



Measuring eco-efficiency and its convergence: empirical analysis from China

Jiayang Tang · Liwei Tang · Yi Li · Zongyi Hu

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Abstract At present, the contradiction between economic development and resource and environmental sustainability has become increasingly acute in China. Improving the quality of the ecological environment has become an important strategic goal for China's national economic and social development. In this paper, we used the panel data of 30 provinces in China from 1986 to 2016 to measure the eco-efficiency and its decomposition indexes based on a non-radial metafrontier Malmquist-Luenberger data envelopment analysis model. The results showed that the eco-efficiency grows at an annual rate of 0.7% on the whole, with the technical efficiency decreasing at an annual rate of 0.6%, the innovation effect increasing at an annual rate of 2.3%, and the technical leadership effect decreasing at an annual rate of 1%. In the sample study period, the cumulative growth rates of eco-efficiency change index, technical efficiency change index, innovation effect, and technical leadership effect were 20.4%, –

19.4%, 70.5%, and –30.7%, respectively. It was also found that regional eco-efficiency decreased from east to west. Furthermore, convergence test results showed that there were four convergence clubs and three divergent individuals in terms of eco-efficiency. Areas with high eco-efficiency tended to converge with areas with high eco-efficiency and vice versa.

Keywords Non-radial metafrontier Malmquist-Luenberger DEA model · Dynamic eco-efficiency · Direct distance function · Convergence

Introduction

Economic and social development is the process of continuous accumulation of capital and continuous optimization of structure. China has transformed from a quantitative growth stage, pursuing the expansion of the total scale, to a high-quality development stage, which meets higher standards and diverse needs and is an inevitable path for successful economic transformation. A good ecological environment is the most inclusive benefit of the people, upholding their simple expectations and basic requirements for a better life. It is not only an inevitable requirement for building a high-quality development system but also an important indicator for improving the quality of economic development. Eco-efficiency, as an important measure of the development level of a regional circular economy, reflects the efficiency of resource use in regional economic development to mitigate environmental pressure. It

J. Tang · Y. Li · Z. Hu
College of Finance and Statistics, Hunan University,
Changsha 410079 Hunan, People's Republic of China

J. Tang
College of Economics & Trade, Hunan University of Technology,
Zhuzhou 412007 Hunan, People's Republic of China

L. Tang (✉)
College of Mathematics and Statistics, Key Laboratory of
Computing and Stochastic Mathematics (Ministry of Education),
Hunan Normal University, Changsha 410081 Hunan, People's
Republic of China
e-mail: liweitang@hunnu.edu.cn

effectively integrates sustainable development goals on a macro scale into micro (enterprise) and meso (regional) development planning and management, and thereby has become an important reference for enterprises and relevant policymakers (Picazo-Tadeo et al. 2014). China has witnessed disparities in economic development and obvious differences in resource, economic, and environmental systems among regions. It is necessary to scientifically measure and assess regional eco-efficiency at different levels to identify weaknesses in eco-efficiency among regions better. This is the premise and foundation for regions to formulate their circular economy development strategies, and an essential strategic step to promote high-quality development in China. Therefore, this study used a non-radial metafrontier Malmquist-Luenberger data envelopment analysis (DEA) model from a regional perspective to measure the eco-efficiency of 30 provinces in China and analyzed the convergence of regional eco-efficiency to provide an empirical reference and decision-making basis for regions to explore the development patterns of the circular economy.

The marginal contributions of this study are two-fold. First, we limit our inputs for measuring eco-efficiency, focusing on pollutant emissions, and use a non-radial metafrontier Malmquist-Luenberger model. This model enables the application of different reduction scales for different pollutants and solves the problem of the lack of a feasible solution. Furthermore, this model also considers the heterogeneity of the region, obtaining an in-depth decomposition of the eco-efficiency. Second, we measure eco-efficiency based on Chinese provincial data of 1986–2016. We then apply Phillips and Sul (2007)'s convergence model (PS convergence model) to study the dynamic evolution and change characteristics of eco-efficiency, this method is rarely used to analyze the convergence of eco-efficiency in China. Owing to the significant differences in regional development and resource endowments, it is inappropriate to apply the traditional convergence model to investigate the convergence of eco-efficiency under homogeneous production technology conditions. The PS convergence model considers the conditions of heterogeneous production technology, and it is a more suitable method to investigate the convergence of eco-efficiency in China.

The remainder of this paper is structured as follows: the “Literature review” section is the literature review. The “A model to measure eco-efficiency” section presents the model to measure the eco-efficiency. The

“Results and discussion” section is the empirical results and discussion. The “Research on the convergence of regional eco-efficiency” section is the convergence analysis. The “Conclusions and policy application” section is where the conclusion, suggestions, and policy applications are discussed.

Literature review

Early methods of eco-efficiency measurement mainly include lifecycle assessment and direct use of GDP/CO₂ as a simple substitute indicator of eco-efficiency. The former is too demanding in terms of the data required, and it is difficult to achieve consensus in selecting weights for sub-indexes in the overall environmental pressure index (Olsthoorn et al. 2001; Ebert and Welsch 2004; Zhou et al. 2006). The latter is characterized by easy calculation and high data feasibility, but it ignores other pollutants generated in the production process, and thus it is gradually being replaced by more complicated methods in practice. To this end, Kuosmanen and Kortelainen (2005) first used the DEA method to measure relative eco-efficiency under static conditions. This method generates weights for all environmental indicators when individuals are in the optimal state, which means that the subjective randomness of weight selection is avoided and the calculation becomes more objective. Then, the authors used this method to measure the eco-efficiency of the three largest urban road transportation systems in Finland. Barba-Gutiérrez et al. (2009) and Camarero et al. (2013) also used the static DEA method to measure eco-efficiency. Gomez et al. (2018) considered the uncertainties in the data to improve the DEA model to measure the eco-efficiency. Gudipudi et al. (2018) found that larger European cities are eco-efficient based in the DEA model and regression model. Kiani Mavi et al. (2019) analyzed the eco-efficiency based on a two-stage network DEA model, and the case study found that Switzerland is the highest in eco-efficiency.

