Social Sciences in Business and Policy Analysis
www.aprdi.org/all-categories/category-journal

Is the Low-carbon Economy Efficient in China?

Yuting Deng [1] Yalin Duan [1,*]

[1]School of Economics, Guangzhou City University of Technology, China

*Corresponding author (E-mail address: duanyl1016@163.com)

ABSTRACT

China has been actively advancing towards a low-carbon economy (LCE), emphasizing the importance of evaluating its efficiency. This study utilizes panel data from 30 regions in China spanning 2005 to 2021. It integrates economic scale and carbon emissions in assessing low-carbon economy efficiency (LCEE) through the Super-slack-based Measure model and analyzes the evolving LCEE dynamics across these regions using the Malmquist Productivity Index. The findings reveal widespread low-carbon economic inefficiencies in these regions, with notable performance disparities in LCEE. Particularly, high-performing regions are predominantly situated in eastern China. Additionally, China has made significant strides in enhancing LCEE performance.

KEYWORDS

LCEE; Super-SBM; China; Malmquist; Productivity Index

http://doi.org/10.62220/j.ssbpa.2024.01.005

Social Sciences in Business and Policy Analysis
www.aprdi.org/all-categories/category-journal

1. Introduction

Energy has always been a pivotal factor in competitiveness. The concept of "a low-carbon economy" first emerged in an energy white paper published by the government of the United Kingdom. It advocates for the establishment of a low-energy-consumption, low-pollution, and low-emission economic system, emphasizing the need for all economies to strive for maximizing output while minimizing energy consumption. With the increasing concern over the anthropogenic effects of rising greenhouse gas emissions on climate change (European Parliament, 2007) [1], more economies are intensifying their efforts to achieve decarbonization. As a developing country with substantial energy consumption, China must intensify its actions. Recognizing that enhanced feedback on low-carbon economic efficiency can enable better control over energy consumption and lead to increased efficiency, the establishment of a scientific and rational standard for low-carbon economic efficiency is now imperative. This paper primarily aims to achieve greater output with less input in low-economy activities. Through our empirical investigation, we seek to conduct a comparative efficiency analysis using the super-SBM model and Malmquist index. Upon reviewing existing literature on low-carbon economic efficiency, we noted a limited number of empirical studies that compare efficiency within China. Given China's critical role in the energy sector, we also intend to identify the most significant variables to provide policy recommendations.

2. Literature review

Supporting research on a low-carbon economy has been undertaken from various disciplinary perspectives. A typical method for assessing the efficiency of a system is data envelopment analysis (DEA) (Beltrán-Esteve,etc., 2017[2]; Gémar, Gómez, etc., 2018[3]; Marcelo Furlan,2021[4];) Data Envelopment Analysis (DEA) has been proposed by American operations researchers A. Charnes and W. W. Cooper since 1978[5], and is mainly used to evaluate the relative effectiveness of the same type of units (decision- making units, DMUs) with comparability, which is based on a number of input indexes and a number of output indexes, and is analyzed in-depth by using the method of linear programming.

Besides, fuzzy comprehensive evaluation and multi-criteria evaluation methods have been commonly utilized in various research studies. Sadia Samar Ali et al. (2020) used a hybrid approach of SEM/PLS machine learning and IRT to validate the positive relationship between sustainable practices and low carbon performance, which is ultimately the responsibility of a sustainable society[6].Rajesh Kumar Mishra et al. (2022) [7]explored an optimal sustainable inventory model that attempts to maximize profits with non-instantaneous deterioration and sub-standard quality products in the presence of carbon emissions and complete stock-outs, providing a solution to obtain a joint optimal strategy for inventory cycle time, inventory consumption time, order quantity and backorder quantity.

Moreover, Super-SBM model is a special kind of efficiency evaluation model, which is extended and optimized based on the SBM (Slacks-Based Measure) model. The SBM model itself is a non-radial and non-angle efficiency evaluation method, which can solve the problems that cannot be solved by the radial model and the angle model, such as the slackness of inputs or outputs. Data Envelopment Analysis (DEA) is a commonly used efficiency assessment method to evaluate the relative efficiency of a set of decision units with multiple inputs and multiple outputs, but the DEA model does not satisfy

Social Sciences in Business and Policy Analysis
www.aprdi.org/all-categories/category-journal

the monotonic linear relationship requirement, and then it is necessary to use the non-expected SBM model proposed by Tone (2001) [8]. However, the traditional SBM model cannot differentiate and rank these decision units while they are all efficiency. Super-SBM model would be the best choice among them without these defects.

In order to study the development status of low-carbon economy more deeply, Zhou Zejiong et al. (2013)[9]used the Super-SBM model and drew on the output-oriented Malmquist productivity index to select corresponding indicators from multiple perspectives (e.g., energy, R&D, industrial structure, urbanization level, etc.) to measure regional inputs, and selected the GDP and CO2 emissions per unit of GDP of each region as the desired and non-desired outputs to measure the development of low-carbon economy in the Central Plains Economic Zone, based on the Central Plains panel data of 15 cities in the economic zone from to 2011, the empirical study was conducted, and the results of the study showed that the backward carbon technology and the scale of development are not the main factors restricting the development of low-carbon economy; in addition, Li Qiaochu et al. (2022) [10] also adopted a super-efficiency SBM model that includes non-desired outputs to incorporate energy, economic and environmental factors into the low-carbon economic efficiency assessment system. They measured the low-carbon economic efficiency of China's energy sector from 2000 to 2018 and concluded that the overall low-carbon economic efficiency of China's energy sector is on an upward trend.

