentials and proposed several improvement solutions. In all, the conclusions of our study can be drawn as follows:

1) China's coast areas experienced a stable upward trend in energy efficiency during 2000 to 2012 and there is still more room to improve their energy efficiency. The relationship between economic development level and energy efficiency is positive in China's coastal areas. Provinces with rapid economic development (e.g., Beijing, Shanghai, Guangdong) have higher energy efficiency, whereas relatively less-developed provinces (e.g., Hebei, Guangxi) have lower energy efficiency.
2) Seven provinces in China's coastal areas have different degrees of redundancy of the three undesirable outputs. The reduction potential rates of three undesirable outputs in Hebei are all more than 50%. More than half of the inefficient provinces have a reduction potential rate of more than 40% of three undesirable outputs, which could result in a great improvement in China's effective energy policy, such as preferential policy on emissions reduction.
3) The Circum-Bohai Sea Economic Region greatly has improved energy efficiency compared to the other two regions during the sample period. However, at the same time, the Circum-Bohai Sea Economic Region has the largest CO_2, SO_2, and NO_X emission reduction potential while the Pearl River Delta Economic Zone has the smallest.
4) The annual growth rate of GML productivity index change is actually less than that of ML. Additionally, the primary overestimation of the ML productivity index is technological progress in China's coastal areas.
5) Technological progress technological progress is the biggest contributor for the

improvement of energy efficiency in China's coastal areas, where as the scale efficiency and management level are the main obstacles.

With regard to energy efficiency improvement and air emissions reductions, it is urgent for China's coastal areas to find new ways for a trade-off between economic growth and air emissions reductions. In the foreseeable future, the economy of China's coastal areas' will still keep a relatively high growth. Government should explore alternatives to the current economic growth pattern. In addition, the government should prioritize energy structure improvements and increase investment to replace fossil fuels with clean energy gradually. The proportion of coal consumption keeps a declining tread during the sample period in China's coastal areas. However, the proportion of coal is still overly high. In 2012, the proportion of three coastal provinces (Jiangsu, Shandong, Hebei,) is greater than 65%. Moreover, the construction of desulfurization, denitrification and dust transformation project are critical for reduce air emissions and require government to supervise and motivate in the face of the high cost. In further, it is essential for China's coastal areas to focus on the energy consumption of the high energy-consuming industries and publish appropriate policies. For example, to deepen the electricity market reforms, with the aim of establishing a competitive power market [61]; to push forward electric vehicles replace the existing personal internal combustion engine vehicles gradually [62]. Finally, implementing incentive and obligatory emission reduction mechanism, such as tax policies, sewage charge levied and making full use of the energy management contract, can promote the transformation of energy utilization and the reduction in air emissions [63].

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