In recent years, research has deepened and researchers argue that although the eco-efficiency assessment under the static DEA model has made a great breakthrough in terms of weight selection, it cannot analyze the dynamic temporal changes of eco-efficiency. Therefore, based on the eco-efficiency assessment model under the static DEA model, Kortelainen (2008) proposed a method of measuring the time-varying

characteristics of eco-efficiency based on the Malmquist productivity index. They decomposed eco-efficiency changes into efficiency changes and technology changes, and empirically analyzed sample data from 20 countries from 1990 to 2003. In addition, Picazo-Tadeo et al. (2012) proposed an eco-efficiency measurement method under static conditions based on the direct distance function. Picazo-Tadeo et al. (2014) further measured the dynamic eco-efficiency of Organization for Economic Co-operation and Development (OECD) member countries under the direct distance function. Godoy-Duran et al. (2017) assessed the eco-efficiency in southeast Spain. Monastyrenko (2017) assessed the eco-efficiency of the European electricity industry based on both the DEA model and the Malmquist-Luenberger productivity index. Moutinho et al. (2018) assessed eco-efficiency of the Latin America countries from 1994 to 2013. Arabi et al. (2016) measured eco-efficiency during an 8-year period of power industry restructuring in Iran by using the DEA model, and they found that the eco-efficiency improvement is significant.

As for the study on China's eco-efficiency, there are also many literature based on the DEA model to evaluate the eco-efficiency. Huang et al. (2014) investigates the dynamics of regional eco-efficiency in China from 2000 to 2010, and they found significant differences of eco-efficiency among the regions. Fan et al. (2017) studied on the eco-efficiency of China's industrial parks in 2012, and the results showed that large differences exist in the eco-efficiency among different industrial parks. Hu et al. (2019) also measured the eco-efficiency of China's 281 centralized wastewater treatment plants in 126 national-level industrial parks based on a slack-based DEA model. Liu et al. (2017) assessed the tourism eco-efficiency of Chinese coastal cities from 2003 to 2013. Long et al. (2017) measured the eco-efficiency of China's cement manufacturers based on directional distance function and directional slack-based measure. Xing et al. (2018) measured the eco-efficiency based on a super-efficiency slack-based model. Zhao et al. (2018) assessed the land eco-efficiency based on a super-efficiency DEA model and Malmquist index, and they found that the average annual growth rate of land eco-efficiency is 14.3%. Shao et al. (2019) measured the eco-efficiency of China's industrial sectors between 2007 and 2015 based on a two-stage network DEA model, and the findings showed that eco-efficiency of China's industries achieved considerable improvement. Wang et al. (2019b) also evaluated the eco-efficiency of China's industrial sectors by using a

hybrid super-efficiency DEA model. Wang and Yang (2019) evaluated the eco-efficiency of 30 Chinese provinces from 2006 to 2015 based on a modified super-efficiency slack-based model, and they found a descending order from the coast to the inland of China. Zhou et al. (2019b) used a non-radial slack-based model to measure the eco-efficiency of Bohai Rim from 2005 to 2015, and they found that the evolution of eco-efficiency in Bohai Rim has polarized regional disparity. Additionally, the other related studied can be found in Zhou et al. (2019a), Hou and Yao (2019), Yang and Deng (2019), Wang and Zhang (2018), and Ma et al. (2018).

Nevertheless, the existing literature evaluating eco-efficiency focuses primarily on a broad definition of eco-efficiency and rarely measures it per a clear definition, especially in China. Furthermore, rarely does the literature consider an infeasible solution based on a clear definition of eco-efficiency to measure it, discriminating the power problem and technology heterogeneities simultaneously. Therefore, these studies may not provide a holistic overview of eco-efficiency. With a clear definition of eco-efficiency, this study improves prior research by considering the infeasible solution, discriminating power problem and the technology heterogeneities, with Chinese data.

A model to measure eco-efficiency

Construction and decomposition of the eco-efficiency index

To construct the eco-efficiency index, it was assumed that there were K decision-making units (DMUs), the time span was T , and the output increase value of economic activities in period t was v^t . In addition, assuming that economic activities generated n types of environmental pressure, then the environmental pressure in period t was expressed as $p^t = (p_1^t, \dots, p_n^t)$. Two basic concepts are involved here: the pressure generation technology set (PGTS), which refers to all possible combinations of increases in value and environmental pressure during period t , and the pressure requirement set (PRS, or technology), which refers to all possible combinations of p for the production increase value v . The two sets must simultaneously satisfy the following assumptions: 1) economic activities are inevitably accompanied by the generation of environmental pressure

(pollutant emissions), 2) lower increase values can be obtained under the same environmental pressure conditions, 3) the environmental pressure can be increased when the increase value is given, and 4) the technology set is a convex set.

