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Measurement and Influencing Factors Analysis of Carbon Emission Efficiency in Coal Resource-Exhausted Cities in China

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Abstract

The economic and social development of coal resource-exhausted cities (CRECs) depends heavily on coal resources. Measures to improve the carbon emission efficiency (CEE) of CRECs are urgently needed because this development path, characterized by high resource dependence, inevitably generates substantial carbon emissions. However, there has not been much focus on the spatial spillover effects and regional heterogeneity of CEE in these cities. To address this gap, this study selects 37 Chinese CRECs as research subjects. It comprehensively evaluates the static characteristics and dynamic changes in these cities' CEE from 2011 to 2023 using the SBM-DDF model and the GML index. It then employs the spatial Durbin model to identify key influencing factors of CEE. According to the empirical results, the average CEE of the sample cities did not reach the production frontier, generally remaining at a moderate level and fluctuating. The main factor driving CEE growth for CRECs in all regions is technological progress. CRECs in the western region had the greatest growth in CEE (0.71%), followed by the northeastern (0.36%) and central (0.05%) regions, while the growth in CEE remained unchanged in the eastern region. The local CEE grew by 0.286 units for every unit increase in CEE in neighboring cities, demonstrating the spillover effects essential for regional sustainability. There is significant regional heterogeneity in the influencing factors of CEE in China's CRECs, necessitating tailored sustainable development strategies.

Keywords: coal resource-exhausted cities; carbon emission efficiency; SBM-DDF-GML; influencing factors; sustainable development

1. Introduction

Approximately 70% of global carbon emissions originate from cities [1]. Meanwhile, cities are regarded as the main battleground for controlling carbon emissions. Academic institutions and government agencies are increasingly concerned with the scientific measurement of urban CEE. Due to their heavy reliance on coal resources, coal-resource-based cities face particular challenges in achieving a low-carbon transition. Such cities are widely distributed across major economies, such as China, Australia, the United States, and Germany [2]. For example, coal-based cities make up the majority of China's 262 resource-based cities. The rapid development of these cities is inextricably associated with coal mining [3]. Many of these cities are progressively entering the stage of resource depletion due to the continuous extraction of coal resources, which has become a major turning point in their development trajectory [4]. CRECs currently have two paths when faced with resource constraints: transformation or decline. Transformation means that CRECs, constrained by the depletion of coal resources, achieve an institutional leap from "heavy reliance on



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high-carbon fossil fuels” to “green, low-carbon, and sustainable development” through energy decarbonization, industrial restructuring, and ecological restoration. For instance, the Wansheng Economic and Technological Development District in Chongqing, China, has been seeking a path to sustainable transformation and carefully developed “new energy and new materials” as its two leading industries to break free from the “coal-dominated” energy and industrial model. To restore the ecosystem, it has also actively promoted the development of eco-tourism and carried out afforestation in subsidence areas. Consequently, Wansheng District ranked third in the 2023 Performance Evaluation of the Transformation of China’s Resource-Depleted Cities. Decline signifies that the systemic functions of cities across multiple dimensions, such as the economy, society, and ecology, gradually weaken, which no city would willingly accept. Therefore, the green and low-carbon transition is a key pathway for CRECs to revitalize themselves [5].

China has identified 69 typical resource-exhausted cities (counties, districts), of which 37 are CRECs, making up 53.62% of the total. Therefore, the total efficacy of China’s green transformation of resource-depleted cities depends critically on the achievement of CRECs’ low-carbon transition. Nevertheless, existing studies have not yet provided an adequate systematic assessment of CEE in CRECs or fully investigated the influencing factors, especially in relation to spatial spillover effects and regional heterogeneity. This study intends to close these gaps by systematically measuring the CEE of CRECs in China and identifying their key determinants. This will provide empirical support for the formulation of tailored low-carbon transition policies.

2. Literature Review

2.1. Measurement Method of CEE

To measure CEE across various sectors, scholars have primarily employed methods like DEA, SFA, the SBM model, and DDF [6]. DEA and SFA served as the main foundation for early research. Cheng et al. applied the DEA model to estimate carbon efficiency across 29 provinces in China [7]. In contrast, Cui developed a networked version of this method to assess the greenhouse gas emission efficiency of 28 international airlines [8]. Zhao et al. (2022) estimated the CEE of the transportation sector across 30 Chinese provinces by combining the EBM and DEA models based on expected output, suggesting that the developed coastal regions had the highest carbon emission efficiency [9]. Yu et al. and Yin et al. used the SFA method to assess CEE across 30 provincial-level administrative regions in China [10,11]. Wang et al. measured CEE in the industrial sector of 11 provinces and municipalities along China’s Yangtze River by further combining the SFA method with carbon productivity [12]. Researchers then turned their attention to environmental constraint indicators, and evaluation models for carbon emission efficiency expanded from traditional radial models to SBM models, which can handle slack variables directly. Wang et al. and Wu et al. adopted the super-efficiency SBM-DEA framework to measure the CEE of Chinese provinces and cities [13,14]. The DDF and its integration with the SBM have become new focal points as the treatment of undesirable outputs in environmental constraints has grown in importance. Tian evaluated the CEE of 282 Chinese cities via the DDF model [15]. Zhang and Zhao employed the SBM-DDF framework to calculate the CEE of Chinese aviation enterprises [16]. Current research indicates that there is a scarcity of literature evaluating CEE using the SBM-DDF framework in conjunction with the Global Malmquist–Luenberger (GML) index, especially when it comes to its application to measuring the CEE in CRECs. The combination of SBM and DDF not only utilizes the flexibility of DDF in direction and its ability to directly handle undesirable outputs, but also leverages the non-radial nature of SBM and its direct consideration of slack variables, enabling a more accurate measurement of CEE.

2.2. Influencing Factors of CEE

Economic development, industrial structure, urbanization, foreign investment, government intervention, technological innovation, intellectual property demonstration policy, the digital economy, artificial intelligence (AI), and other aspects are the main areas of study for scholars. Gong et al. pointed out that economic development and industrial structure had a favorable influence on CEE across 98 municipalities in the Yellow River Basin [17]. According to Liu and Hao, higher levels of urbanization are detrimental to the enhancement of CEE in provinces and cities along the Yangtze River [18]. Jin et al. also found that foreign investment, urbanization, and government intervention have a detrimental impact on the CEE in this region [19]. Li et al., Zhang et al., and Park et al. noted that technological innovation can improve CEE [20–22]. Yao et al. indicated that intellectual property demonstration policies significantly enhance CEE [23]. The development of the digital economy can improve urban CEE, according to research by Han et al., Hou et al., and Liu et al. [24–26]. Zhang et al., Xiao et al., Wu et al., and Wen et al. analyzed the impact of AI on CEE across various cities and found that its application can improve urban CEE [27–30].

When analyzing the influencing factors of CEE, scholars mainly employ the SDA [31], IDA [32,33], LMDI [34–37], and the Tobit model [38,39]. Few studies use spatial econometric models to investigate the key determinants of CEE in CRECs. There may be spatial dependence between the CEE and the influencing factors since many Chinese cities are geographically close to or even directly adjacent to one another. Ignoring this spatial dependence could result in errors in model estimates and hinder the detection of the key determinants affecting these cities' CEE.

