



# The path analysis of carbon emission reduction: A case study of the Silk Road Economic Belt

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## ABSTRACT

This paper uses super-efficiency DEA model and Malmquist index to evaluate the carbon emission efficiency (CEE) values of the nine western provinces along the “Silk Road Economic Belt” for the period from 2000 to 2015, and analyses the influencing factors of the CEE. The major findings of this study are the following: (1) the overall CEE of the nine western provinces is not high, and there are significant inter-provincial differences in the CEE. Meanwhile, the provinces with higher levels of economic development generally have higher CEE. (2) The annual total factor productivity (TFP) of the nine western provinces, which is mainly determined by technological change, is greater than 1. Moreover, the total average growth rate of the TFP is 15.5%. (3) The CEE of the nine western provinces is not spatially dependent. In addition, the urbanization, openness, use of energy-saving technologies and research and development (R&D) investment have a significant positive impact on the CEE values, while the industrial structure, foreign direct investment, fixed asset investment, government expenditure levels and energy structure have a significant negative impact on the CEE. Among them, R&D investment is the primary factor in promoting the development of CEE, and the government expenditure has the greatest negative impact on the CEE.

**Keywords:** Carbon emission efficiency, Malmquist index, Moran's I index, Super-efficiency DEA

## 1. Introduction

In the past 40 y, Chinese economy has grown rapidly. This rapid period of change created a miracle of economic growth which consumed a lot of fossil fuels. In addition, weak awareness of environmental protection and backwardness in energy saving and emission reduction technologies have intensified environmental pollution and the greenhouse effect. China inevitably replaced the United States as the largest energy-consuming and carbon-emitting country in 2007 [1]. As it is well known, soaring economic development is often accompanied by high environmental costs. According to previous related research, the environmental cost caused by air and water pollution was equivalent to 3% - 8% of global GDP [2]. As the greenhouse effect continues to intensify, governments have set their national development goals for the 21st century to improve carbon emission efficiency (CEE) so as to achieve low-carbon economy. Because of huge economic aggregates and carbon emissions, China has greater responsibility for carbon emission reduction. In order to better coordinate the relationship between

economic development and environment protection, China has promised to achieve the goal of curbing the ongoing growth of carbon dioxide emissions by 2030. Therefore, China has formulated a series of resource-saving policies to alleviate carbon dioxide emissions. Notwithstanding, the key to carbon emission reduction is to improve CEE. Before formulating a scientific and rational energy-saving emission reduction policy, it is necessary to evaluate the CEE and research the factors affecting the CEE based on the current situation of carbon emissions.

There are many relevant studies on CEE. For example, Lu et al. [3] used a hybrid efficiency DEA model to measure the CO<sub>2</sub> emission efficiency in 32 OECD countries. Chang et al. [4] measured the CEE of different regions with a non-radial DEA model to research. In addition, SFA and MCPI methods were also applied to calculate the CEE [5, 6]. Domestic research mostly focused on the assessment of CEE and its influencing factors in nationwide provinces or several large regions [7, 8]. Different kinds of methods, such as non-radial and non-angle DEA, cross-efficiency DEA, super-efficiency DEA and SDDF models, were put forward to study the CEE and its



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Received October 31, 2018 Accepted February 10, 2019

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influencing factors across the country [9-12]. Meanwhile, there is also some research using SBM and three-stage DEA models to evaluate the CEE of some special regions like Beijing-Tianjin-Hebei and coastal areas [13, 14].