According to Kortelainen (2008), eco-efficiency can be defined as the ratio of economic added value to environmental pressure indicators. If the increase value rises relative to environmental pressure, it indicates that eco-efficiency has improved. Under this definition, the eco-efficiency of period t can be expressed as follows:

$$\text{Eco-performance}^t = \frac{v^t}{w_1 p_1^t + \dots + w_n p_n^t} \tag{1}$$

where v is the added value, p is the environmental pressure indicator, and w is the weight. Following the methods of Kortelainen (2008) and Picazo-Tadeo et al. (2014), we measured the relative eco-efficiency. Its value can be calculated using the direct distance function (Wang et al. 2019a). The directional distance function (DDF) of period t can be expressed as follows:

$$\begin{aligned} \vec{D}^t [v^t, p^t; g] &= (g_v, -g_p) \\ &= \max \left[\beta | (p^t - \beta g_p) \in \text{PRS}^t(v^t + \beta g_v) \right] \end{aligned} \tag{2}$$

where $g = (g_v, -g_p)$ is the direction vector. To model the current, real-world situation, the direction vector was set to $g = (0, -p)$, i.e., the maximum reduction degree of the environmental pressure was measured when the output increase value was constant. To describe the dynamic temporal characteristics of eco-efficiency, we constructed the eco-efficiency change index and its decomposition indexes based on the Luenberger productivity index (Boussemart et al. (2003) compared the Malmquist index and Luenberger index in detail and argued that the Luenberger index had a more considerable application prospect in the future). The eco-efficiency change index (Ecoch) between periods t and $t + 1$ can be expressed as follows¹:

$$\begin{aligned} \text{Ecoch}^{t,t+1}(v^t, p^t, v^{t+1}, p^{t+1}; g) \\ = \vec{D}^t(v^t, p^t) - \vec{D}^t(v^{t+1}, p^{t+1}) \end{aligned} \tag{3}$$

Due to the selection arbitrariness of the reference technology set, the eco-efficiency change index can also be expressed as follows:

$$\begin{aligned} \text{Ecoch}^{t,t+1}(v^t, p^t, v^{t+1}, p^{t+1}; g) \\ = \vec{D}^{t+1}(v^t, p^t) - \vec{D}^{t+1}(v^{t+1}, p^{t+1}) \end{aligned} \tag{4}$$

In order to eliminate the influence of arbitrariness, we took the average of Eqs. (3) and (4):

$$\begin{aligned} \text{Ecoch}^{t,t+1}(v^t, p^t, v^{t+1}, p^{t+1}; g) \\ = \frac{1}{2} \left(\left[\vec{D}^t(v^t, p^t) - \vec{D}^t(v^{t+1}, p^{t+1}) \right] + \left[\vec{D}^{t+1}(v^t, p^t) - \vec{D}^{t+1}(v^{t+1}, p^{t+1}) \right] \right) \end{aligned} \tag{5}$$

The technical efficiency change index (EC) between periods t and $t + 1$ can be expressed as follows:

$$\begin{aligned} \text{EC}^{t,t+1}[v^t, p^t, v^{t+1}, p^{t+1}; g] \\ = \vec{D}^t(v^t, p^t) - \vec{D}^{t+1}(v^{t+1}, p^{t+1}) \end{aligned} \tag{6}$$

The technological progress change index (TC) between periods t and $t + 1$ has the same structure as the eco-efficiency change index and can be expressed as follows:

$$\begin{aligned} \text{TC}^{t,t+1}[v^t, p^t, v^{t+1}, p^{t+1}; g] \\ = \frac{1}{2} \left(\left[\vec{D}^{t+1}(v^t, p^t) - \vec{D}^t(v^t, p^t) \right] + \left[\vec{D}^{t+1}(v^{t+1}, p^{t+1}) - \vec{D}^t(v^{t+1}, p^{t+1}) \right] \right) \end{aligned} \tag{7}$$

The relational expression between the eco-efficiency change index and its decomposition indexes can be obtained by combining Eqs. (5) to (7):

$$\text{Ecoch}^{t,t+1}(v^t, p^t, v^{t+1}, p^{t+1}; g) = \text{EC}^{t,t+1} + \text{TC}^{t,t+1} \tag{8}$$

Non-radial metafrontier Malmquist-Luenberger DEA model

The DDF for the decision-making unit k' at the technological level of period t can be solved as follows:

¹ For eases of expression, the distance function $\vec{D}(v, p; -p)$ was expressed as $\vec{D}(v, p)$.

$$\begin{aligned}
 \vec{D}^t(v^t, p^t) &= \max \beta \\
 &\sum_{k=1}^K \lambda_k p_{k,1}^t \geq v_{k'}^t \\
 &\sum_{k=1}^K \lambda_k p_{k,1}^t \leq (1-\beta) p_{k',1}^t \\
 \text{s.t.} & \\
 &\vdots \\
 &\sum_{k=1}^K \lambda_k p_{k,n}^t \leq (1-\beta) p_{k',n}^t \\
 &\lambda_k \geq 0 \quad k = 1, \dots, K
 \end{aligned}
 \tag{9}$$

The decomposition indexes constructed based on Eq. (9) requires all pollutants to be reduced on the same scale when the increase value is fixed. However, due to the existence of slack, when a certain pollutant p_1 reaches the maximum reduction scale β , another pollutant p_2 may not have already reached the maximum reduction scale (assuming that the scale is β_1 and $\beta_1 > \beta$) and may be further reduced, the problem also names as discriminating power problem (Dirik et al. 2018). Additionally, in contrast to the DDF defined for the same period, the DDF of the mixed period may have no feasible solution (Arabi et al. 2015). Therefore, to solve this problem, a global non-radial DDF (NDDF) according to Zhou et al. (2012), Chang et al. (2012), Tang and Li (2019), Pan et al. (2019), and Oh (2010a) (Eq. (9)) can be transformed as follows:

$$\begin{aligned}
 \vec{D}^G(v^t, p^t) &= \max \frac{1}{n} \sum_{i=1}^n \beta_i \\
 &\sum_{t=1}^T \sum_{k=1}^K \lambda_k^t v_k^t \geq v_{k'}^t \\
 &\sum_{t=1}^T \sum_{k=1}^K \lambda_k^t p_{k,1}^t \leq (1-\beta_1) p_{k',1}^t \\
 \text{s.t.} & \\
 &\vdots \\
 &\sum_{t=1}^T \sum_{k=1}^K \lambda_k^t p_{k,n}^t \leq (1-\beta_n) p_{k',n}^t \\
 &\lambda_k^t \geq 0, \beta_i > 0 \quad k = 1, \dots, K
 \end{aligned}
 \tag{10}$$