2.3. Literature Gaps

Even if there is abundant research on CEE, few studies have analyzed the spatiotemporal evolution of CEE in CRECs and its influencing factors. At the same time, existing literature has predominantly emphasized the CEE of resource-based cities [40–43], while few studies directly measure the CEE of resource-exhausted cities. The CEE of resource-exhausted cities is rarely measured in current research, which mainly addresses issues such as urban CO₂ emissions and corporate carbon emission intensity [44–46]. Although a substantial body of research has examined the determinants of urban CEE [17–30], the “carbon lock-in” effect caused by CRECs' persistent reliance on coal implies that the influencing factors of their CEE may differ from those observed in other city types. Accordingly, there is substantial theoretical and practical significance to measuring CEE and analyzing its determinants in this specific kind of city. Additionally, the limited research on CEE in resource-based cities has predominantly relied on non-spatial approaches. For example, Song et al. employed Tobit regression to analyze influencing factors such as energy intensity and urbanization rate [40], while Niu et al. applied a panel threshold model to reveal the moderation of income inequality in the relationship between AI and CEE [42]. The independence of observations is a common implicit premise throughout various approaches. However, the spatial dependence of their CEE cannot be ignored because many of China's 37 CRECs are geographically proximate or directly adjacent. Currently, few studies have employed spatial econometric models to explore the spatial spillover effects of CEE in CRECs, and even less research has investigated the spatial heterogeneity of the driving factors of CEE. Consequently, this study employs the SBM-DDF framework and the GML index to conduct comprehensive static and dynamic evaluations of CEE across 37 CRECs in China from 2011 to 2023. Building on this, this study analyzes the spatiotemporal evolution of CEE and further applies spatial econometric models to examine both the spatial spillover effects and the spatial heterogeneity of its influencing factors.

3. Methodology and Data

3.1. Methodology

3.1.1. SBM-DDF Framework

If there are slack variables in the input-output system and the model fails to include both input and output dimensions, conventional DEA specifications naturally tend to overstate efficiency. Therefore, Fukuyama and Weber [47] proposed the SBM-DDF model by integrating the SBM model [48] with slack variables and a directional distance function. In addition to resolving issues with multiple inputs and outputs, this model also effectively addresses accuracy problems caused by excessive inputs or insufficient outputs, thereby more accurately reflecting the relationships between inputs, outputs, and pollution emissions.

Assume that each decision-making unit (DMU) in a city employs N inputs to generate M desired and H undesired outputs. Denoting the input vector as x , the desired output vector as y , and the undesirable output vector as b , the SBM-DDF model is formulated below:

$$\begin{aligned} \vec{D}^t(x^{t,k}, y^{t,k}, b^{t,k}, g^x, g^y, g^b) = \max_{s^x, s^y, s^b} & \left[\frac{1}{N} \sum_{n=1}^N \frac{s_n^x}{g_n^x} + \frac{1}{M+H} \left(\sum_{m=1}^M \frac{s_m^y}{g_m^y} + \sum_{h=1}^H \frac{s_h^b}{g_h^b} \right) \right] / 2 \\ \text{s.t. } & \sum_{k=1}^K z_k^t x_{kn}^t + s_n^x = x_{k'n}^t, \forall n \\ & \sum_{k=1}^K z_k^t y_{km}^t - s_m^y = y_{k'm}^t, \forall m \\ & \sum_{k=1}^K z_k^t b_{kh}^t + s_h^b = b_{k'h}^t, \forall h \\ & \sum_{k=1}^K z_k^t = 1, z_k^t \geq 0, \forall k \\ & s_n^x \geq 0, \forall n; s_m^y \geq 0, \forall m; s_h^b \geq 0, \forall h \end{aligned} \quad (1)$$

where $(x^{t,k}, y^{t,k}, b^{t,k})$ represents the inputs and outputs during the period t , and (g^x, g^y, g^b) refers to the direction vectors for reducing inputs, increasing desired output, and abating undesired output. (s_n^x, s_m^y, s_h^b) is the slack vector, denoting redundant inputs, inadequate desired output, and superfluous undesired output, respectively. k stands for the number of decision-making units.

3.1.2. GML Index

Most studies fail to provide insights into the temporal evolution in CEE because they utilize cross-sectional data and DEA to measure environmental performance. Therefore, the GML approach is adopted to track the dynamic trajectory of CEE. The GML index is presented below:

$$\begin{aligned} GML_t^{t+1}(x^t, y^t, b^t, x^{t+1}, y^{t+1}, b^{t+1}) &= \frac{1 + \vec{D}^t(x^t, y^t, b^t)}{1 + \vec{D}^{t+1}(x^{t+1}, y^{t+1}, b^{t+1})} \\ &= \frac{1 + \vec{D}^t(x^t, y^t, b^t)}{1 + \vec{D}^{t+1}(x^{t+1}, y^{t+1}, b^{t+1})} \times \frac{[1 + \vec{D}^G(x^t, y^t, b^t)] / [1 + \vec{D}^t(x^t, y^t, b^t)]}{[1 + \vec{D}^G(x^{t+1}, y^{t+1}, b^{t+1})] / [1 + \vec{D}^{t+1}(x^{t+1}, y^{t+1}, b^{t+1})]} \\ &= EC \times TC \end{aligned} \quad (2)$$

where $\vec{D}^t(x^t, y^t, b^t)$ and $\vec{D}^{t+1}(x^{t+1}, y^{t+1}, b^{t+1})$ denote directional distance functions for the periods t and $t+1$, while $\vec{D}^G(x^t, y^t, b^t)$ and $\vec{D}^G(x^{t+1}, y^{t+1}, b^{t+1})$ are their global counterparts. The GML index is decomposed into the efficiency change component (EC) and the technical change component (TC). $GML_t^{t+1} > 1$ signals an improvement in the overall efficiency, whereas $GML_t^{t+1} < 1$ indicates a decline. $EC > 1$ signifies progress in technological efficiency, and $TC > 1$ reflects advancement in production technology, while values below 1 denote deterioration.

3.1.3. Spatial Durbin Model

The SDM holds that not only local independent variables but also independent and dependent variables in adjacent spatial units influence the dependent variable in a given spatial unit. China's CRECs are not isolated from each other; many are interconnected. For example, Xuzhou, Huaibei, and Zaozhuang are all core cities within the Huaihai Economic Zone. As a result, this study accounts for spatial effects when analyzing the influencing factors of CEE in CRECs. In the meantime, it uses the Lagrange Multiplier (LM) test and finds that the SDM should be adopted to analyze the influencing factors of CEE in CRECs. SDM is as follows:

$$CEE_{it} = \beta_{it}x_{it} + \rho \sum_{j=1}^n W_{ij}CEE_{jt} + \phi \sum_{j=1}^n W_{ij}x_{jt} + \mu_i + v_t + \varepsilon_{it} \quad (3)$$

where CEE_{it} represents the dependent variable, i.e., the CEE; x_{it} refers to the independent variables, i.e., the influencing factors of CEE in CRECs; i and j denote the cities i and j , respectively; t is time (i.e., the year); β_{it} denotes the regression coefficient of the independent variable, ρ stands for the spatial correlation coefficient, W_{ij} indicates the inverse-distance weighting matrix, and ϕ denotes the spatial lag regression coefficient of the independent variable. μ_i , v_t , and ε_{it} represent the individual random effects, time fixed effects, and random errors, respectively.

The geographic distance d_{ij} (measured in kilometers) between city i and city j was measured using the Haversine formula, based on the longitude and latitude coordinates of the two city centers to calculate the great-circle distances. The elements of the inverse-distance weight matrix are defined as $w_{ij} = 1/d_{ij}$ for $i \neq j$, with all diagonal entries $w_{ii} = 0$. No distance-based truncation threshold was applied, but all cities were included in the weighting scheme, assuming that each city pair exhibits a certain degree of spatial interdependence. This approach is consistent with the underlying rationale of the inverse-distance matrix. Consequently, this study row-standardized the resulting weight matrix for estimation.