In terms of the factors influencing the development of a low carbon economy, Muhammad Yousaf Raza et al. (2023) Decomposing the main two dimensions such as changes in carbon sources and carbon damages from 1986 to 2020 into eight factors, the results of the study showed that the main influencing factors are economic development, population and land, while energy intensity and emission factors are the main forces in the reduction of CO2 emissions[11].Ghosh Subrata et al. (2023) Adopted an integrated evaluation methodology to assess spatial carbon emissions, carbon sink capacity, carbon sink balance and carbon resilience of Himalayan cities using ecological support coefficients, which showed that population size, household size and concentration of built-up land are the main causes of carbon emissions[12].

3. Research methodology

3.1 The principle of the Super-SBM model with undesirable outputs

In this paper, we use the Super-SBM model based on the structural form of the efficiency model CCR with the variable returns to scale (VRS) condition.

First, it is assumed that there are n DMUs has q input factors to produce s1 desirable outputs and s2 undesirable outputs, represented by three vectors,$x \in R^m, y^d \in R^{s_1}, and y^{ud} \in R^{s_2}$,respectively.The three matrices,$X, Y^d and\ Y^{ud}$,can be formed when n DMUs are considered:

$$X = [x1, x2, \dots, xn] \in R^{m*n} > 0$$

$$Y^d = [y_1^d, y_2^d, \dots, y_n^d] \in R^{s1*n} > 0$$

$$Y^{ud} = [y_1^{ud}, y_2^{ud}, \dots, y_n^{ud}] \in R^{s2*n} > 0$$

Social Sciences in Business and Policy Analysis
www.aprdi.org/all-categories/category-journal

The base model is specified as follows:

$$\rho^* = min\frac{\frac{1}{q}\sum_{i=1}^{q}\frac{x_i}{x_{i0}}}{\frac{1}{s_1+s_2}\left(\sum_{r=1}^{s_1}\frac{\bar{y}_r^d}{y_{r0}^d}+\sum_{r=1}^{s_2}\frac{\bar{y}_l^{ud}}{y_{l0}^{ud}}\right)}$$

$$Subject\ to\ \bar{x} \geq \sum_{j=1,\ \neq 0}^{n}\lambda_j x_j,\ \ \bar{y}^d \leq \sum_{j=1,\ \neq 0}^{n}\lambda_j y_j^d, \bar{y}^{ud} \geq \sum_{j=1,\neq 0}^{n}\lambda_j y_j^{ud}$$

$$\bar{x} \geq x_0,\ \ \bar{y}^d \leq y_0^d,\ \ \bar{y}^{ud} \geq y_0^{ud}$$

$$\sum_{i=1}^{n}\lambda_i = 1,\ \ \bar{y}^{ud} \geq 0,\ \ \lambda \geq 0$$

Where ρ^* is an objective function, whose value can be larger than 1. In using the Super-SBM model, it is requested that the inputs (x) and outputs (y_g, y_b) are correlated (Li & Shi, 2014[13]; López, Ho, & Ruiz-Torres, 2016[14]). λ is the weight vector.

3.2 The principle of the Malmquist Productivity Index

In fact, it is important to understand the dynamic changes among different regions over a period. Thus, the Malmquist Productivity Index (MPI)is introduced. Fare et al. (1997) [15] defined MPI as follows:

Let t and s (t<s)refer to two observed time points. Assuming that $\rho^t(x_j^t, y_j^{td}, y_j^{tud})$ and $\rho^s(x_j^t, y_j^{td}, y_j^{tud})$ are the efficiency values of DMUj based on the data measured in the time t under the technological condition in the time t and s, respectively. Also, $\rho^t(x_j^s, y_j^{sd}, y_j^{sud})$ and $\rho^s(x_j^s, y_j^{sd}, y_j^{sud})$ are the efficiency value of DMUj based on the data measured in the time s. The value of MPI is defined as follows:

$$MPI_j(t,s) = \left[\left(\frac{\rho^t(x_j^s, y_j^{sd}, y_j^{sud})}{\rho^t(x_j^t, y_j^{td}, y_j^{tud})}\right)\left(\frac{\rho^s(x_j^s, y_j^{sd}, y_j^{sud})}{\rho^s(x_j^t, y_j^{td}, y_j^{tud})}\right)\right]^{1/2}$$

where $MPI_j(t,s) > 1$ represents an increase in total factor productivity compared to the previous period and vice versa; $MPI_j(t,s)$= 1or <1, which means that productivity remains the same, or even deteriorated from t to

Social Sciences in Business and Policy Analysis
www.aprdi.org/all-categories/category-journal

4. Indicator Selection and Data Sources

4.1 Selection of indicators

Based on an extensive literature review, decision-making criteria, sub-criteria, tertiary criteria, and indicators of low-carbon economic efficiency have been identified. Initially, a comprehensive list of criteria was compiled, followed by the categorization of decision-making factors into two groups, as illustrated in Table 1. The sub-criteria encompass four categories: non-energy inputs, energy inputs, desired outputs, and non-desired outputs. Non-energy inputs primarily comprise production factors excluding energy consumption in the production or service process, such as X1 transportation (TRA), X2 greening (GRE), X3 total labor force (TLF), and X4 capital (CAP) inputs. Specifically, TRA represents the number of resident-owned cars, GRE signifies forest coverage, TLF denotes the total labor force, and CAP indicates the growth rate of fixed asset investments. Energy inputs refer to the total natural gas consumption resources expressed as X5 total energy use (TEU). Output indicators are essential metrics that quantify the outcomes and benefits of production activities, encompassing both desired and undesired outputs. Desired outputs reflect the maximum expected outputs of the decision-making unit (DMU), directly showcasing the positive effects of production activities, represented in this study by Yd Gross Domestic Product (GDP). Conversely, non-desired outputs signify negative effects typically linked to environmental pollution, represented by Yud total CO2 emissions.