Then, Eqs. (7) and (8) can be transformed as follows:

$$\begin{aligned}
 TC^{t,t+1}[v^t, p^t, v^{t+1}, p^{t+1}; g] &= \left(\vec{D}^G(v^t, p^t) - \vec{D}^t(v^t, p^t) \right) - \left(\vec{D}^G(v^{t+1}, p^{t+1}) - \vec{D}^{t+1}(v^{t+1}, p^{t+1}) \right)
 \end{aligned}
 \tag{11}$$

$$\begin{aligned}
 Ecoch^{t,t+1}(v^t, p^t, v^{t+1}, p^{t+1}; g) &= \vec{D}^G(v^t, p^t) - \vec{D}^G(v^{t+1}, p^{t+1}) \\
 &= EC^{t,t+1} + TC^{t,t+1}
 \end{aligned}
 \tag{12}$$

As we know, there are significant differences in the development levels of eastern, central, and western China. Therefore, a more reasonable choice is to consider the heterogeneity of the region, based on a metafrontier, to measure the eco-efficiency change index (Oh 2010b). According to Li and Song (2016), Oh (2010b), Chang and Hu (2018), and the Luenberger index, the eco-efficiency change index can be decomposed as the technical efficiency change index (the same as Eq.(6)), best-practice gap change (BPC) index, and a technology gap change (TGC) index as follows:

$$\begin{aligned}
 BPC^{t,t+1}[v^t, p^t, v^{t+1}, p^{t+1}; g] &= \left(\vec{D}^I(v^t, p^t) - \vec{D}^t(v^t, p^t) \right) - \left(\vec{D}^I(v^{t+1}, p^{t+1}) - \vec{D}^{t+1}(v^{t+1}, p^{t+1}) \right)
 \end{aligned}
 \tag{13}$$

$$\begin{aligned}
 TGC^{t,t+1}[v^t, p^t, v^{t+1}, p^{t+1}; g] &= \left(\vec{D}^G(v^t, p^t) - \vec{D}^I(v^t, p^t) \right) - \left(\vec{D}^G(v^{t+1}, p^{t+1}) - \vec{D}^I(v^{t+1}, p^{t+1}) \right)
 \end{aligned}
 \tag{14}$$

$$\begin{aligned}
 Ecoch^{t,t+1}(v^t, p^t, v^{t+1}, p^{t+1}; g) &= \vec{D}^G(v^t, p^t) - \vec{D}^G(v^{t+1}, p^{t+1}) \\
 &= EC^{t,t+1} + BPC^{t,t+1} + TGC^{t,t+1}
 \end{aligned}
 \tag{15}$$

where $\vec{D}^I(v^t, p^t)$ ($\vec{D}^I(v^{t+1}, p^{t+1})$) is a group-based global NDDF ($I=3$, including eastern, central, and western China, respectively). The details are available in Oh (2010b) and Li and Song (2016). $BPC >$ (or $<$) 0 indicates that the contemporaneous technology frontier shifts toward the intertemporal technology frontier and reflects the innovation effect (Li and Song 2016; Oh 2010b). $TGC >$ (or $<$) 0 means that a technical gap between a specific group and global technology decreases (increases). Hence, TGC captures the technical leadership effect of a given group (Oh 2010b; Li and Song 2016). Moreover, Eqs. (11), (13)–(15) show that it is easy to obtain $TC = BPC + TGC$.

Results and discussion

Data and descriptive statistics

This study used China's provincial panel data of 1986–2016 as the research sample. Referring to the method of Picazo-Tadeo et al. (2014), we used the gross domestic product (GDP, with 2000 being the base period) of each region as a proxy indicator of the output added value and expressed the air pollution index with industrial sulfur dioxide (SO₂), carbon dioxide (CO₂), and industrial smoke dust (Smoke) emissions. We also referred to the study of Li and Lu (2010) to investigate the carbon emissions of various provinces in China by using the CO₂ emission coefficient per unit of energy and 2.13 tons of CO₂/ton of standard coal equivalent. This study estimated the CO₂ emissions of 30 provinces except Tibet, Hong Kong, and Taiwan in 1986–2016. The energy data came from China Energy Statistical Yearbook and China Statistical Yearbook. SO₂ and smoker emissions came from China Statistical Yearbook. Descriptive statistics for each variable are listed in Table 1.

Measurement and decomposition of provincial eco-efficiency of China

Table 2 presents the eco-efficiency change index of each province and its decomposition indexes.

It can be seen from Table 2 that China's eco-efficiency change index (Ecoch) grew at an average annual rate of 0.7% on the whole, with the average annual growth rates of EC, innovation effect (BPC) and technical leadership effect (TGC) being -0.6%, 2.3%, and -1%, respectively. During our sample, the cumulative growth rates of the eco-efficiency change index, technical efficiency change index, innovation effect, and technical leadership effect were 20.4%, -19.4%, 70.5%, and -30.7%, respectively. Among them, eco-efficiency growth was mainly driven by innovation

effect, whereas the efficiency of resource utilization did not play a promoting role and even slowed down the growth of eco-efficiency (the mean value of EC is less than zero). The positive growth of eco-efficiency indicates that the environmental pressure generated by the increase in GDP in China was declining, and the environmental pressure of economic growth eased. The negative efficiency growth indicates that extensive economic growth was still the dominant pattern of China's economic development, and inefficient use of resources is still an issue which needs to be addressed. Positive innovation effect (BPC) is the main contributor to development for the whole country (the mean value of BPC is great than zero). The mean value of technical leadership effect (TGC) is less than zero which means the technology gap between the intertemporal technology for a specific group and the global technology becomes larger. That is to say, the technology difference between eastern, central, and western China becomes larger during our sample. Furthermore, innovation effect is larger than technical leadership effect (that is $TC = BPC + TGC > 0$), which means that technological progress shows that China made improvements in technology introduction and technological innovation. To analyze the changes in efficiency and technology of provinces, this study takes the EC as the ordinate and the TC as the abscissa to draw a scatter plot, as shown in Fig. 1.