However, the scientific assessment methods of CEE have not been unified. Additionally, these previous studies neglected the dynamic change of CEE under the background of carbon market and most of the analysis of influencing factors did not take the spatial auto-correlation and differences among provinces into consideration [15, 16], resulting in the lack of credibility with the empirical results. Furthermore, fewer studies selected the western regions as target areas. However, the CEE values of the western regions are far lower than that of the central and eastern regions due to the irrational industrial structure and extensive production modes in the context of low-carbon economic development. Thus, the economic gaps between the western regions and the central or eastern regions had been continuously widening. In order to coordinate the economic development of the west regions and other regions, the State Council issued the “Western Development” strategy in 2000 and the National Development and Reform Commission officially proposed the Belt and Road in March 2015. There are two things that need to be done to ensure coordination and sustainable development among regions. First, the eastern regions should continue to support the development of the western provinces. Second, the western provinces must seek an apt low-carbon economic development path based on their own characteristics. In view of the above discussions, this paper selects nine provinces (except Tibet) along the “Silk Road Economic Belt” as the research areas. Firstly, the super-efficiency DEA model, which could take into account the slackness problems of inputs and outputs caused by the radial and angular choices and directly address the input excess and output shortfall in efficiency measurements, was used to evaluate the nine provinces’ CEE. Secondly, we used the Malmquist index to analyze their dynamic characteristics and then the Moran’s I index was adopted to exclude the spatial dependence of CEE in the nine western provinces. Finally, the Tobit model was applied to analyze its influencing factors. In a nutshell this paper seeks the key paths for low-carbon economic development in the nine western provinces and provides new insights for coordinated regional development.

## 2. Empirical Research Design

### 2.1. Methodology

#### 2.1.1. Super-efficiency DEA

The super-efficiency DEA was proposed by Andersen in 2013. Compared with the traditional DEA model, the super-efficiency DEA model excludes the decision-making unit to be evaluated from the decision-making set. Additionally, its frontier surface changes accordingly so that the efficiency value can be measured, while the inefficiency value does not change. Therefore, it is possible to subdivide and reorder multiple decision units and distinguish multiple decision units in production foreword.

To facilitate the presentation of the essential ideals without loss of generality, this paper assumes that there are  $N$  decision-making units, using  $K$  kinds of inputs to produce  $M$  kinds of outputs.

We use vectors  $X_j (X_j = (X_{j1}, x_{j2}, x_{j3}, \dots, x_{jK})')$  and  $Y_j (Y_j = (y_{j1}, y_{j2}, y_{j3}, \dots, y_{jM})')$  to represent DMU  $j$ , the decision making unit. When evaluating the efficiency of the decision-making unit  $j_0$ , the specific calculation formula of the super-efficiency DEA model can be constructed as follows.

$$\min \left\{ \theta - \varepsilon \left( \sum_{i=1}^m S_i^- + \sum_{r=1}^s S_r^+ \right) \right\} \quad (1)$$

$$s.t. \begin{cases} \sum_{\substack{j=1 \\ j \neq j_0}}^n X_j \lambda_j + s^- = \theta X_{j_0} \\ \sum_{\substack{j=1 \\ j \neq j_0}}^n Y_j \lambda_j - s^+ = Y_{j_0} \\ \lambda_j \geq 0 (j = 1, 2, \dots, n) \\ s^+ \geq 0, s^- \geq 0 \end{cases} \quad (2)$$

If  $\theta \geq 1$ , and  $s^+ = s^- = 0$ , then the DMU  $j_0$  is said to be DEA valid; if  $\theta \geq 1$ , and  $s_i^- \neq 0$  or  $s_r^+ \neq 0$ , then the DMU  $j_0$  is said to be DEA weakly valid; if  $\theta < 1$ ,  $s_i^- \neq 0$  and  $s_r^+ \neq 0$ , then the DMU  $j_0$  is represented as DEA, invalid. For the invalid evaluation unit, the super efficiency DEA and the traditional DEA efficiency value have the same evaluation results. Nevertheless, for the evaluation unit whose efficiency value reaches 1, we can compare their relative efficiency value. As shown in Fig. 1, it is assumed that point A, B, and C are all high decision making units with an efficiency value of 1, and point E represents a low production efficiency point. When calculating the efficiency value of the point B1, the point B is excluded, so that the two points A and C are used as the frontier surface, and the line segment BB<sub>1</sub> is the amplitude that the input amount can be increased. Therefore, the super-efficiency value of the point B is calculated by  $(OB + BB_1) / OB$ . This value is greater than 1. The point E, which will not affect the production frontier when excluded, is the lower efficiency point. Hence, the super-efficiency DEA model has no effect on the low-efficiency evaluation subject results and can be used to compare the relative size of the high-efficiency evaluation subjects.