Table1　List of Decision Criteria

	Sub- criteria	Indicators
Input	Non-energy inputs	X1(Transportation)
		X2(Greening)
		X3(Labor)
		X4(Capital)
	Energy inputs	X5(Total energy use)
Output	Desired outputs	Y^{d} (Gross Domestic Product)
	Non-desired outputs	Y^{ud} (CO2)

4.2 Data sources

The data collected from 30 sample regions for the period 2005 to 2021are available from China Carbon Accounting Databases (CEADs)， China Statistical Yearbook and China Environmental Yearbook. The

Social Sciences in Business and Policy Analysis
www.aprdi.org/all-categories/category-journal

volume of the data is too large to be included in this paper. Instead, the main features of the data are presented in Table 2.

Table 2 Main features of the data collected for analysis

Indicator	unit	Minimum	Maximum	Median	Mean	Std.dev.
X1(TRA)	10^4	12.18	2740.07	314.405	467.7813	481.2306
X2(GRE)	%	4	66.8	36.45	33.47314	17.95096
X3(TLF)	10^4	543	12684	3850	4518.959	2770.612
X4(CAP)	%	-56.6	41.3	14.3	14.33843	11.46547
X5(TEU)	10^8m^3	0.01	192.43	16.975	29.72994	35.62254
Yd(GDP)	10^8Yuan	499.4	124719.5	13848.5	20305.32	19825.07
Yud(CO2)	10^4tonnes	1633.32	104528.9	24438.87	31043.5	21017.4

Data source: China Carbon Accounting Databases (CEADs)， China Statistical Yearbook and China Environmental Yearbook

According to the result, the differences in inputs and outputs among the regions are very significant， which shows the irrationality of resource allocation.

In order to eliminate the quantitative outline between the data, the data would be standardized through the following method.

$$Z_{ij} = 0.9 * \frac{P_{ij} - min(P_{ij})}{max(P_{ij}) - min(P_{ij})} + 0.1$$

Where P_{ij} represents the i indicator of the j province or city, max(P_{ij}) and min(P_{ij}) denotes the maximum and minimum， i=1,2,…,n； j=1, 2,…,m

5. Results and Discussion

5.1 Results

By applying the data to the Super-SBM model, the results of ρ (LCEE performance) from 2005 to 2021 are calculated in Table 3.

Social Sciences in Business and Policy Analysis
www.aprdi.org/all-categories/category-journal

Table 3 The 30 regions in LCEE performance from 2005 to 2021

		2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	Average
Eastern Area	Beijing	0.61	0.59	0.59	0.62	0.56	0.56	0.61	0.60	0.62	0.65	0.66	0.71	0.76	1.00	1.00	0.93	1.04	0.71
	Tianjin	0.86	0.78	0.74	0.72	0.70	0.71	0.78	0.73	0.73	0.71	0.73	0.69	0.72	0.74	0.69	0.71	0.72	0.73
	Hebei	0.65	0.65	0.67	0.68	0.63	0.66	0.61	0.62	0.61	0.58	0.57	0.56	0.51	0.49	0.48	0.48	0.51	0.59
	Shanghai	1.00	0.86	0.92	1.01	1.01	1.01	1.00	0.96	0.89	0.93	0.88	0.86	0.86	0.92	1.00	1.01	1.04	0.95
	Jiangsu	1.04	1.00	0.93	1.03	0.94	1.00	1.01	0.89	0.87	0.87	0.86	0.97	1.00	0.93	0.92	0.94	1.06	0.96
	Zhejiang	0.86	0.86	0.85	0.86	0.80	0.79	0.78	0.74	0.72	0.69	0.73	0.76	0.77	0.77	0.81	0.81	0.78	0.79
	Fujian	1.01	1.00	1.00	1.01	1.00	0.92	1.00	0.91	0.89	0.87	0.87	0.94	0.93	0.92	0.96	1.02	1.03	0.96
	Shandong	0.68	0.74	0.77	0.72	0.76	0.73	0.68	0.66	0.65	0.68	0.75	0.77	0.71	0.61	0.64	0.61	0.64	0.69
	Guangdong	0.78	1.00	1.02	1.01	0.96	1.03	0.55	0.58	0.59	0.61	0.66	0.69	0.78	0.82	0.88	1.02	1.04	0.83
	Hainan	1.02	0.98	0.96	0.92	0.91	1.00	1.00	1.00	0.91	0.92	0.93	1.00	1.00	1.02	1.01	1.00	1.01	0.98
Central Area	Shanxi	0.77	0.68	0.67	0.65	0.57	0.58	0.57	0.55	0.54	0.59	0.53	0.53	0.52	0.51	0.50	0.55	0.61	0.58
	Anhui	0.80	0.73	0.72	0.72	0.67	0.67	0.67	0.67	0.68	0.69	0.70	0.69	0.73	0.78	0.79	0.79	0.84	0.73
	Jiangxi	1.00	0.90	0.89	1.00	0.87	0.89	0.88	0.86	0.85	0.82	0.82	0.79	0.76	0.75	0.74	0.73	0.76	0.84
	Henan	0.67	0.66	0.71	0.76	0.73	0.76	0.76	0.78	0.76	0.75	0.80	0.84	0.83	0.83	0.85	0.84	0.85	0.78
	Hubei	0.80	0.76	0.73	0.76	0.71	0.73	0.73	0.73	0.72	0.71	0.73	0.75	0.78	0.82	0.81	1.00	0.83	0.77
	Hunan	0.79	0.76	0.76	0.77	0.71	0.75	0.75	0.73	0.67	0.69	0.71	0.72	0.75	0.77	0.84	0.92	1.01	0.77
Western Area	Inner Mongolia	1.00	0.77	0.73	0.73	0.70	0.68	0.59	0.63	0.66	0.66	0.70	0.64	0.68	1.02	0.62	0.65	0.66	0.71
	Guangxi	1.00	0.92	0.87	0.87	0.82	0.83	0.86	0.87	0.87	0.87	0.87	0.84	0.80	0.81	0.80	0.69	0.67	0.84
	Chongqing	0.60	0.59	0.60	0.59	0.58	0.58	0.59	0.61	0.65	0.65	0.66	0.67	0.67	0.69	0.71	0.74	0.76	0.64