It can be seen from Fig. 1 that no province has its technical efficiency change index greater than zero from 1986 to 2016, and only Beijing witnessed no decrease in the technical efficiency level or no increase in the technical efficiency level. The overall inefficiency and the inefficiency of most provinces further indicate that resource utilization efficiency in China did not improve over the sample period at both the overall level and the provincial level. This means that the eco-efficiency improvement was always generated by technological progress (The TC of all the province is great than zero). Among all provinces, only Beijing witnessed no loss

Table 1 Statistics of variables

Variable	Unit	Mean	Maximum	Minimum	Standard deviation
GDP	CNY100,000,000	5687.928	59,017.121	34.540	7986.105
CO ₂	100,000,000 tons	1.647	8.285	.039	1.457
SO ₂	10,000 tons	55.170	176.006	1.026	36.499
Smoke	10,000 tons	53.882	211.647	0.787	38.188

Table 2 Mean of eco-efficiency change index of 30 provinces during 1986–2016

Province	Ecoch	EC	BPC	TGC
Beijing	0.032	0.000	0.032	0.000
Tianjin	0.011	-0.007	0.018	0.000
Hebei	0.004	-0.004	0.009	0.000
Shanxi	0.002	-0.003	0.011	-0.005
Inner Mongolia	0.003	-0.002	0.013	-0.008
Liaoning	0.004	-0.004	0.009	0.000
Jilin	0.007	-0.002	0.035	-0.025
Heilongjiang	0.006	-0.007	0.036	-0.022
Shanghai	0.012	-0.020	0.032	0.000
Jiangsu	0.009	-0.004	0.013	0.000
Zhejiang	0.009	-0.009	0.018	0.000
Anhui	0.006	-0.011	0.038	-0.021
Fujian	0.009	-0.023	0.032	0.000
Jiangxi	0.007	-0.001	0.033	-0.026
Shandong	0.006	-0.005	0.011	0.000
Henan	0.007	-0.006	0.038	-0.026
Hubei	0.007	-0.010	0.042	-0.026
Hunan	0.007	-0.002	0.035	-0.026
Guangdong	0.011	-0.011	0.022	0.000
Guangxi	0.006	-0.001	0.026	-0.019
Hainan	0.007	-0.025	0.032	0.000
Chongqing	0.006	-0.004	0.036	-0.025
Sichuan	0.006	-0.004	0.025	-0.016
Guizhou	0.003	-0.003	0.013	-0.008
Yunnan	0.004	-0.009	0.023	-0.010
Shaanxi	0.005	-0.002	0.025	-0.018
Gansu	0.004	-0.002	0.017	-0.011
Qinghai	0.002	-0.005	0.011	-0.004
Ningxia	0.001	-0.004	0.008	-0.003
Xinjiang	0.002	-0.004	0.014	-0.007
Average value	0.007	-0.006	0.023	-0.010
Cumulative growth	0.204	-0.194	0.705	-0.307

in EC and TC during the sample period. Other provinces all underperformed. For example, Shanghai, Fujian, and Hainan had higher technological growth rates, but their contribution to eco-efficiency growth was offset by a high rate of resource inefficiency, making the overall eco-efficiency growth unsatisfactory. It can be seen from the results of Table 2 and Fig. 1 that the provinces should improve the efficiency of resource utilization while maintaining the introduction of advanced equipment and independent innovation and R&D. This will

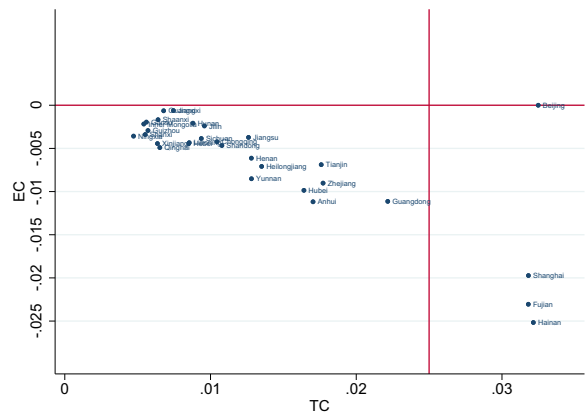


Fig. 1 Distribution of EC and TC among provinces

enable municipalities to shift from an extensive resource-based economic development pattern to an intensive economic development pattern. In this way, technological progress and efficiency improvements can be made simultaneously to achieve the goal of sustainable economic and ecological development.

The above analysis is a static analysis of provincial eco-efficiency. To clarify dynamic temporal changes in China’s eco-efficiency, this study calculated the mean of eco-efficiency and its decompositions from the temporal perspective, as presented in Table 3. China witnessed eco-efficiency growth in 1986–2002. There was a temporary decline in 2003–2005. Since 2006, the eco-efficiency rebounded and then kept rising. The temporary decline in eco-efficiency in 2003–2005 was mainly due to a significant decline in resource utilization efficiency, and the small growth in technological progress could not compensate for the significant decline in efficiency. The reason for this change may be that the proportion of the secondary industry relative to other industries has increased during this period, resulting in a decline in energy efficiency (Tang and Hu 2016). This shows that in 2003–2005, the extensive growth pattern was obvious, and the energy-saving and emission-reduction efforts were insufficient in China. Moreover, during the whole sample period, the EC and technical leadership effect (TGC) growth alternated, while the innovation effect (BPC) showed significant positive growth after 2003. This indicates that the provinces attached great importance to the introduction of advanced technologies and R&D of new technologies, which offset the negative impact of declines in efficiency and technical gap between a specific group and the

global technology on eco-efficiency and thereby led to a positive growth trend in eco-efficiency overall.