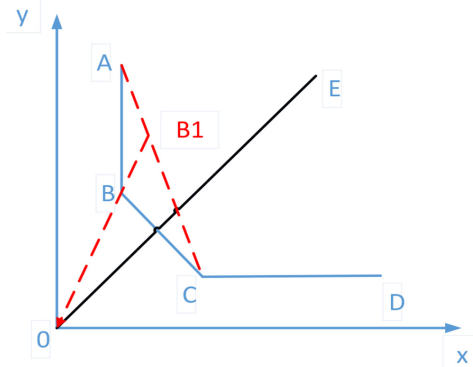


Fig. 1. Super efficiency DEA model.

#### 2.1.2. Malmquist productivity index

The Malmquist Productivity Index (MPI) was first proposed by Sten Malmquist in 1953. The index was commonly used to measure

the productivity change. It was applied to measure the efficiency changes in the 1980s, which was quickly forgotten for some reasons. Until 1994, the MPI was widely accepted and adopted when first used in conjunction with DEA. Suppose that  $D^t(x_t, y_t)$  and  $D^{t+1}(x_t, y_t)$  are the efficiency values of decision-making unit at the period  $t$  for the reference technology at the period  $t$  and  $t+1$ . Further suppose that  $D^t(x_{t+1}, y_{t+1})$  and  $D^{t+1}(x_{t+1}, y_{t+1})$  are the efficiency values of DMU at the time  $t+1$  for the reference technology at the time  $t$  and  $t+1$ . The MPI defines total factor productivity (TFP) as:

$$TFP = \left[ \frac{D^t(x_{t+1}, y_{t+1})}{D^t(x_t, y_t)} \times \frac{D^{t+1}(x_{t+1}, y_{t+1})}{D^{t+1}(x_t, y_t)} \right]^{\frac{1}{2}} \tag{3}$$

$$= \frac{D^{t+1}(x_{t+1}, y_{t+1})}{D^t(x_t, y_t)} \times \left[ \frac{D^t(x_{t+1}, y_{t+1})}{D^{t+1}(x_{t+1}, y_{t+1})} \times \frac{D^t(x_t, y_t)}{D^{t+1}(x_t, y_t)} \right]^{\frac{1}{2}}$$

For better presentation, the above formula can be simplified to:

$$TFP = EC \times TC = PE \times SE \times TC \tag{4}$$

Eq. (4) shows that TFP is equal to the product of technical efficiency change (EC) and technological change (TC), while TC equals the product of pure technical efficiency (PE) and scale efficiency (SE). If the  $TFP > 1$ , it indicates that the efficiency of the TFP is increased from time  $t$  to the time  $t+1$ . On the contrary, if the  $TFP < 1$ , indicating that the TFP is reduced during the period from  $t$  to  $t+1$ .

### 2.1.3. Moran's I index

The Moran's I index can be applied to test whether there is spatial auto-correlation in the carbon emission efficiency of the nine western provinces. The specific formula of Moran's I index is the following:

$$I = \frac{n \sum_{i=1}^n \sum_{j=1}^n w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^n \sum_{j=1}^n w_{ij} \sum_{i=1}^n (x_i - \bar{x})^2} \tag{5}$$

Where  $n$  is the number of spatial units, representing the number of provinces, and  $w_{ij}$  represents the element  $(i, j)$  of the spatial weight matrix, which is a binary virtual variable. In this paper,  $w_{ij}$  is used to measure whether the regions are adjacent. If any two regions are adjacent, the value of  $w_{ij}$  is one, otherwise zero. We all know that  $I \in [-1, 1]$ , on the basis that the test result is significant, if  $I \in (0, 1]$ , it means that the value of CEE between the regions exhibits agglomeration. Apparently, it is shown that the province with higher CEE has a higher CEE in its neighboring provinces. Similarly, when  $I \in [-1, 0)$ , on the basis that the test result is significant, the province with high CEE has a lower CEE in their neighboring provinces. On the contrary, if the value equals to zero or test result is not significant, it indicates that there is no spatial correlation among the provinces. While the closer the value is to one, the stronger the spatial correlation among provinces.