	Sichuan	0.43	0.45	0.45	0.46	0.45	0.49	0.50	0.52	0.53	0.55	0.56	0.57	0.63	0.66	0.67	0.78	1.00	0.57
	Guizhou	0.76	1.01	0.92	1.00	0.80	0.77	0.74	0.75	0.75	0.73	0.74	0.73	0.70	0.71	0.74	0.70	0.71	0.78
	Yunnan	0.67	0.89	0.89	0.93	1.00	1.00	1.00	1.00	1.00	1.00	1.01	0.97	0.96	0.97	0.97	0.93	1.03	0.96
	Shanxi	0.60	0.58	0.57	0.58	0.56	0.57	0.57	0.57	0.59	0.59	0.58	0.60	0.60	0.60	0.61	0.58	0.63	0.59
	Gansu	1.04	0.84	0.82	0.78	0.75	0.71	0.68	0.66	0.65	0.64	0.65	0.65	1.11	0.67	0.64	0.63	0.63	0.74
	Qinghai	1.05	1.00	1.00	1.00	0.87	1.01	1.00	0.90	0.90	0.88	0.90	0.90	0.91	0.95	0.96	1.05	1.00	0.96
	Ningxia	0.80	0.78	0.77	0.73	0.75	0.71	0.67	0.65	0.64	0.64	0.66	0.66	0.68	1.02	0.68	0.66	1.00	0.74
	Xinjiang	1.01	1.00	1.00	1.00	0.88	0.90	0.92	1.00	1.00	0.67	0.70	0.79	0.67	1.10	0.84	0.75	1.01	0.90
Northeastern Area	Liaoning	0.65	0.64	0.68	0.70	0.69	0.67	0.68	0.71	0.71	0.68	0.79	1.52	0.57	0.57	0.58	0.57	0.60	0.71
	Jilin	0.72	0.69	0.72	0.73	0.73	0.72	0.71	0.69	0.67	0.63	0.65	0.65	0.64	0.63	0.69	0.61	0.61	0.68
	Heilongjiang	0.75	0.73	0.75	0.75	0.68	0.64	0.64	0.65	0.63	0.65	0.64	0.62	0.60	0.63	0.59	0.60	0.59	0.66

Meanwhile, this paper presents the dynamic changes of LCEE among 30 regions from2005 to 2021 by using the MPI model. The results of MPI(DLCEE)are showed in Table 4. It shows that China has been experiencing an improvement in terms of LCEE performance, as evidenced by the overall average DLCEE value of 1.0062 during the surveyed period. Sichuan is the best performer, with an average DLCEE value of 1.06, while Guangxi is the worst.

Table 4 The DLECC values of the 30 regions from2005/2006 to 2020/2021

regions	2005-2006	2006-2007	2007-2008	2008-2009	2009-2010	2010-2011	2011-2012	2012-2013	2013-2014	2014-2015	2015-2016	2016-2017	2017-2018	2018-2019	2019-2020	2020-2021	Average
Sichuan	1.04	0.99	1.03	0.97	1.09	1.03	1.03	1.03	1.03	1.03	1.01	1.10	1.05	1.02	1.17	1.28	1.06
Beijing	0.97	1.00	1.05	0.91	1.00	1.09	0.98	1.04	1.04	1.01	1.07	1.08	1.31	1.00	0.93	1.12	1.04

Social Sciences in Business and Policy Analysis
www.aprdi.org/all-categories/category-journal