Analysis of regional differences

To further analyze the differences in regional eco-efficiency of China, this study compared the changes in the eco-efficiency change index and its decomposition indexes (EC and TC) among the eastern, central, and western regions² (Fig. 2).

It can be found that the eco-efficiency change index and its decomposition indexes differed significantly across different regions in China. The eco-efficiency change index and technological progress change index (BPC + TGC) showed an obvious decrease from east to west. The EC of the central and western regions was approximately equal, but the eastern region clearly lags behind. The three indexes all showed a ladder-like distribution. Namely, the ladder-like changes in the eco-efficiency change index and technological progress change index show that the gap between the overall eco-efficiency and technological level of the eastern, central, and western regions and the frontier narrowed down at decreasing rates. This means that the relative gap among the three regions was widening. This gap may be mainly due to the ladder-like development patterns in China (Lin and Huang 2011). In China, the initial resource endowments and economic and social development levels were the highest in the eastern region, followed by the central region and then the western region. The higher resource endowments and economic development levels allowed the eastern region to reduce the pace of economic development in exchange for higher resource utilization efficiency and better quality of economic development. The central and western regions faced the dual pressures of accelerating economic growth to match the development of the eastern region and reducing emissions and pollution to meet national emission reduction targets. However, because other conditions such as resource endowments and the economic foundation are relatively backward in the central and western regions, it is difficult to achieve great improvement in resource utilization efficiency and technological progress.

² Eastern provinces are Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan; central provinces are Shanxi, Inner Mongolia, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, Guangxi, and Hunan; western provinces are Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang.

Table 3 Mean of eco-efficiency from 1986 to 2016

Year	Ecoch	EC	BPC	TGC
1986/1987	0.002	0.033	-0.031	-0.001
1987/1988	0.004	-0.038	0.044	-0.002
1988/1989	0.002	-0.026	0.030	-0.001
1989/1990	0.002	-0.022	0.025	-0.002
1990/1991	0.003	-0.022	0.026	-0.001
1991/1992	0.006	-0.089	0.098	-0.003
1992/1993	0.009	0.001	0.013	-0.005
1993/1994	0.012	0.028	-0.009	-0.007
1994/1995	0.015	0.102	-0.076	-0.011
1995/1996	0.005	0.111	-0.100	-0.006
1996/1997	0.006	-0.042	0.053	-0.004
1997/1998	0.006	0.003	0.002	0.001
1998/1999	0.007	0.017	-0.003	-0.006
1999/2000	0.002	-0.025	0.030	-0.003
2000/2001	0.003	-0.007	0.014	-0.004
2001/2002	0.002	0.015	-0.009	-0.004
2002/2003	0.000	-0.034	0.030	0.004
2003/2004	-0.002	-0.011	0.008	0.001
2004/2005	-0.002	-0.048	0.044	0.001
2005/2006	0.004	-0.022	0.031	-0.005
2006/2007	0.005	-0.008	0.023	-0.009
2007/2008	0.007	-0.012	0.030	-0.011
2008/2009	0.008	-0.010	0.029	-0.012
2009/2010	0.006	0.003	0.015	-0.012
2010/2011	0.005	-0.023	0.038	-0.009
2011/2012	0.008	0.006	0.019	-0.016
2012/2013	0.019	-0.011	0.045	-0.015
2013/2014	0.007	-0.026	0.031	0.002
2014/2015	0.017	-0.020	0.062	-0.024
2015/2016	0.036	-0.017	0.194	-0.141

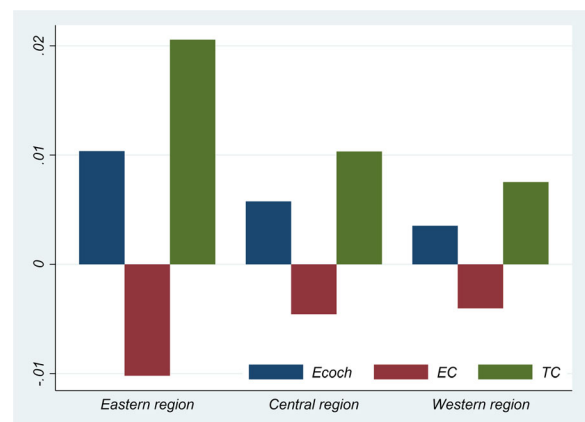


Fig. 2 Comparison among provinces

Research on the convergence of regional eco-efficiency

This study tested the convergence of regional eco-efficiency to further analyze the geographical aggregation characteristics of eco-efficiency in each region and judge whether the eco-efficiency of each province showed a trend of convergence (club convergence) or divergence. Due to the significant differences in regional development and resource endowments, as well as in the regional eco-efficiency in China, it is not appropriate to apply the traditional convergence model used to investigate the convergence of eco-efficiency under the homogeneous production technology conditions. The differences in eco-efficiency among regions can be more accurately described only when the convergence of provincial eco-efficiency can be investigated under heterogeneous production technology conditions. The PS convergence model can effectively express the convergence characteristics of variables under heterogeneous conditions. Therefore, this study used the PS convergence model to analyze the convergence of China's provincial eco-efficiency. The PS convergence model was proposed by Phillips and Sul (2007). The advantages of this model are as follows: 1) This model is constructed based on a nonlinear time-varying factor model including temporary heterogeneity, which eliminates the biases of the traditional convergence test model under heterogeneous conditions due to endogenous errors (Phillips and Sul 2007); 2) this method does not rely on any special assumptions about stable trends; and 3) when there is no convergence in the full sample data, it is possible to further test whether there is a club convergence and also allow the existence of divergent individuals. The core of this method is the $\log t$ test, and the core test equation is as follows:

$$\log\left(\frac{V_1}{V_t}\right) - 2\log L(t) = c + b\log t + u_t, t = [rT], [rT] + 1, \dots, T \quad (16)$$