## 2.2. Variable Selection and Data Source

Previous studies established the input-output index system of CEE on the basis of production function. Compared with the

Cobb-Douglas production function, natural resources, substituted by the total energy consumption, are added into the input factors. Meanwhile, labor force and capital are replaced by total employed population and fixed assets investment, respectively. Accordingly, this paper chooses fixed assets investment, total employed population and total energy consumption as input indicators, while the GDP is selected as the desirable output indicator. Additionally, the carbon dioxide emission, usually treated as an input variable, is the undesirable output indicator [13, 17, 18]. In the paper, the CEE is calculated by the above input-output indicator system. Based on existing relevant literature, the factors affecting CEE include industrial structure, energy structure [19], urbanization [20], research and development (R&D) investment [18], foreign investment, openness, government expenditure and fixed assets investment [17, 21, 22]. In addition, the indicator of environmental protection technology, which can improve the efficiency of carbon dioxide emissions, has not been taken into consideration in this paper because a lot of data are missing. Therefore, we define the ratio of GDP to CO<sub>2</sub> emissions as a measure of energy-saving technology use. The higher the ratio, the less carbon dioxide produced per unit of GDP. In addition, we use Stata software to perform Stepwise Regression, the results show that all indexes should be included in the model, reflecting that there is no multicollinearity. The symbolic representation of each variable and its specific meaning are shown in Table 1.

The data in this paper is obtained from the Wind Financial Database and the China Statistical Yearbook (2000-2015). The "Silk Road Economic Belt" involves ten western provinces including Inner Mongolia, Guangxi, Chongqing, Yunnan, Tibet, Shaanxi, Gansu, Ningxia, Qinghai and Xinjiang. However, due to the serious lack of data in Tibet, only the remaining nine provinces are selected for investigation in this article. Meanwhile, because of lack of data from the time period before 2000 and after 2015. The authors

**Table 1.** The Variables and Their Specific Meanings

Variable	Name	Meaning
$y$	CEE	The value of CEE
$x_1$	Industrial structure	The proportion of the secondary industry
$x_2$	Degree of urbanization	The proportion of urban population
$x_3$	Openness	The ratio of total import and export trade to local GDP
$x_4$	Energy-saving technology	The ratio of environmental protection investment to local GDP
$x_5$	Foreign direct investment	The ratio of foreign direct investment to local GDP
$x_6$	Fixed assets investment	The ratio of fixed assets investment to local GDP
$x_7$	R&D investment	The ratio of R&D investment to local GDP
$x_8$	Government expenditure	The ratio of local fiscal expenditure to local GDP
$x_9$	Energy structure	The ratio of coal consumption to total resource consumption

selected the duration from 2000 to 2015 as study period. In addition, the economic indicators, such as GDP and fixed asset investment were adjusted on the basis of constant price for the year 2000. The CO<sub>2</sub> emissions of each province are calculated according to the energy consumption carbon footprint model in the IPCC (2006) National Greenhouse Gas Inventories Guide, which estimates by primary energy consumption including raw coal, crude oil and natural gas use. The CO<sub>2</sub> emissions coefficient of various energy sources is determined as follows:

$$CO_2 = \sum_{i=1}^n E_i \times NCV_i \times CEF_i \times COF_2 \times \frac{44}{12} \quad (6)$$

Where,  $E_i$  is the consumption of carbon-containing energy,  $NCV_i$  represents the average low calorific value,  $CEF_i$  displays the amount of carbon contained in the unit calorific value and  $COF_i$  indicates

the carbon oxidation factor.