Liaoning	0.98	1.06	1.04	0.98	0.98	1.02	1.03	1.01	0.95	1.16	1.92	0.38	1.00	1.02	0.98	1.04	1.03
Guangdong	1.28	1.02	0.99	0.95	1.06	0.54	1.05	1.03	1.03	1.08	1.04	1.13	1.05	1.07	1.15	1.03	1.03
Ningxia	0.99	0.98	0.95	1.02	0.94	0.94	0.98	0.98	1.00	1.03	1.01	1.02	1.50	0.67	0.97	1.52	1.03
Yunnan	1.33	1.00	1.04	1.08	1.00	1.00	1.00	1.00	1.00	1.00	0.97	0.99	1.01	1.00	0.96	1.11	1.03
Xinjiang	0.99	1.00	1.00	0.88	1.02	1.02	1.09	1.00	0.67	1.04	1.13	0.85	1.64	0.77	0.89	1.34	1.02
Hunan	0.96	1.00	1.01	0.93	1.06	1.00	0.97	0.92	1.02	1.03	1.02	1.04	1.02	1.09	1.10	1.09	1.02
Chongqing	0.99	1.01	1.00	0.98	1.00	1.01	1.03	1.06	1.01	1.00	1.03	0.99	1.04	1.02	1.05	1.02	1.02
Henan	0.98	1.07	1.06	0.96	1.04	1.00	1.02	0.98	0.99	1.06	1.05	0.99	1.01	1.02	0.99	1.01	1.02
Hubei	0.95	0.96	1.05	0.93	1.02	1.01	1.00	0.98	0.99	1.03	1.03	1.04	1.06	0.99	1.24	0.82	1.01
Shanghai	0.86	1.07	1.09	1.00	1.00	1.00	0.96	0.93	1.04	0.95	0.98	1.00	1.07	1.09	1.01	1.03	1.00
Jiangsu	0.97	0.93	1.11	0.91	1.07	1.01	0.88	0.98	1.00	0.99	1.14	1.03	0.93	0.99	1.02	1.12	1.00
Shaanxi	0.97	1.00	1.01	0.96	1.02	1.01	1.00	1.03	1.00	0.97	1.05	0.99	1.00	1.01	0.96	1.08	1.00
Anhui	0.91	0.99	1.00	0.93	1.00	1.01	1.00	1.02	1.01	1.01	0.99	1.05	1.07	1.01	1.00	1.06	1.00
Fujian	0.99	1.00	1.01	0.99	0.92	1.09	0.91	0.98	0.98	1.00	1.08	0.98	0.99	1.05	1.06	1.01	1.00
Guizhou	1.33	0.92	1.09	0.80	0.96	0.97	1.01	1.00	0.97	1.02	0.99	0.95	1.02	1.04	0.95	1.01	1.00
Hainan	0.96	0.98	0.96	0.99	1.09	1.00	1.00	0.91	1.01	1.01	1.08	1.00	1.02	0.98	1.00	1.01	1.00
Qinghai	0.95	1.00	1.00	0.87	1.15	1.00	0.89	1.00	0.98	1.02	1.00	1.01	1.05	1.01	1.10	0.95	1.00
Shandong	1.08	1.05	0.93	1.06	0.95	0.94	0.96	0.98	1.05	1.11	1.03	0.91	0.86	1.05	0.95	1.05	1.00
Zhejiang	1.00	0.99	1.01	0.93	0.99	0.98	0.95	0.98	0.96	1.06	1.03	1.01	1.01	1.05	0.99	0.97	0.99
Inner Mongolia	0.77	0.95	0.99	0.97	0.97	0.86	1.07	1.06	0.99	1.06	0.92	1.06	1.50	0.60	1.06	1.02	0.99

Social Sciences in Business and Policy Analysis

www.aprdi.org/all-categories/category-journal

Jilin	0.95	1.05	1.01	1.01	0.98	0.99	0.97	0.98	0.94	1.03	1.01	0.98	0.98	1.11	0.87	1.00	0.99
Tianjin	0.91	0.95	0.98	0.97	1.02	1.10	0.94	0.99	0.97	1.03	0.95	1.05	1.03	0.93	1.02	1.02	0.99
Gansu	0.81	0.97	0.96	0.96	0.95	0.96	0.98	0.98	0.99	1.02	1.00	1.70	0.61	0.96	0.98	1.00	0.99
Shanxi	0.89	0.99	0.96	0.88	1.01	0.98	0.97	0.98	1.10	0.90	1.00	0.98	0.99	0.98	1.10	1.10	0.99
Heilongjiang	0.98	1.02	1.00	0.90	0.94	1.00	1.02	0.97	1.04	0.98	0.97	0.97	1.04	0.93	1.03	0.99	0.99
Hebei	1.00	1.03	1.01	0.92	1.05	0.93	1.01	0.98	0.96	0.97	0.98	0.91	0.97	0.98	1.00	1.06	0.99
Jiangxi	0.90	0.98	1.13	0.87	1.02	1.00	0.98	0.98	0.97	0.99	0.97	0.95	0.99	0.99	0.98	1.04	0.98
Guangxi	0.92	0.95	1.00	0.95	1.01	1.03	1.01	1.00	1.00	1.00	0.97	0.95	1.00	0.99	0.86	0.98	0.98

5.2 Discussion

5.2.1 the best and worst performers

According to the results of LCEE performance the 30 selected regions can be classified into some groups by their average values in terms of LECC performance in Table 5.