$$V_t = \frac{1}{N} \sum_{i=1}^N (h_{it}-1)^2 \xrightarrow{t \rightarrow \infty} 0 \quad (17)$$

$$h_{it} = \frac{\log y_{it}}{N^{-1} \sum_{i=1}^N \log y_{it}} = \frac{\delta_{it} \mu_t}{N^{-1} \sum_{i=1}^N \delta_{it} \mu_t} = \frac{\delta_{it}}{N^{-1} \sum_{i=1}^N \delta_{it}} \quad (18)$$

where $\log y_{it}$ is the logarithmic form of eco-efficiency; h_{it} is the relative transition parameter which traces out an individual trajectory for each i relative to the average, and it measures the extent of the divergent behavior; and h_{it} will converge to unit as the δ_{it} converge to a constant δ (Phillips and Sul 2009). μ_t is the common factor, and δ_{it} is the heterogeneous component, $r \in (0, 1)$,³ and $L(t) = \log t$. A unilateral heteroscedastic and sequence-related robust t test can be performed to check whether b is significant. If the statistics of the t test indicate that b is not negative, then a convergence exists; otherwise, if $t_b < -1.65$ (a critical value at the 5% significance level), there is no convergence in the full sample. If the convergence hypothesis is rejected at a given significance level, a further test can be performed to check for club convergence and divergence areas (Phillips and Sul 2007).

According to the method of estimating the productivity of the base period proposed by Krüger (2003), the productivity index of period t can be expressed as the multiplication of the distance function for the base period and the productivity change index of the subsequent period. However, this study calculated the eco-efficiency index and its decomposition indexes via the direct distance function. The smaller the value of the distance function was, the closer the distance was to the frontier. When the value of the direct distance function was zero, the index was located at the frontier. It can be seen from Eq. (10) that $\bar{D}^G(v^t, p^t) \leq 1$. Therefore, $1 - \bar{D}^G(v^{1986}, p^{1986})$ was used as the eco-efficiency estimate of the base period. The level of eco-efficiency during period t can be expressed as follows:

$$\text{Eco}^t = 1 - \bar{D}^G(v^{1986}, p^{1986}) + \sum_{t=1986}^{t-1} \text{Ecoch}^{t,t+1} \quad (19)$$

According to the results calculated using Eq. (19), the eco-efficiency convergence test was then performed using Eq. (16). It can be seen that the t value of the convergence test of the full sample was $-46.18 < t_{\text{critical}} = -1.65$, indicating that the eco-efficiency of the 30 provinces did not converge overall. A further test was performed to check for club convergences. According to the procedure for testing club convergences, we found four convergence clubs and three divergent municipalities based on provincial eco-efficiency.

³ Through the Monte Carlo simulation experiment, PS (2007) recommended that $r = 0.3$ be an appropriate choice when $T < 50$.

Club 1 included Shanghai, Tianjin, Jiangsu, Zhejiang, Fujian, Guangdong, and Hainan. The eco-efficiency levels of the seven provinces ranked among the top ten in China during the sample study period. These provinces are all in the eastern coastal areas and have common development advantages, i.e., faster access to advanced technologies than inland areas and a higher likelihood to use technological progress to drive eco-efficiency (He 2011). The mean value of the technological progress change index (BPC + TGC) during the sample study period was 0.024 (or 2.4%), which was about 1.8 times of technological progress change index of the whole country and 2.6 times of the technological progress change index in other non-eastern provinces. Club 2 included Liaoning, Heilongjiang, Jilin, Shandong, Anhui, Jiangxi, Henan, Hubei, Hunan, Guangxi, Chongqing, and Sichuan and thereby spans the eastern, central, and western regions. The eco-efficiency convergence of Club 2 indicates that the eco-efficiency of these provinces tended to be the same. Club 3 included Liaoning, Hebei, Shaanxi, and Gansu, which all are central and eastern provinces. Club 4 included Shanxi, Xinjiang, Qinghai, and Guizhou. These four provinces had small improvements in eco-efficiency during the sample study period, and their annual growth rates also were the lowest in China. The average annual growth rates of the eco-efficiency between the four provinces is about 0.2%, which is less than one third of the whole sample. They were areas with high pollution discharge. It is well known that Shanxi is a major coal province in China. Its economic growth is heavily dependent on coal resource consumption. Excessive use of coal resources leads to huge emissions of carbon dioxide, sulfur dioxide, and solid particulate matter. In addition, the resource utilization efficiency in Shanxi lags behind other regions, which restricts the area's growth in eco-efficiency. Guizhou, Xinjiang, and Qinghai belong to the western region. With economic growth as the primary development goal, they did not attach importance to the improvement of resource utilization efficiency in the development process, which made the pollutant emission level relatively high. As a result, their eco-efficiency was low.

Compared with other provinces, Beijing, Inner Mongolia, and Ningxia had unique change dimensions. These three provinces failed to form a club with the four convergence clubs, and each was individually defined by divergent characteristics. Beijing is the most developed province in China. Their eco-efficiency levels witnessed different changes, possibly due to their respective characteristics. For example, Beijing is the capital of China locating in coastal areas and has

superior geographical positions and convenient ways to access information. The eco-efficiency levels of Beijing were also among the top one in China (annual growth rate is 3.2%). Inner Mongolia and Ningxia witnessed incompatible change trends with the lowest eco-efficiency. The eco-efficiency's average annual growth rate of the two provinces was only 1/3 of the national average growth rate, which is caused by the negative annual growth rates of EC and TGC. Therefore, these provinces should focus on improving the resource utilization efficiency and decreasing the technical gap from the development area to narrow the gap with other provinces with high eco-efficiency.