3.2. Data Source

China has identified 37 CRECs (districts, counties), including Chongqing (the municipality directly under the central government, including Wansheng District and Nanchuan District), 16 prefecture-level cities, 20 district- and county-level areas, and mining areas. Due to the lack of relevant statistical data at the district and county levels, as well as in mining areas, their low-carbon transitions cannot be independently evaluated in the prefecture-level cities. Thus, data from their respective prefecture-level cities would be used as a substitute. For example, statistical data for Beipiao City, Jiawang District, and Yingshouyingzi Mining District were replaced with data from Chaoyang City, Xuzhou City, and Chengde City, respectively. As of 2011, all 37 CRECs (districts and counties) in China had been identified. This study uses the panel data for 37 CRECs covering the period from 2011 to 2023 based upon data accessibility and analytical validity.

The empirical data were drawn from multiple official sources, including the China City Statistical Yearbook, the China Energy Statistical Yearbook, various provincial and municipal statistical yearbooks, and national economic development bulletins. Figures of CO₂ emission were obtained from the Emissions Database for Global Atmospheric Research (EDGAR). Missing observations were addressed through linear interpolation and panel data for the 37 CRECs were compiled after calculation and collation. The 37 CRECs are summarized in Table 1.

Table 1. List of 37 CRECs.

Region	Province	City
Eastern China	Hebei	Shijiazhuang, Zhangjiakou, Chengde
	Jiangsu	Xuzhou
	Shandong	Zibo, Zaozhuang, Taian
	Guangdong	Shaoguan
Central China	Shanxi	Lvliang, Linfen
	Anhui	Huaibei
	Jiangxi	Pingxiang
	Henan	Jiaozuo
	Hubei	Huangshi, Jingzhou
	Hunan	Hengyang, Chenzhou, Loudi
Western China	Neimenggu	Baotou, Wuhai
	Guangxi	Laibin
	Chongqing	Chongqing
	Sichuan	Guang'an
	Shaanxi	Tongchuan
	Gansu	Lanzhou
	Ningxia	Shizuishan
Northeastern China	Liaoning	Fushun, Fuxin, Chaoyang, Huludao
	Jilin	Changchun, Liaoyuan, Tonghua, Baishan
	Heilongjiang	Hegang, Shuangyashan, Qitaihe

3.3. Variables

3.3.1. Variables Used to Calculate CEE

This study employs the SBM-DDF model for static estimation and applies the GML index for dynamic evaluation to evaluate the CEE of 37 CRECs over the 2011–2023 period. Three inputs (labor, capital, and energy), one desirable output (regional GDP), and one undesirable output (carbon emissions) are selected as indicators, drawing on the indicator system in References [14,17–19,25,49], as shown in Table 2. To guarantee comparability of data and eliminate price influences, the stock of fixed capital and regional GDP are adjusted using 2011 as the base year.

Table 2. Input-output Indicators for the Measurement of CEE.

Indicator	Primary Indices	Secondary Indices	Unit
Input	Labor	Number of employees	10 ⁴ people
	Capital	Stock of fixed capital	10 ⁸ yuan
	Energy	Energy consumption	10 ⁴ tons of standard coal
Output	Desirable	GDP at constant prices	10 ⁸ yuan
	Undesirable	CO ₂ emissions	10 ⁴ tons

According to Zhang et al. [50], the stock of fixed capital is measured via the perpetual inventory method, specified as:

$$K_{it} = K_{it-1}(1 - \delta) + I_{it} \quad (4)$$

where K_{it} and K_{it-1} denote the stock of fixed capital of city i in years t and $t - 1$, respectively; δ is the depreciation rate, set at 9.6%; and I_{it} represents the fixed asset investment of city i in year t . For the initial fixed capital stock in the base year (2011), this study adopts the

simplified method of Zhang et al. [50], which calculates it as the fixed asset investment of each city in 2011 divided by 10%.

3.3.2. Variables of Influencing Factors

Drawing on pertinent studies [17–19], the level of economic development (LED), the level of urbanization (LU), the industrial structure (IS), the energy efficiency (EE), the level of government intervention (LGI), and the degree of openness (DO) are selected as factors influencing CEE in CRECs in this study (see Table 3).

Table 3. Influencing factors of CEE.

Primary Indices	Secondary Indices	Unit
Level of economic development (LED)	GDP per capita at constant prices	yuan per person
Level of urbanization (LU)	Urbanization rate	%
Industrial structure (IS)	The GDP proportion of secondary industry	%
Energy efficiency (EE)	GDP generated per unit of energy consumed	yuan per ton
Level of government intervention (LGI)	Local general public budget expenditure as a share of GDP	%
Degree of openness (DO)	Total imports and exports as a proportion of GDP	%

4. Results and Discussion

4.1. Analysis of CEE in the CRECs

4.1.1. Static Evaluation

The static CEE for 37 CRECs from 2011 to 2023 was calculated based on Equation (1) (see Table 4).

Table 4. CEE in the CRECs.

City	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	Mean
Shijiazhuang	0.77	0.79	0.81	0.79	0.80	0.82	0.80	0.77	0.72	0.72	0.73	0.74	0.73	0.77
Zhangjiakou	0.69	0.70	0.71	0.71	0.72	0.73	0.70	0.69	0.68	0.68	0.68	0.68	0.67	0.70
Chengde	0.76	0.77	0.77	0.78	0.79	0.81	0.73	0.72	0.71	0.71	0.72	0.72	0.70	0.74
Xuzhou	0.78	0.82	0.76	0.78	0.82	1.00	0.88	0.88	0.94	0.93	1.00	0.99	1.00	0.89
Zibo	0.76	0.77	0.78	0.80	0.80	0.91	0.88	0.83	0.72	0.71	0.73	0.73	0.74	0.78
Zaozhuang	0.76	0.77	0.77	0.79	0.81	0.82	0.78	0.80	0.70	0.70	0.71	0.71	0.71	0.76
Taian	0.80	0.80	0.79	0.90	0.96	0.92	0.78	0.83	0.71	0.71	0.70	0.71	0.71	0.79
Shaoguan	0.71	0.72	0.73	0.74	0.75	0.76	0.73	0.72	0.71	0.71	0.72	0.71	0.71	0.72
Lvliang	1.00	1.00	0.97	0.92	0.85	0.86	0.70	0.69	0.69	0.68	0.71	0.73	0.71	0.81
Linfen	0.74	0.73	0.73	0.72	0.74	0.75	0.68	0.68	0.68	0.67	0.70	0.71	0.69	0.71
HuaiBei	0.70	0.71	0.70	0.71	0.72	0.73	0.71	0.71	0.72	0.73	0.75	0.75	0.74	0.72
Pingxiang	0.71	0.72	0.71	0.72	0.73	0.74	0.65	0.72	0.70	0.69	0.72	0.72	0.71	0.71
Jiaozuo	0.72	0.72	0.72	0.73	0.73	0.73	0.73	0.77	0.79	0.72	0.71	0.72	0.71	0.73
Huangshi	0.68	0.70	0.70	0.71	0.70	0.71	0.70	0.70	0.71	0.69	0.70	0.70	0.68	0.70
Jingzhou	0.76	0.75	0.77	0.78	0.79	0.80	0.76	0.75	0.79	0.75	0.76	0.77	0.76	0.77
Hengyang	0.82	0.90	0.98	1.00	1.00	1.00	0.91	0.92	0.94	0.94	0.98	1.00	1.00	0.95
Chenzhou	0.82	0.84	0.86	0.92	0.96	1.00	0.80	0.81	0.79	0.78	0.82	0.86	0.92	0.86
Loudi	0.75	0.76	0.75	0.76	0.78	0.78	0.73	0.73	0.73	0.72	0.73	0.74	0.75	0.75
Baotou	0.81	0.86	0.85	0.88	0.88	1.00	0.71	0.75	0.72	0.72	0.76	0.78	0.83	0.81
Wuhai	0.70	0.72	0.72	0.73	0.73	0.74	0.69	0.71	0.73	0.74	0.91	1.00	0.81	0.76
Laibin	0.70	0.70	0.70	0.72	0.71	0.73	0.73	0.72	0.70	0.70	0.72	0.73	0.74	0.71
Chongqing	0.73	0.71	0.71	0.72	0.74	0.80	0.80	0.79	0.84	0.85	0.88	0.88	0.93	0.80

Table 4. Cont.