Remarks:

(1) Low (position) heat equal to 29,307 kJ of fuel, referred to as 1 kg of standard coal (1 kgce)

(2) The first two columns of the above Table are from the General Rules for the Calculation of Comprehensive Energy Consumption (GB/T 2589-2008) (reference year is missing)

(3) The last two columns of the Table 2 are derived from the “Guidelines for the Preparation of Provincial Greenhouse Gas Inventories” (Development and Reform Office Climate [2011] No. 1041)

The data of total energy consumption (10,000 tons of standard coal) in the nine western provinces can be obtained from the China Statistical Yearbook (2000-2015). The carbon dioxide emissions of the nine western provinces for the time period from 2000 to 2015 can be calculated from the carbon emission coefficient of raw coal. The specific values are shown in Table 3:

**Table 2.** Carbon Emission Coefficients Table for Various Energy Sources

Energy name	Average low calorific value (kJ/kg)	Coefficient of conversion to standard coal (kgce/kg)	The amount of carbon contained in the unit calorific value (ton/TJ)	Carbon oxidation rate	Carbon dioxide emission coefficient (kg-co <sub>2</sub> /kg)
Raw coal	20,908	0.7143	26.37	0.94	1.9003
Coke	28,435	0.9714	29.5	0.93	2.8604
Crude	41,816	1.4286	20.1	0.98	3.0202
Fuel oil	41,816	1.4286	21.1	0.98	3.1705
Gasoline	43,070	1.4714	18.9	0.98	2.9251
Kerosene	43,070	1.4714	19.5	0.98	3.0179
Diesel	42,652	1.4571	20.2	0.98	3.0959
Liquefied petroleum gas	50,179	1.7143	17.2	0.98	3.1013
Refinery dry gas	46,055	1.5714	18.2	0.98	3.0119

**Table 3.** Carbon Dioxide Emissions in the Nine Western Provinces (2000-2015) (unit: 10,000 tons)

Year	Inner Mongolia	Guangxi	Chongqing	Yunnan	Shaanxi	Gansu	Qinghai	Ningxia	Xinjiang
2000	9,443	7,101	6,459	9,227	7,266	8,012	2,387	3,138	8,853
2001	10,836	7,101	8,024	9,285	8,665	7,728	2,474	2,436	9,301
2002	12,131	8,300	7,172	10,990	9,878	8,444	2,711	3,666	9,905
2003	15,371	9,373	8,165	11,839	11,094	9,378	2,987	5,360	11,111
2004	20,279	11,182	9,764	13,860	12,706	10,396	3,630	6,178	13,061
2005	25,715	12,952	13,150	16,026	14,822	11,620	4,444	6,747	14,649
2006	29,851	14,340	14,282	17,613	16,306	12,618	5,064	7,528	16,088
2007	33,992	15,955	15,821	18,975	18,024	13,593	5,574	8,187	17,494
2008	37,512	17,285	17,219	19,982	19,733	14,223	6,063	8,591	18,807
2009	40,819	18,822	18,702	21,368	21,399	14,583	6,247	9,012	20,021
2010	44,748	21,067	20,899	23,076	23,630	15,758	6,833	9,793	22,055
2011	49,847	22,856	23,390	25,381	25,967	17,281	8,484	11,483	26,408
2012	52,637	24,354	24,684	27,757	28,268	18,641	9,375	12,138	31,476
2013	47,038	24,209	21,413	26,795	28,226	19,386	10,024	12,719	36,266
2014	48,709	25,313	22,861	27,814	29,855	20,009	10,620	13,158	39,709
2015	50,353	25,968	23,768	27,553	31,169	20,014	10,998	14,379	41,637

### 3. Analysis of Empirical Results

#### 3.1. Static Analysis of CEE

The annual CEE values of the nine western provinces from 2000 to 2015 are calculated by the EMS 1.3 software. The specific values are shown in Table 4. In addition, Fig. 2 further depicts the trends in the nine western provinces.