Table 5 LCEE performance classification for the surveyed regions

Performance group	LCEE scale(ρ)	Regions
Best	>1	None
Excellent	0.9-1	Hainan Fujian Qinghai Jiangsu Yunnan Shanghai
Better	0.8-0.9	Xinjiang，Jiangxi，Guangxi，Guangdong
Good	0.7-0.8	Zhejiang, Guizhou, Henan, Hunan, Hubei, Gansu, Ningxia, Tianjin, Anhui
Poor	0.6-0.7	Shandong, Jilin, Heilongjiang, Chongqing
Very Poor	0.5-0.6	Shaanxi, Hebei, Shanxi, Sichuan

As Table 5 shows, Hainan, Fujian and Qinghai are the top three performers. Their LCEE values are all >0.9 during the surveyed period. They are the pioneering regions in promoting LCE with various measures. Such as, Hainan Province Government has been developing a green transportation system based on electric

Social Sciences in Business and Policy Analysis
www.aprdi.org/all-categories/category-journal

vehicles, public transportation and non-motorized vehicles to reduce carbon emissions in the transportation sector. Besides, it implements a series of energy-saving and carbon-reducing special actions to strengthen publicity and education on the construction of a low-carbon society, and raise the awareness and recognition of carbon peaking and carbon neutrality throughout society. Fujian Province also has carried out a great deal of work to promote the pilot construction of national low-carbon cities and practice the concept of green and low-carbon development.

On the other hand, the data shows that Hebei, Shanxi and Sichuan are the three worst performers. In fact, Shanxi is poor at developing economy which is evidenced from its GDP. Although GDP of Hebei Province is relatively large, its carbon emissions per unit of GDP times higher than the global average value. Thus, it can be found that regions like Hebei and Hunan with similar scales of economy can be very different in LCEE performance. The poor performance of Hebei mainly results from its inefficient industrial structure. The secondary industry in Hebei Province is dominated by heavy industries that consume high amounts of energy and emit high levels of emissions, which has led to high energy consumption and carbon emission intensity.

5.2.2 A regional perspective of LCEE performance

Table 3 demonstrates that China's low carbon economic efficiency presents the overall distribution characteristics of higher efficiency in the eastern regions and lower low-carbon economic efficiency in the central, western and northeastern regions. The average value of the efficiency in the eastern region is 0.82, while that in the central, western and northeastern regions is 0.74, 0.77 and 0.68 respectively. From the perspective of the provinces, Shanghai, Jiangsu, Fujian and Hainan, which belong to the eastern region, have higher low-carbon economic efficiency, with an average value of 0.9 or above. The reason for this is that these regions are ahead of the rest of the country in terms of investment and technological development in economic development and environmental protection, and therefore have remarkable results in the development of low-carbon economy. However, Shandong, Hebei and other regions have low values of low carbon economic efficiency, with average values of 0.69 and 0.59 respectively, which is closely related to their high carbon emissions caused by the industrial structure with a high proportion of heavy industry. The regions with low LCE values are mainly concentrated in the central-western and northeastern regions, such as Shanxi, Sichuan, Heilongjiang and other provinces. Most of these regions are backward in the development of various industries due to the lack of optimization of the energy structure.

Social Sciences in Business and Policy Analysis
www.aprdi.org/all-categories/category-journal