City	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	Mean
Guang'an	0.76	0.82	0.74	0.74	0.87	0.82	0.71	0.70	0.69	0.69	0.69	0.67	0.68	0.74
Tongchuan	0.68	0.69	0.70	0.69	0.69	0.67	0.67	0.64	0.64	0.65	0.66	0.67	0.66	0.67
Lanzhou	0.68	0.69	0.69	0.71	0.72	0.73	0.72	0.73	0.73	0.73	0.74	0.74	0.74	0.72
Shizuishan	0.67	0.68	0.69	0.69	0.70	0.72	0.70	0.73	0.70	0.70	0.72	0.74	0.72	0.71
Fushun	0.71	0.73	0.73	0.73	0.73	0.69	0.69	0.71	0.68	0.67	0.68	0.69	0.70	0.70
Fuxin	0.69	0.70	0.71	0.71	0.70	0.68	0.67	0.68	0.69	0.70	0.71	0.71	0.71	0.70
Chaoyang	0.76	0.77	0.79	0.79	0.72	0.69	0.69	0.70	0.69	0.69	0.70	0.70	0.71	0.72
Huludao	0.69	0.71	0.70	0.69	0.70	0.69	0.71	0.73	0.73	0.72	0.73	0.73	0.73	0.71
Changchun	0.81	0.84	0.85	0.86	0.90	0.93	0.81	0.96	0.81	0.85	0.86	0.82	0.82	0.85
Liaoyuan	0.82	1.00	0.87	0.88	0.95	1.00	0.70	0.84	0.70	0.71	0.73	0.73	0.72	0.82
Tonghua	0.80	0.88	0.89	0.88	0.91	0.78	0.41	0.73	0.70	0.71	0.67	0.67	0.67	0.75
Baishan	0.74	0.79	0.81	0.80	0.82	0.86	0.65	0.75	0.70	0.69	0.71	0.71	0.71	0.75
Hegang	0.71	0.76	0.70	0.68	0.69	0.69	0.69	0.70	0.76	0.79	0.83	1.00	0.92	0.76
Shuangyashan	0.74	0.76	0.74	0.69	0.69	0.69	0.70	0.69	0.70	0.71	0.72	0.73	0.73	0.71
Qitaihe	0.81	0.73	0.67	0.66	0.67	0.68	0.69	0.70	0.69	0.68	0.69	0.71	0.71	0.70
Mean	0.75	0.77	0.76	0.77	0.78	0.80	0.72	0.75	0.73	0.73	0.75	0.76	0.75	0.76

Table 4 indicates that none of the 37 CRECs reached the production frontier in terms of average CEE between 2011 and 2023. There is still space for improvement, since the average CEE for Hengyang, Xuzhou, Chenzhou, Changchun, Liaoyuan, Baotou, Lvliang, and Chongqing ranges from 0.8 to 1. The average CEE for the remaining 29 cities ranged from 0.6 to 0.8, indicating a moderate level. These cities have significant potential to improve their CEE, and the key lies in implementing appropriate carbon policies.

The annual CEE results for CRECs indicate that their overall level was generally moderate. The average CEE of sample cities nationwide, as well as those in the eastern, central, western, and northeastern regions are used as the respective regional CEE for CRECs. The results demonstrate that the CEE of CRECs across all regions exhibited fluctuations of repeated rises and declines throughout the study (see Figure 1). This implies that the low-carbon transformation of China's CRECs has not been easy.

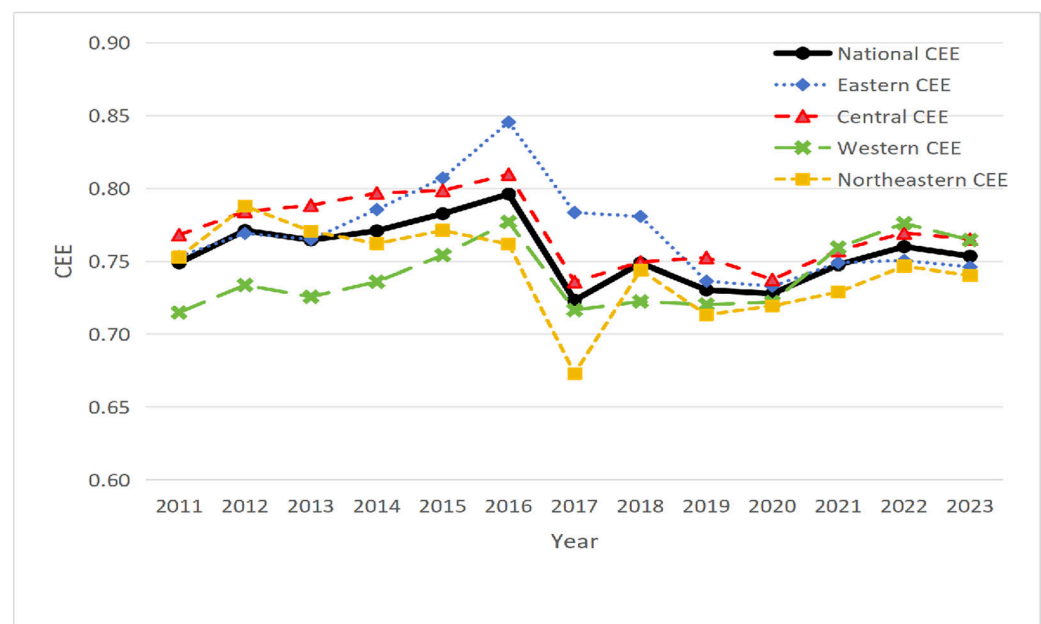


Figure 1. Changes in CEE in CRECs from 2011 to 2023.

For CRECs as a whole, CEE shows an inverted U-shaped trend of first rising, then falling, and then stabilizing during the study period, but it remains relatively stable with little fluctuation, with a stable value of around 0.75 and an average value of 0.76, indicating a relatively low level of CEE (see Figure 1).

At the regional level, the average efficiency is 0.77 in the eastern and central regions, which is higher than the national average, whereas it is 0.74 in the western and northeastern regions. The efficiency trajectory in the western region roughly mirrors the national pattern in terms of temporal dynamics, while the central region consistently outperforms the national average across all years. Compared to the other three regions, the eastern region has noticeably higher CEE in selected years. This discrepancy is largely attributable to the eastern area's marked superiority in low-carbon technology innovation. Existing studies have confirmed that low-carbon technology innovation improves CEE [51,52]. For the majority of regions, CEE peaked in 2016, while for a number of regions, 2020 represents a trough. The CEE of all four regions in 2021 is higher than in 2020. China put forth the “dual carbon” goals in 2020. The CEE of the four regions increased in both 2021 and 2022, implying that national policy interventions have exerted a notable influence on steering the low-carbon transition of China's CRECs.