As shown in Table 4, the Mean 1 displays the annual average CEE of the nine western provinces and the Mean 2 indicates the average CEE for each province from 2000 to 2015. Overall, the numerical values of Mean 1 show less fluctuations, first increase and then decrease. The Mean 1 reached a maximum value of 1.01 in 2007, while the values for the remaining years were less than 1 except for 2007, 2008, and 2009. The overall average CEE was 0.98, which was in the stage of diminishing returns to scale, implying that the total average CEE of the nine western provinces from 2000 to 2015 is at a lower level. Comparing Mean 2, we can easily find that the average value of Xinjiang's CEE ranks first, reaching 1.33, while Qinghai ranks last with a minimum value of 0.70. The Mean 2 of Xinjiang, Guangxi, Chongqing, Shaanxi and Yunnan are greater than or equal to 1 and are in a decreasing order, while the values of other four provinces are less than 1. Based on the above results the following conclusion can be made:

Firstly, the overall level of CEE in the nine western provinces is not high and the fluctuations are small. The average CEE of the nine western provinces is in the stage of diminishing returns to scale for most of the years, this is related to the lower level of economic development, excessive proportion of the secondary industry and extensive production method in the western regions, as well as the lack of technological innovation.

Secondly, there are significant inter-provincial differences in CEE among provinces. Furthermore, those provinces with more developed economies have higher CEE as a whole. From 2000 to 2015, the economic development levels of the nine western provinces, from high to low, are ranked as follow: Guangxi, Yunnan, Shaanxi, Chongqing, Inner Mongolia, Xinjiang, Gansu, Ningxia and Qinghai. This might be because in provinces with higher economic levels, the governments have greater capacity to conduct

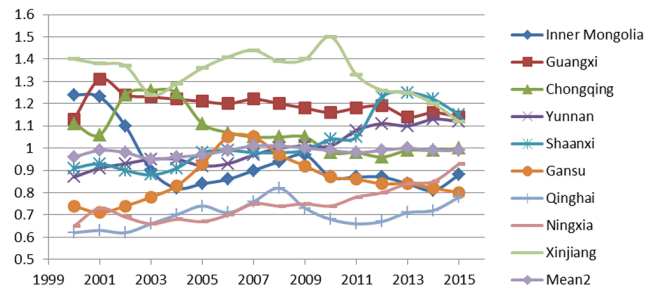


Fig. 2. Changes of average CEE in the nine western provinces (2000-2015).

research on energy-saving technologies and advocate energy conservation and emission reduction. Therefore, companies and residents in the province have stronger awareness of ecological protection, which ultimately facilitates the improvement of carbon emission efficiency. Only the rankings' of Inner Mongolia and Chongqing interchanged between 2008 and 2011, while the rankings' of other provinces remained completely unchanged. Moreover, the list when the the average CEE of each province ranked from high to low is as follows; Xinjiang, Guangxi, Chongqing, Shaanxi, Yunnan, Inner Mongolia, Gansu, Ningxia and Qinghai. This depicts that showing that the provinces with higher economic development levels have higher CEE with the exception of Xinjiang. This province is sparsely-populated and located in the northwest of China and has vigorously developed its import-export trade with many countries and has kept a lower proportion of secondary industry in contrast with the other eight provinces in the last sixteen years. This is conducive to energy saving and emission reduction, thereby greatly improving the CEE.

#### 3.2. Dynamic Analysis of CEE

Using Eq. (4), the CEE of the nine western provinces can be calculated by the DEAP 2.1 software and dynamically decomposed according to the decision-making unit and time (shown in Table 5 and Table 6).

In general, the average TFP growth rate of the nine western provinces from 2000 to 2015 was 15.5%, and the average growth

Table 4. The CEE of the Nine Western Provinces (2000-2015)