The above analysis tells us that we can divide eco-efficiency into four convergent clubs and three divergent individuals, among 30 provinces, using the *log_t* test. However, the convergent analysis is only a static outcome, which cannot provide a dynamic evolution about eco-efficiency. Therefore, according to Camarero et al. (2013), Panopoulou and Pantelidis (2009), and Phillips and Sul (2007), we use the relative transition paths from Eq. (18) to describe the dynamic evolution of each club and divergent individuals. Figure 3 plots the relative transition paths (h_{it}) of four convergent clubs (calculated as the cross-sectional mean of h_{it} of the members of each club) and three divergent individuals. As the full panel diverges (previous analysis shows that the full sample does not converge), the transition paths do not tend to unify. However, we cannot find a convergent trend for each clubs (or individuals) consistent with the former static convergence analysis that no clubs (or individuals) can be merged, with obvious differences between different clubs and individuals. This findings are also similar to the findings in Fig. 2, which show differences in eco-efficiency between the subjective groups (eastern, central, and western China, respectively). Moreover, from Fig. 3, we can find that *div3_Ningxia* and *club4* are increasing relative to the core,⁴ which means that any differences among these two and the whole sample are increasing. That is, their eco-efficiency is worsening relative to the whole sample. We also find *div_Beijing* is increasing relative to the core; therefore, its eco-efficiency is also worsening relative to the sample. Overall, the main findings from the time trend of the

⁴ It is to note that all the eco-efficiency is less than one, and its absolute value will grow larger with low eco-efficiency after taking the logarithm, so that we have seen h_{it} decreasing with higher eco-efficiency in clubs (or individuals) and increasing with lower eco-efficiency in clubs (or individuals).

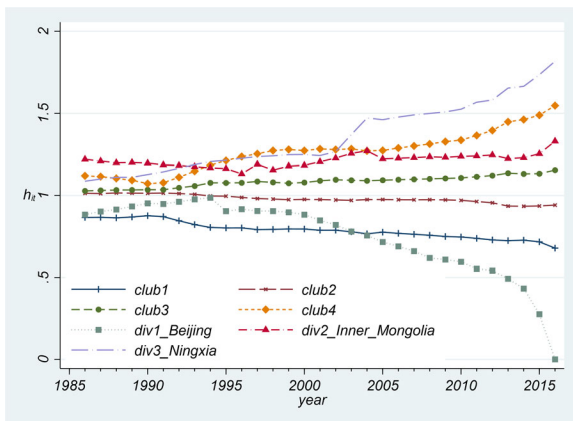


Fig. 3 Relative transition paths (h_{it}) of clubs (individuals)

relative transition paths for clubs and divergent individuals are consistent with the previous static convergence analysis. Furthermore, the time trend of the relative transition paths increases our understanding of the differential change in clubs and divergent individuals.

Conclusions and policy application

This study used China's provincial panel data from 1986 to 2016 and employed the non-radial metafrontier Malmquist-Luenberger DEA model to measure China's eco-efficiency and its decompositions. On this basis, the geographical aggregation characteristics and dynamic evolution trends of China's provincial eco-efficiency were analyzed. The results showed that China's eco-efficiency increased at an average annual rate of 0.7% overall, with the technical efficiency decreasing at an annual rate of 0.6%, the innovation effect increasing at an annual rate of 2.3%, and the technical leadership effect decreasing at an annual rate of 1%. In the sample study period, the cumulative growth rates of eco-efficiency change index, technical efficiency change index, innovation effect, and technical leadership effect were 20.4%, -19.4%, 70.5%, and -30.7%, respectively. In China, regional eco-efficiency was mainly driven by innovation effect, and technical efficiency did not play its expected role of positively affecting eco-efficiency. Instead, the contribution of technical efficiency actually slowed down the growth rate of eco-efficiency. The eco-efficiency and its decomposition indexes exhibited a decreasing trend from east to west.

Furthermore, the findings showed four convergence clubs and three divergent provinces in terms of China's

regional eco-efficiency. Areas with high eco-efficiency tended to converge with other areas with high eco-efficiency, and these were mostly coastal areas. Areas with low eco-efficiency tended to converge with other areas with low eco-efficiency, and these were mostly provinces with low resource efficiency. Compared with other provinces, Beijing, Inner Mongolia, and Ningxia exhibited trends in eco-efficiency levels which did not conform to any convergence clubs. Finally, a relative transition paths analysis allows us to better understand the temporal differences in eco-efficiency among clubs and individuals.

For the purpose of improving the overall eco-efficiency and narrowing the gaps between regions in China, the government must scientifically and individually analyze regional eco-efficiency and their evolution trends, giving consideration to both efficiency and fairness, and build an energy-saving and emission-reduction regional distribution mechanism. Furthermore, an industrial development regional balance mechanism must be defined to promote balanced and coordinated development of regional energy, economic, and environmental systems. In order to achieve incremental change, the government should focus on supervising and assisting provinces with low resource utilization efficiency and severe environmental pollution, such as Ningxia, in strengthening efforts in energy conservation and emission reduction, learning and using new technologies. In this way, the adjustment of the industrial structure can be accelerated and the industrial layout can be optimized, so that these provinces can catch up with areas with high eco-efficiency. Provinces with high eco-efficiency levels such as Shanghai, Tianjin, Jiangsu, Zhejiang, Fujian, and Hainan should be appropriately monitored so that they can further consolidate their existing advantages, tap the potential of energy conservation and emissions reduction, and lift their eco-efficiency to new levels. Moreover, in order to maintain balance, the government should mainly control convergence clubs with low eco-efficiency levels and appropriately control divergence individuals with low eco-efficiency levels. Finally, the governments should strengthen their efforts in promoting and implementing the concepts of energy conservation, emission reduction, and ecological development. Governments should also raise enterprises' and industries' awareness of sustainable development and encourage industries and enterprises to adapt to local conditions and effectively improve the technology utilization efficiency to achieve their own efficient and sustainable development.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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