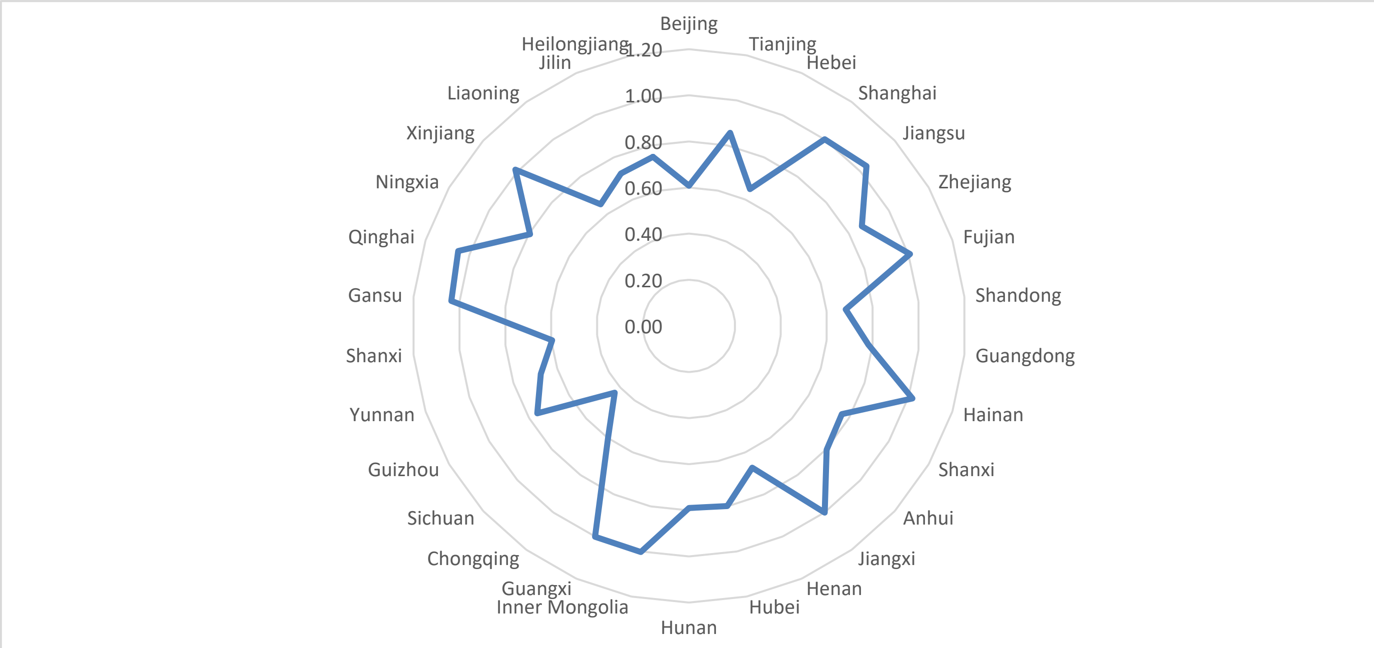

Figure 1 The LCEE value of 30 regions in 2005

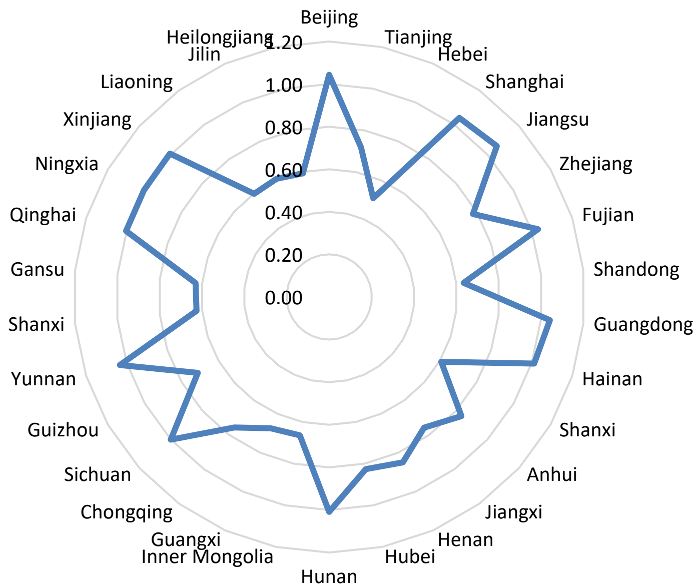

Figure 2 The LCEE value of 30 regions in 2021

The average LCEE value among these regions is 0.822, indicating that the LCEE performance of China is

Social Sciences in Business and Policy Analysis
www.aprdi.org/all-categories/category-journal

still inefficient. According to Figure 1 and 2, the low-carbon economic efficiency of all regions in China is continuously improving, and gradually approaching the efficient state. However, there are still large differences in the changes of low-carbon economic efficiency among regions. As Figure 1 shows, in 2021, the ρ values in Beijing, Shanghai, Fujian, Guangdong, Hainan, Hunan, Sichuan, Yunnan, Qinghai, Ningxia and Xinjiang are larger than 1, which means their low-carbon economy are efficient. However, Residual areas behave inefficiently.

5.2.3 The dynamic perspective of LCEE

As Table 4 shows, China has experienced an improvement in their LCEE performance, with an average value of MPI=1.0062 during the surveyed period, indicating that LCEE has improved by 0.62% annually since 2005.During this period,18 of 30 regions achieved average DLCEE values>1, while the residual regions had a value of DLCEE<1. Therefore, the 30 regions can be divided into two groups as progression group and deterioration group.

We find an interesting phenomenon. According to the results showed in Figure 3, Sichuan Province ranked at the bottom of the list in terms of low-carbon economic efficiency, but it did have the highest MPI value. This means that Sichuan's low-carbon economic efficiency grew significantly faster than other regions during this period. This is due to a series of low-carbon development and emission reduction policies it has put in place. Sichuan is rich in hydropower, wind and solar energy resources, and it has vigorously developed its clean energy industry. Moreover, it supports the R&D and innovation of low-carbon technologies, promotes the transformation of scientific and technological achievements, and improves the market competitiveness of low-carbon technologies. In addition, according to its GDP value, its economy has developed rapidly during this period.

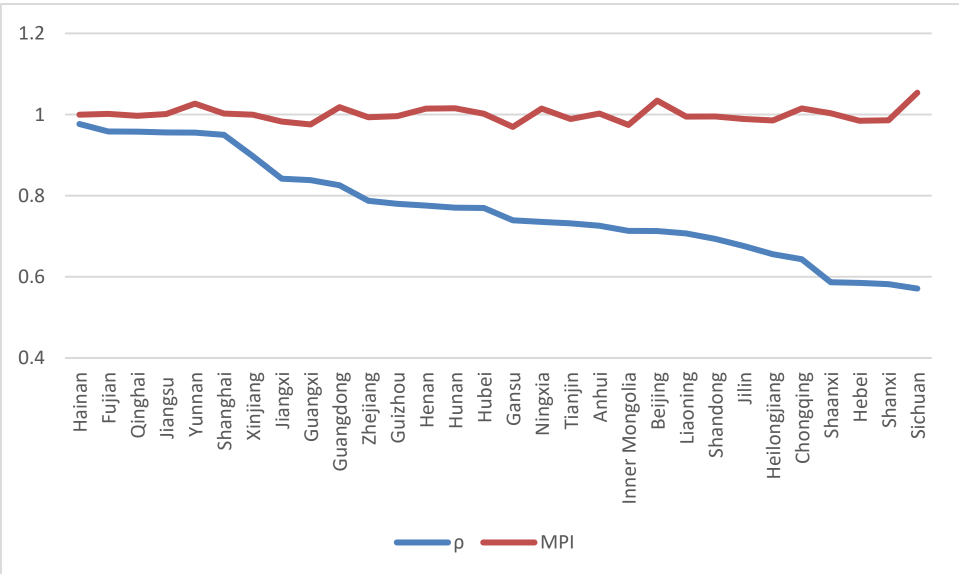

Figure 3 A comparison of LCEE Value(ρ) with MPI among 30 regions

Social Sciences in Business and Policy Analysis
www.aprdi.org/all-categories/category-journal