Province	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	Mean2	Ranking
Inner Mongolia	1.24	1.23	1.10	0.90	0.82	0.84	0.86	0.90	0.94	0.97	0.87	0.87	0.87	0.84	0.81	0.88	0.93	6
Guangxi	1.13	1.31	1.24	1.23	1.22	1.21	1.20	1.22	1.20	1.18	1.16	1.18	1.19	1.14	1.16	1.14	1.19	2
Chongqing	1.11	1.06	1.24	1.26	1.25	1.11	1.07	1.05	1.05	1.05	0.98	0.98	0.96	0.99	0.99	1.00	1.07	3
Yunnan	0.87	0.91	0.93	0.95	0.95	0.92	0.93	0.97	1.00	1.01	1.01	1.08	1.11	1.10	1.13	1.12	1.00	5
Shaanxi	0.91	0.93	0.90	0.88	0.91	0.98	0.99	0.98	0.98	0.99	1.04	1.05	1.23	1.25	1.22	1.15	1.02	4
Gansu	0.74	0.71	0.74	0.78	0.83	0.93	1.05	1.05	0.97	0.92	0.87	0.86	0.84	0.84	0.82	0.80	0.86	7
Qinghai	0.62	0.63	0.62	0.66	0.70	0.74	0.71	0.76	0.82	0.73	0.68	0.66	0.67	0.71	0.72	0.78	0.70	9
Ningxia	0.65	0.73	0.69	0.66	0.68	0.67	0.70	0.75	0.74	0.75	0.74	0.78	0.80	0.84	0.85	0.93	0.75	8
Xinjiang	1.40	1.38	1.37	1.24	1.29	1.36	1.41	1.44	1.39	1.40	1.50	1.33	1.26	1.25	1.20	1.12	1.33	1
Mean 1	0.96	0.99	0.98	0.95	0.96	0.97	0.99	1.01	1.01	1.00	0.99	0.98	0.99	1.00	0.99	0.99	0.98	

rate of EC and the average growth rate of TC were 0.3% and 15.1%, respectively. By comparing the TC with EC in Table 5 using Eq. (4), it is clear that the TFP mainly depends on the TC, while the TC depends on the provinces' governments support for technology introduction and technological innovation, which has greatly improved the emission reduction efficiency. As shown in Table 5, the average value of TFP for the nine western provinces is greater than 1 and the differences in TFP growth rates between provinces are less than 5%, indicating that the TFP of the nine western provinces has been improving over the past 16 y. The TFP of Inner Mongolia ranks first while the value of Xinjiang ranks last among the nine western provinces. According to the Eq. (4), the authorities of Xinjiang should focus on improving the province's PE and SE. As represented above, the governments of the nine western

**Table 5.** Malmquist Exponential Decomposition of Annual CEE in Nine Western Provinces (2000-2015)

Province	EC	TC	PE	SE	TFP	Ranking
Inner Mongolia	1.025	1.159	1.031	0.994	1.188	1
Guangxi	1.006	1.134	1.005	1.001	1.141	8
Chongqing	1.001	1.15	1	1.001	1.151	6
Yunnan	0.994	1.153	0.987	1.007	1.146	7
Shaanxi	1	1.154	1	1	1.154	5
Gansu	1.018	1.155	1.012	1.006	1.175	2
Qinghai	1	1.155	1	1	1.155	4
Ningxia	0.996	1.163	0.997	0.999	1.158	3
Xinjiang	0.989	1.138	0.99	0.999	1.125	9
mean	1.003	1.151	1.002	1.001	1.155	

**Table 6.** The Average Malmquist Index of Each Year in the Nine Western Province and Its Decomposition

Year	EC	TC	PE	SE	TFP
2000-2001	1.004	1.122	0.992	1.013	1.127
2001-2002	0.931	1.204	0.98	0.95	1.121
2002-2003	1.057	1.137	1.021	1.035	1.201
2003-2004	0.983	1.163	0.97	1.013	1.143
2004-2005	0.958	1.051	1.019	0.94	1.007
2005-2006	0.979	1.172	1	0.98	1.148
2006-2007	0.976	1.193	1	0.976	1.165
2007-2008	1.014	1.164	1.01	1.003	1.18
2008-2009	1	1.288	1.001	0.999	1.289
2009-2010	1.02	1.163	1.003	1.017	1.186
2010-2011	1.017	1.075	1.005	1.012	1.093
2011-2012	1.015	1.194	0.986	1.029	1.211
2012-2013	1.005	1.22	1.014	0.991	1.225
2013-2014	1.003	1.16	1.005	0.998	1.164
2014-2015	1.095	0.992	1.031	1.063	1.086
mean	1.003	1.151	1.002	1.001	1.155

provinces should attach greater importance to introducing more relevant supporting incentive policies to facilitate the use and creation of new technologies. Table 6 presents the dynamic evolution of various indicators in the nine provinces from 2000 to 2015, in which the TFP reached a maximum value of 1.289 between 2008 and 2009 while a minimum value of 1.007 was observed during the time period from 2004 and 2005. In addition, the TFP and the TC have the similar trends. In summary, more feasible measures need to be taken to achieve technological advancement that improves TFP.