4.1.2. Analysis of Dynamic Changes

This study decomposes changes in CEE within the CRECs into changes in EC and TC based on Equation (2) (see Tables 5–7).

Table 5. Overall CEE in the CRECs from 2011 to 2023.

Year	EC	TC	GML
2011–2012	0.9914	1.0401	1.0291
2012–2013	0.9802	1.0205	0.9926
2013–2014	0.9908	1.0180	1.0082
2014–2015	0.9864	1.0326	1.0149
2015–2016	0.9934	1.0241	1.0168
2016–2017	0.9781	0.9409	0.9174
2017–2018	1.0410	1.0105	1.0446
2018–2019	0.9780	1.0078	0.9780
2019–2020	1.0010	0.9984	0.9966
2020–2021	1.0065	1.0197	1.0261
2021–2022	1.0091	1.0095	1.0156
2022–2023	1.0101	0.9832	0.9929
Mean	0.9972	1.0088	1.0027

Table 6. Decomposition of the CEE in the 37 CRECs from 2011 to 2023.

City	EC	TC	GML	City	EC	TC	GML
Shijiazhuang	0.9880	1.0146	0.9959	Wuhai	1.0325	1.0027	1.0166
Zhangjiakou	0.9935	1.0045	0.9979	Laibin	1.0010	1.0041	1.0048
Chengde	0.9850	1.0094	0.9940	Chongqing	1.0161	1.0061	1.0208
Xuzhou	1.0029	1.0250	1.0241	Guang'an	0.9964	1.0147	0.9935
Zibo	0.9825	1.0206	0.9996	Tongchuan	0.9964	1.0018	0.9981
Zaozhuang	0.9803	1.0163	0.9951	Lanzhou	1.0175	0.9926	1.0076
Taian	0.9844	1.0109	0.9933	Shizuishan	1.0028	1.0052	1.0068
Shaoguan	0.9979	1.0024	0.9998	Fushun	0.9941	1.0052	0.9988
Lvliang	0.9789	0.9974	0.9732	Fuxin	1.0036	0.9999	1.0032
Linfen	0.9904	1.0052	0.9955	Chaoyang	0.9870	1.0095	0.9952
Huaipei	0.9995	1.0056	1.0046	Huludao	1.0084	0.9983	1.0048
Pingxiang	0.9945	1.0064	1.0013	Changchun	0.9890	1.0171	1.0047
Jiaozuo	0.9920	1.0079	0.9993	Liaoyuan	0.9882	1.0177	0.9997
Huangshi	0.9965	1.0037	0.9999	Tonghua	0.9943	1.0175	1.0179
Jingzhou	0.9891	1.0126	1.0009	Baishan	0.9923	1.0090	1.0017
Hengyang	1.0000	1.0176	1.0176	Hegang	1.0234	1.0124	1.0246
Chenzhou	1.0019	1.0117	1.0124	Shuangyashan	1.0026	0.9983	0.9996
Loudi	0.9928	1.0075	1.0001	Qitaihe	0.9923	1.0201	0.9896
Baotou	1.0067	1.0134	1.0083				

Table 7. Decomposition of CEE in the CRECs for Different Regions.

Region	EC	TC	GML
Eastern	0.9893	1.0129	1.0000
Central	0.9936	1.0076	1.0005
Western	1.0087	1.0051	1.0071
Northeastern	0.9977	1.0095	1.0036
Nationwide	0.9972	1.0088	1.0027

Table 5 indicates that for CRECs as a whole, the CEE grew by an average of 0.27% annually between 2011 and 2023. Technological efficiency decreased by 0.28% over this time, while technological progress increased by 0.88%. Thus, the growth in CEE was primarily driven by technological progress. CEE grew in most years when examining changes in CEE across different time periods. Looking at the technological efficiency changes over different periods, it declined year by year from 2011 to 2017 and increased year by year from 2020 to 2023, generally following a V-shaped trend. The main reason is that after the first batch of CRECs was designated in 2007, alternative industries such as new energy and new materials had weak output due to insufficient technological accumulation and capital investment. However, the traditional coal industry rapidly contracted due to resource depletion, leading to a gap in the transition from old to new growth drivers. The allocation of production factors remained in a state of “inefficiency” for a long time due to the sharp increase in adjustment costs during the transitional period, resulting in a continuous decline in technological efficiency. In 2020, China proposed the “dual carbon” goals. The state continues to support CRECs through special transfer payments, industrial subsidies, and green credit, providing institutional safeguards for improving the efficiency of factor allocation. Alternative industries, such as new energy and new materials, have also begun to generate effective output after years of cultivation, with technological efficiency having been steadily improving. Thus it can be seen that technological efficiency is significantly influenced by policy.

Shijiazhuang, Zhangjiakou, Chengde, Zibo, Zaozhuang, Taian, Shaoguan, Lvliang, Linfen, Jiaozuo, Huangshi, Guang'an, Tongchuan, Fushun, Chaoyang, Liaoyuan, Shuangyashan, and Qitaihe had GML indices below 1 between 2011 and 2023 (see Table 6), indicating that the CEE in these cities was declining. However, the GML indices for the remaining 19 cities were greater than 1, demonstrating that their CEE is increasing. Hegang's GML index grew the fastest over the 13 years, while Lvliang's declined the most.

Further analysis of the GML index components reveals that the GML index above 1 in nine cities—Xuzhou, Hengyang, Chenzhou, Baotou, Wuhai, Laibin, Chongqing, Shizuishan, and Hegang—was driven by concurrent improvements in both EC and TC. TC was the only cause of the GML index above 1 in seven cities: Huaibei, Pingxiang, Jingzhou, Loudi, Changchun, Tonghua, and Baishan. In contrast, improvements in EC were the only reason why the GML index for three cities—Lanzhou, Fuxin, and Huludao. Overall, most cities with a GML index below 1 have an EC below 1, suggesting that the primary cause of reduced CEE is declining technological efficiency.

Table 7 indicates that the CEE increased in CRECs across the other three regions between 2011 and 2023, while it remained unchanged in eastern CRECs. Among them, the CEE grew the fastest in western CRECs, with an average annual growth rate of 0.71%, followed by the Northeast at 0.36%, and finally the central region at 0.05%. In particular, the synergistic effects of EC and TC led to the increase in CEE in western CRECs, whereas TC was the main driver of development in central and northeastern CRECs.

4.2. Analysis of the Influencing Factors of CEE in the CRECs

4.2.1. Spatial Correlation Test of CEE

This study employed STATA 18 to derive the Moran's I coefficients of CEE across the 37 CRECs (see Table 8).

Table 8. Moran's I Values.

Year	Moran's I	p-Value
2011	0.1122	0.0019
2012	0.0784	0.0206
2013	0.1270	0.0006
2014	0.0719	0.0302
2015	0.1357	0.0004
2016	0.1393	0.0003
2017	0.1381	0.0003
2018	0.1182	0.0016
2019	0.1162	0.0018
2020	0.1089	0.0032
2021	0.0682	0.0404
2022	0.0637	0.0511
2023	0.0966	0.0088

Table 8 reports the Moran's I values between 2011 and 2023. All of which are positive and significant, suggesting that the CEE of the 37 CRECs exhibits significant spatial autocorrelation. Therefore, it is essential to account for spatial effects and employ a spatial econometric model for estimation when analyzing the influencing factors of CEE across these 37 CRECs.

4.2.2. Spatial Model Selection

This study first uses the LM test and its robust counterpart to select the appropriate model, with results reported in Table 9.

Table 9. The Results of the LM Test and Its Robust Counterpart.