6. Conclusion

Overall, China's low-carbon economy demonstrates subpar efficiency levels. Hainan, Fujian, and Qinghai provinces emerge as the top performers in average low-carbon economic efficiency, while Hebei, Shanxi, and Sichuan lag behind. The regions excelling in performance are predominantly situated in the eastern part of the country, characterized by robust economic development. Conversely, the underperforming regions are clustered in central, western, and northeastern China, often adopting less sophisticated economic development models, resulting in heightened carbon emissions and undermining low-carbon economy efficiency. However, the study reveals a positive trend, with 60% of regions showing improved low-carbon economic efficiency from 2005 to 2021, although many still fall below average efficiency benchmarks. Notably, Sichuan Province ranks lowest in low-carbon economic efficiency but has witnessed significant growth due to effective policies, achieving efficient status by 2021. This comprehensive evaluation of 30 regions in China provides valuable insights for low-carbon economic development, highlighting the need for diverse economic, technological, and human resource policies. Tailored analyses for different regions and stakeholders can enhance understanding of their successes and challenges in low-carbon economic development. By fostering knowledge exchange on regional development strategies, China can advance towards efficient low-carbon practices. This study lays the groundwork for further research on influencing factors and development trajectories in the low-carbon economy.

References

[1] European Parliament. (2007, February 14). European Parliament resolution on the Green Paper "Towards a European strategy for the rights of the child" (P6_TA(2007)0032). European Parliament. Retrieved June 10, 2024, from https://www.europarl.europa.eu/doceo/document/TA-6-2007-02-14_EN.htmlBeltrán-Esteve, M., Reig-Martínez, E., & Estruch-Guitart, V. (2017). Assessing eco-efficiency: A metafrontier directional distance function approach using life cycle analysis. Environmental Impact Assessment Review, 63, 116-127.

[2] Beltrán-Esteve, M., Reig-Martínez, E., & Estruch-Guitart, V. (2017). Assessing eco-efficiency: A metafrontier directional distance function approach using life cycle analysis. Environmental Impact Assessment Review, 63, 116-127.

[3] Gémar, G., Gómez, T., Molinos-Senante, M., Caballero, R., & Sala-Garrido, R. (2018). Assessing changes in eco-productivity of wastewater treatment plants: The role of costs, pollutant removal efficiency, and greenhouse gas emissions. Environmental Impact Assessment Review, 69, 24-31.

[4] Bortoluzzi, M., de Souza, C. C., & Furlan, M. (2021). Bibliometric analysis of renewable energy types using key performance indicators and multicriteria decision models. Renewable and Sustainable Energy Reviews, 143, 110958.

[5] Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. European journal of operational research, 2(6), 429-444.

Social Sciences in Business and Policy Analysis
www.aprdi.org/all-categories/category-journal

[6] Ali, S. S., Kaur, R., Ersöz, F., Altaf, B., Basu, A., & Weber, G. W. (2020). Measuring carbon performance for sustainable green supply chain practices: A develo** country scenario. Central European Journal of Operations Research, 28(4), 1389-1416.

[7] Kumar, R., Mishra, S. K., Kumar, A., Kumar, I., Kumar, M., Yun, J. H., ... & Singh, A. K. (2023). Investigation of efficient photoconduction and enhanced luminescence characteristics of Ce-doped ZnO nanophosphors for UV sensors. Luminescence, 38(7), 1405-1415.

[8] Tone, K. (2001). A slacks-based measure of efficiency in data envelopment analysis. European journal of operational research, 130(3), 498-509.

[9] ZHOU Zejiong,HU Jianhui. Research on performance evaluation of low-carbon economic development based on Super-SBM model[J]. Resource Science,2013,35(12):2457-2466.(in Chinese)

[10] LI Qiaochu, CHEN Junhua, JING Lei, ZHAO Xiaolan. Research on low carbon economic efficiency of China's energy sector under dual carbon target[J]. Natural Gas Technology and Economy,2022,16(01):67-72. (in Chinese)

[11] Raza, M. Y., & Dongsheng, L. I. (2023). Analysis of energy-related CO2 emissions in Pakistan: carbon source and carbon damage decomposition analysis. Environmental Science and Pollution Research, 30(49), 107598-107610.

[12] Ghosh, S., Dinda, S., Chatterjee, N. D., & Bera, D. (2023). Linking ecological vulnerability and ecosystem service value in a fast-growing metropolitan area of eastern India: a scenario-based sustainability approach. Environment, Development and Sustainability, 1-31.

[13] Li, H., & Shi, J. F. (2014). Energy efficiency analysis on Chinese industrial sectors: an improved Super-SBM model with undesirable outputs. Journal of Cleaner Production, 65, 97-107.

[14] López, F. J., Ho, J. C., & Ruiz-Torres, A. J. (2016). A computational analysis of the impact of correlation and data translation on DEA efficiency scores. Journal of Industrial and Production Engineering, 33(3), 192-204.

[15] Färe, R., Grosskopf, S., & Norris, M. (1997). Productivity growth, technical progress, and efficiency change in industrialized countries: reply. The American Economic Review, 87(5), 1040-1044.