Test Type	Spatial Error			Spatial Lag		Hausman
	Moran'I	LM	Robust LM	LM	Robust LM	Value
Result	1.993 **	2.835 *	17.826 ***	3.638 *	18.629 ***	17.28

***, ** and * indicate significance at the 1%, 5%, and 10% levels, respectively.

As shown in Table 9, the SDM is the more appropriate option. To determine whether a fixed-effects or random-effects specification was more suitable for the data, the Hausman test was conducted. With a chi-squared statistic of 17.28 (df = 13) returned and a *p*-value of 0.1869, the test fell well above the 5% significance threshold (the critical value $\chi_{0.05}^2(13) = 22.36$). This result supports the use of a random-effects SDM because this study cannot reject the null hypothesis in favor of random effects.

To further validate this choice, this study decomposed the between- and within-group variation for the core explanatory variables. In comparison to their within-group equivalents, which were 0.1638, 0.0584, 0.4859, and 0.0285, the between-group standard deviations for lnLED, LU, lnEE, and DO were 0.3636, 0.1267, 0.5470, and 0.0614, respectively. Given that a fixed-effects estimator relies primarily on within-group variation, much of the between-group information would be absorbed and potentially lost, causing imprecise estimates. The random-effects technique, on the other hand, exploits both sources of variation, making it more efficient in this context. Therefore, the random-effects SDM was adopted for the main analysis.

Next, this study performs a likelihood ratio (LR) test to evaluate whether the SDM can be simplified to the SLM or the SEM (see Table 10). The test results demonstrate that the random-effects SDM is suitable because both null hypotheses were rejected at the 1% significance level.

Table 10. LR Test Results.

H0	Test Value
SLM nested in SDM	76.19 ***
SEM nested in SDM	47.04 ***

*** indicates significance at the 1% level.

4.2.3. Empirical Results of Influencing Factors

This study conducts STATA 18 to perform spatial panel regression on the processed panel data after applying logarithmic transformations to the LED and EE variables (see Table 11).

Table 11. Estimation Results of the Random-effects SDM.

Variable	Nationwide						
	Main	Direct	Indirect	Total			
lnLED	0.115 ***	0.115 ***	−0.0806 *	0.0340			
	(0.0209)	(0.0211)	(0.0453)	(0.0360)			
LU	−0.00894	−0.00579	0.434	0.428 *			
	(0.0692)	(0.0657)	(0.281)	(0.239)			
IS	0.145 ***	0.147 ***	−0.196	−0.0496			
	(0.0522)	(0.0490)	(0.148)	(0.134)			
lnEE	0.103 ***	0.103 ***	−0.000462	0.102 ***			
	(0.0114)	(0.0108)	(0.0223)	(0.0217)			
LGI	−0.0433	−0.0430	−0.00810	−0.0511			
	(0.0308)	(0.0309)	(0.0897)	(0.0962)			
DO	−0.0544	−0.0451	0.171	0.126			
	(0.0799)	(0.0800)	(0.397)	(0.401)			
rho		0.286 ***					
		(0.0802)					
Eastern				Central			
Main	Direct	Indirect	Total	Main	Direct	Indirect	Total
0.213 ***	0.215 ***	0.0783	0.294 ***	0.139 ***	0.145 ***	0.168	0.314 **
(0.0300)	(0.0359)	(0.0664)	(0.0824)	(0.0346)	(0.0532)	(0.107)	(0.146)
−0.0560	−0.0622	−0.540 ***	−0.602 ***	−0.279 *	−0.304 **	−0.614	−0.918
(0.0711)	(0.0722)	(0.198)	(0.168)	(0.146)	(0.146)	(0.586)	(0.652)
−0.289	−0.273	−0.778 *	−1.051 **	0.0260	0.0291	0.0258	0.0549
(0.265)	(0.252)	(0.411)	(0.513)	(0.0383)	(0.0368)	(0.0426)	(0.0427)
0.103 ***	0.100 ***	−0.0328	0.0675 *	0.104 ***	0.102 ***	−0.0565 *	0.0454
(0.0198)	(0.0217)	(0.0236)	(0.0355)	(0.00511)	(0.0168)	(0.0333)	(0.0476)
−0.101	−0.102	−0.531	−0.633	0.0597	0.0576	−0.0871	−0.0294
(0.0788)	(0.0787)	(0.454)	(0.485)	(0.0966)	(0.0945)	(0.216)	(0.231)
−0.0806	−0.0744	0.204	0.130	−0.170 **	−0.168 **	−0.0110	−0.179
(0.115)	(0.117)	(0.170)	(0.248)	(0.0662)	(0.0671)	(0.211)	(0.212)
	0.0275				0.107		
	(0.0746)				(0.0966)		

Table 11. Cont.

Variable	Nationwide							
	Main	Direct	Indirect	Total				
	Western				Northeastern			
	Main	Direct	Indirect	Total	Main	Direct	Indirect	Total
0.0254	0.0274	0.0305	0.0579	0.145 *	0.147 *	−0.0646	0.0821	
(0.0228)	(0.0441)	(0.0740)	(0.0734)	(0.0788)	(0.0841)	(0.0715)	(0.0973)	
0.435	0.422	0.257	0.679 **	−0.112	−0.112	0.279	0.167	
(0.365)	(0.349)	(0.163)	(0.297)	(0.0738)	(0.0742)	(0.177)	(0.136)	
0.433 ***	0.442 ***	−0.377 **	0.0649	0.193 ***	0.195 ***	−0.242 *	−0.0474	
(0.109)	(0.112)	(0.148)	(0.228)	(0.0701)	(0.0656)	(0.143)	(0.130)	
0.107 ***	0.105 ***	−0.00742	0.0977	0.0660 ***	0.0654 **	0.0134	0.0788	
(0.0282)	(0.0329)	(0.0456)	(0.0645)	(0.0143)	(0.0310)	(0.0628)	(0.0843)	
−0.00707	−0.00733	0.0439 **	0.0366 **	−0.197 ***	−0.196 ***	0.00860	−0.187 *	
(0.00804)	(0.0169)	(0.0201)	(0.0183)	(0.0294)	(0.0339)	(0.107)	(0.108)	
−0.0439	−0.0288	−0.267	−0.295	−0.0908	−0.110	−0.886 ***	−0.996 ***	
(0.209)	(0.199)	(0.182)	(0.230)	(0.197)	(0.210)	(0.250)	(0.315)	
	−0.0288					0.167		
	(0.108)					(0.128)		

***, ** and * indicate significance at the 1%, 5%, and 10% levels, respectively. The data of () indicates the robust standard error.

Only the rho for overall national CEE is significantly positive (see Table 11), namely, improvements in CEE in neighboring regions enhance local CEE. The influencing factors of CEE in CRECs exhibit substantial regional heterogeneity when the significance levels of each variable are examined more closely. This study performs a mechanistic analysis of the differentiated results by combining the mean values of the core explanatory variables for each region to explain regional heterogeneity (see Table 12).

Table 12. Means of Key Explanatory Variables by Region (2011–2023).

Region	LED (Yuan per Person)	LU (%)	IS (%)	EE (Yuan per Ton)	LGI (%)	DO (%)
Eastern	49,865.03	57.86	43.10	12.51	17.26	10.17
Central	39,707.81	55.15	49.69	15.89	18.75	8.17
Western	61,874.12	67.37	48.11	7.42	22.63	6.95
Northeastern	39,454.50	59.69	41.19	11.89	27.70	6.03
Nationwide	47,725.36	60.02	45.52	11.93	21.59	7.83

lnLED has a significant positive direct effect in the eastern, central, and northeastern regions. This suggests that growth in real per capita GDP positively affects CEE for CRECs in these regions. This result is in line with the findings by Gong et al. [17], who also found that the LED has a positive effect on CEE. A reasonable explanation is that CRECs in these regions have recently implemented large-scale shutdowns and phasing out of energy-intensive, outdated production capacity, optimized their energy structures, and fostered emerging industries. Consequently, the industrial low-carbon transition and technological upgrading have been the main drivers of the development in real per capita GDP. Notably, neither the direct effect nor the total effect of lnLED on CEE passed the significance test, despite the average per capita GDP among CRECs in the western region being the highest (61,874.12 yuan per person). Cities like Baotou and Wuhai still rely on resource-based industries to maintain a high per capita GDP, and improvements in their LED have not significantly increased CEE. This seemingly contradictory result may reflect the divergent characteristics among CRECs within the western region.

In the eastern, central, and western regions, LU has a significant negative indirect effect and total effect, a significant negative direct effect, and a significant positive total effect, respectively. The fact that the western CRECs have the highest total LU (67.37%) could be one reason. The agglomeration effects of urbanization are still being achieved through improvements in infrastructure and the expansion of market scale, which partially counteract the pressure on carbon emissions brought on by the heavy industrial structure and encourage an overall increase in CEE. This is consistent with the findings by Hou et al. [25], who thought that improving energy utilization efficiency can enhance CEE. The negative effects of urbanization on CEE in the eastern and central CRECs are in line with the results of Liu and Hao [18] and Jin et al. [19].

In the eastern, western, and northeastern regions, IS boasts a significant negative indirect effect and total effect, a significant positive direct effect, and a significant negative indirect effect, respectively. This demonstrates that increasing the share of secondary industry in GDP can reduce CEE for eastern CRECs, whereas it will increase CEE for western and northeastern CRECs. Because the share of secondary industry in eastern CRECs to GDP is 43.10%, only slightly higher than the 41.19% in the Northeast. Although the tertiary industry has already made significant contributions to carbon emission reductions, further increasing its proportion tends to squeeze out the cleaner tertiary sector and lead to a decrease in CEE. Both western and northeastern CRECs have higher ECs than eastern CRECs (see Table 7). The expansion of the scale of the secondary sector is conducive to adopting more advanced low-carbon technologies, leveraging economies of scale, optimizing resource allocation, and generating a “low-carbon catch-up effect,” thereby improving the CEE.

InEE has a significant positive direct effect in all regions, suggesting that improving energy efficiency can advance the CEE in CRECs.

LGI has a significant positive indirect effect and total effect in the western region, and a significant negative direct effect and total effect in the northeastern region. Table 12 shows that the LGI for CRECs in the northeastern region (27.70%) is the highest, followed by the western region (22.63%). The difference between the two regions may be attributed to the fact that CRECs in the western region have benefited from national policies such as the “Western Development Strategy” and the “Belt and Road Initiative.” The fiscal expenditures of these cities are guided by clear regional coordination objectives and generate positive spatial spillovers to neighboring cities through green technology transfers and other channels, improving the region’s overall CEE. By comparison, social security and basic public services receive a higher proportion of fiscal expenditures in northeastern CRECs, causing insufficient effective investment in green development. Therefore, increasing the amount of expenditure on local public budgets actually diminishes CEE’s control.

DO has a significant negative direct effect in the central region and a significant negative indirect and total effect in the northeastern region. This can be explained by the fact that low-carbon technologies have insufficient spillover effects since traditional heavy industry and energy-intensive products dominate foreign trade in CRECs in the central and northeast regions. Consequently, the increase in openness actually lessens CEE.

4.2.4. Statistical Test of Regional Heterogeneity

Table 11 demonstrates that there is significant regional heterogeneity in the influencing factors of CEE in CRECs. To further confirm whether this regional heterogeneity is statistically significant, this study employs Seemingly Unrelated Regression (SUR) to test for differences in coefficients among the four regions (see Table 13).

Table 13. SUR Test Results.

Variable	df	χ^2 Statistic	p-Value
lnLED	3	25.11	0.0000
LU	3	26.28	0.0000
IS	3	34.05	0.0000
lnEE	3	40.80	0.0000
LGI	3	15.52	0.0014
DO	3	1.68	0.6418
Joint test of all variables	18	172.64	0.0000

Table 13 shows that, except for DO, all five variables' coefficients passed the significance test for differences across the four regions, and the combined test for all variables was also significant at the 1% level. This suggests that the influencing factors of CEE in CRECs exhibit significant regional heterogeneity.

4.2.5. Robustness Test

This study conducted three sets of supplementary tests to ensure the robustness of the findings. The results are presented in Tables 14–16.

Table 14. Robustness Test Results with Economic-distance Weight Matrix.

Variable	Main	Direct	Indirect	Total
lnLED	0.0966 *** (0.0184)	0.0973 *** (0.0189)	0.00626 (0.0419)	0.104 ** (0.0420)
LU	0.0715 (0.0569)	0.0687 (0.0558)	0.147 (0.120)	0.215 (0.142)
IS	0.101 ** (0.0475)	0.106 ** (0.0459)	−0.126 (0.0820)	−0.0199 (0.0698)
lnEE	0.0949 *** (0.00980)	0.0950 *** (0.00954)	−0.0158 (0.0108)	0.0792 *** (0.0131)
LGI	−0.0463 (0.0353)	−0.0449 (0.0358)	−0.0164 (0.0280)	−0.0613 * (0.0350)
DO	−0.0846 (0.0707)	−0.0790 (0.0712)	−0.203 (0.138)	−0.282 (0.182)
rho			0.000557 (0.0534)	

***, ** and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 15. Robustness Test Results Excluding the Pandemic Years (2020–2022).

Variable	Main	Direct	Indirect	Total
lnLED	0.115 *** (0.0184)	0.114 *** (0.0185)	−0.0925 (0.0645)	0.0220 (0.0569)
LU	−0.00762 (0.0595)	−0.00404 (0.0561)	0.481 (0.313)	0.477 * (0.285)
IS	0.101 *** (0.0348)	0.101 *** (0.0332)	−0.156 (0.124)	−0.0553 (0.120)
lnEE	0.105 *** (0.0115)	0.104 *** (0.0109)	−0.00882 (0.0224)	0.0956 *** (0.0217)
LGI	−0.0422 (0.0310)	−0.0423 (0.0313)	−0.0413 (0.0976)	−0.0836 (0.104)
DO	−0.0961 (0.0760)	−0.0892 (0.0758)	0.125 (0.326)	0.0357 (0.336)
rho			0.255 *** (0.0811)	

*** and * indicate significance at the 1% and 10% levels, respectively.

Table 16. Robustness Test Results Based on the Subsample of 16 Prefecture-level Cities.

Variable	Main	Direct	Indirect	Total
lnLED	0.0830 ** (0.0341)	0.0859 ** (0.0341)	0.0637 (0.0632)	0.150 *** (0.0451)
LU	−0.165 ** (0.0687)	0.162 ** (0.0670)	0.0383 (0.221)	0.201 (0.232)
IS	0.0719 * (0.0427)	0.0748 * (0.0398)	−0.0398 (0.0608)	0.0350 (0.0491)
lnEE	−0.259 *** (0.0220)	−0.259 *** (0.0215)	0.0618 ** (0.0291)	−0.197 *** (0.0225)
LGI	−0.151 * (0.0827)	−0.141 * (0.0802)	0.253 * (0.140)	0.112 (0.0962)
DO	−0.00380 (0.142)	0.00843 (0.143)	0.193 (0.371)	0.202 (0.413)
rho			0.161 (0.105)	

***, ** and * indicate significance at the 1%, 5%, and 10% levels, respectively.

First, the spatial weight matrix was modified in this study by replacing the inverse-distance matrix with the economic distance matrix (see Table 14). The overall regression results remained consistent, despite some differences in the signs, magnitudes, and significance levels of the coefficients when compared to the baseline results.

Second, the samples during the pandemic were excluded. Considering that the COVID-19 pandemic from 2020 to 2022 may disrupt urban economic production and energy consumption patterns—which could have led to biased results—this study eliminated the data of this period and re-estimated the model (see Table 15). The direction and significance levels of the coefficients for the core variables were mostly in accordance with the baseline results, and the spatial spillover effect remained strongly positive.

Third, only prefecture-level city samples were used to conduct a sensitivity analysis. Due to the inclusion of districts, counties, and mining areas in the complete sample, the proxy data from their respective prefecture-level cities were used to exclude these observations to assess the potential measurement errors. Thus, this study retained only 16 prefecture-level city samples and re-estimated the spatial Durbin model (see Table 16). The results indicate that the signs and significance of the coefficients for lnLED, IS, and DO stay stable across both the full ($N = 37$) and restricted ($N = 16$) samples, implying that these three variables exhibit good cross-sample robustness. Moreover, the signs of the coefficients for LU and LGI keep consistent, but their significance changes, reflecting that the use of proxy data reduces estimation precision. Additionally, the sign of the coefficient for lnEE is opposite, suggesting that it is relatively sensitive to sample composition. Furthermore, the robustness of the positive spatial correlation in CEE was confirmed by the rho, which remained positive and consistent across both samples.

The above three tests demonstrate that the empirical findings are robust.

5. Conclusions and Recommendations

The key to driving the low-carbon transition of CRECs is to improve CEE. This study used the SBM-DDF framework for static measurement and the GML index for dynamic tracking of CEE in CRECs. The SDM was also employed to explore the underlying factors that shape CEE. The main findings are the following:

- (1) The average CEE of the 37 CRECs did not reach the production frontier from 2011 to 2023. While CEE across regions fluctuated between rises and declines, efficiency levels in these cities were generally moderate.

- (2) Technological progress emerges as the dominant driver of CEE improvement in China's CRECs. The fastest CEE growth occurred in the western area, with an average annual increase of 0.71%, followed by the northeastern region (0.36%) and the central region (0.05%).
- (3) Although technological efficiency and technological progress work together to promote CEE in CRECs in the western region, technological progress is the main driver of CEE improvement in the central and northeastern regions.
- (4) CEE in China's CRECs exhibits a positive spillover effect: the CEE of the city in question increases by 0.286 units for every 1-unit increase in CEE in a neighboring city.
- (5) The influencing factors of CEE in China's CRECs have considerable regional variation. The main influencing factors of CEE vary by region: east—LED, LU, IS, and EE; central—LED, LU, EE, and DO; west—LU, IS, EE, and LGI; northeast—LED, IS, EE, LGI, and DO.

To improve the CEE in China's CRECs, the recommendations are as follows:

- (1) While local governments should preserve the stability and continuity of low-carbon policies, the central government needs to intensify its efforts to promote the low-carbon transition of CRECs. The government can construct a special fund for industrial development to prioritize support for the establishment and growth of successor industries, such as new energy and new materials. In the meantime, it should establish platforms for technology transfer and implement differentiated industrial land use policies to enable replacement industries to produce efficient output as quickly as possible. This will ensure an orderly transition between old and new growth drivers and improve technological efficiency. Furthermore, a cross-provincial alliance for the urban low-carbon transition should be organized and formed to offer 37 CRECs strong institutional and collaborative support. Local governments should also develop long-term plans for the low-carbon transition and ensure their implementation to prevent policy instability caused by leadership changes or external shocks. They should also control fluctuations in CEE and progressively guide these cities toward convergence from their current intermediate levels to the production frontier.
- (2) Chinese CRECs should remove administrative barriers and shift from the traditional "individual city" strategy to a "regional collaboration" model to collectively advance carbon reduction efforts. To standardize emission reduction requirements and exchange energy-saving and carbon-reduction technology and governance experiences, they can, on the one hand, establish cross-city low-carbon collaboration alliances. For example, Xuzhou has set up a public service platform that serves neighboring cities for the accounting and monitoring of greenhouse gas emissions. However, geographically adjacent cities (such as Liaoyuan, Tonghua, and Baishan) should jointly phase out old coal-based production capacity and collaborate on regional clean energy projects, circular-economy industrial parks, and carbon-monitoring platforms.
- (3) All CRECs should increase their GDP per unit of energy consumed. On the one hand, by suppressing new high-energy projects, such as coal chemical and electrolytic aluminium, industrial upgrading should gradually phase out outdated production capacity. Meanwhile, low-energy, high-value sectors, like high-tech manufacturing, deep processing of agricultural products, and cultural tourism should be expanded to achieve higher GDP output with the same energy input. On the other hand, the broader use of smart energy-use technologies and clean energy sources (such as solar and wind) can accelerate the transition to a cleaner energy structure.
- (4) Differentiated strategies for urban low-carbon transition should be implemented. CRECs in the eastern region should increase their real per capita GDP and decrease the GDP proportion of secondary industry while also promoting the transition of industries toward high-end and service-oriented sectors. To improve the spillover

effects of low-carbon technologies, CRECs in the central region should also boost their real per capita GDP and vigorously develop foreign trade in low-carbon products. In addition to making full use of national policies such as the “Western Development Strategy” and the “Belt and Road Initiative” to secure greater fiscal support, CRECs in the western region should continue to advance urbanization and raise the GDP proportion of secondary industry. While Baotou and Wuhai should further lessen their dependency on resource-based sectors, given that their per capita GDP is currently rather high. CRECs in the northeastern region should increase the GDP share of secondary industry and local government spending on green development, as well as actively develop foreign trade in low-carbon products.

6. Limitations and Further Research

This study has certain limitations, even though it offers some guidance for improving CEE in China’s CRECs. First, the measurement indicators of CEE, such as ecological and environmental indicators (vegetation carbon sinks, biomass resource consumption, the carbon health index, and waste treatment), are neglected in favor of traditional indicators like energy consumption, economic output, and CO₂ emissions. Therefore, it should further develop a more comprehensive system of ecological and environmental indicators. Second, this study primarily considers traditional factors (such as urbanization, industrial structure, and energy efficiency) when analyzing the influencing factors of CEE and does not handle emerging drivers, including low-carbon city pilot programs, new forms of productive forces, green technological innovation, and fintech. Thus, it should further analyze the impact of these innovative factors on CEE in CRECs. Third, the SDM is the main tool used in the analysis of influencing factors of CEE; nevertheless, any potential structural breaks or nonlinear characteristics in efficiency changes have not yet been investigated. Consequently, future research could incorporate the threshold effect model to investigate structural breaks and threshold effects in changes to CEE. Finally, only 16 are prefecture-level cities out of the 37 sample cities, while the rest are districts, counties, and mining areas. This study used the data from the corresponding prefecture-level cities as proxies because statistical data for these non-prefecture-level units are not entirely available. The estimation results from this method will inevitably contain some measurement errors. Once such data become accessible, empirical analyses at the district or county level could be further conducted in future work, improving estimation precision. Moreover, the causal mechanisms of the regional heterogeneity of the influencing factors of CEE in CRECs need to be further explored through mediation models, interaction term analysis, or subsample analysis in future research.

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