### 3.3. Analysis of Factors Affecting CEE

This paper took the value of CEE ( $y_1$ ) as the dependent variable and selected the industrial structure ( $x_1$ ), urbanization ( $x_2$ ), openness ( $x_3$ ), energy-saving technology ( $x_4$ ), foreign direct investment ( $x_5$ ), fixed asset investment ( $x_6$ ), R&D investment ( $x_7$ ), government expenditure ( $x_8$ ) and energy structure ( $x_9$ ) as independent variables. Before constructing the model, the spatial auto-correlation of CEE values in the nine provinces was tested by Moran's I index. (The specific test results can be seen from the supplementary materials; Table S1)

It is known that the null hypothesis of Moran's I index is "no spatial auto-correlation". If and only if the value of global Moran's I index is significant and not zero, the test result rejects the null hypothesis, implying that there is spatial auto-correlation. The global Moran's I index values from 2000 to 2014 are negative and not significant. Only the index value in 2015 is positive, but it is still not significant. Obviously, all the values of global Moran's I index are not significant, representing that the null hypothesis of "no spatial auto-correlation" is accepted and further indicating that there is no spatial dependence on the province's CEE values. That is, the spatial evolution process of CEE in the nine western provinces is unique and independent. Therefore, it is not necessary to use the spatial measurement model. Since all the calculated CEE values exceed 0.5 and the collected data are truncated, ordinary least square method (OLS) cannot fully present the data, resulting in estimation deviation, so the Tobit regression model is apt for the analysis of influencing factors. (The specific regression results can be seen from Table S2).

The empirical results of all independent variables passed the significance test, and most of the regression results were consistent with expectations. Among them, the urbanization, openness, energy-saving technology and R&D investment have a significant positive impact on the values of CEE in the nine western provinces and the specific impact values are 0.00693, 0.000415, 0.425 and 6.592, respectively. On the contrary, the industrial structure, foreign direct investment, fixed asset investment, government expenditure and energy structure have a significant negative impact on the CEE values of the nine western provinces, with the impact values of 0.0594, 0.00721, 0.306, 0.718 and 0.426, respectively.

Specifically, it is not difficult to find that the R&D investment has the greatest promotion effect on the CEE of the nine western provinces, with an impact value of 6.592, indicating that R&D investment is the primary driving force for the development of a low-carbon economy. The nine western provinces have increased the investment in technology introduction and independent in-

novation, which not only encourages companies to produce more green products and make full use of renewable energy technologies to save energy consumption [23, 24], but also facilitates the adjustment and upgrading of industrial structure. There is no doubt that the above measures are conducive to the promotion of carbon fixation and utilization technology, thereby reducing carbon intensity [25]. In contrast, government expenditure has the greatest negative impact on CEE, because only a small part of government fiscal expenditure is spent on environment protection. Most of the government fiscal expenditures are still used in high energy consumption and high emission areas such as infrastructure. This has the effect of driving the development of related high energy consumption and high emission industries, thus having a significant negative impact on the value of CEE. In summary, R&D investment and government expenditure are the two most important factors that should be attached to greater importance in the development of a low-carbon economy. The governments of the nine western provinces are supposed to increase the proportion of environmental protection expenditures while increasing R&D investment.

In addition, the energy-saving technology, urbanization and openness have a significant positive impact on the value of CEE, and the degree of their impacts is reduced in turn. The energy-saving technology has a significant positive effect on CEE, indicating that the improvement and upgrading of energy-saving technologies can reduce carbon emissions so as to improve CEE. The regression coefficient of the urbanization is significantly positive, implying that cities with a higher degree of urbanization depend more on high-tech industries. In order to improve economic development, local governments can impose more restrictions on high-energy and high-emissions given off by enterprises which will lead to the improvement of the value of CEE. Moreover, the regression coefficient of the openness, that is, the proportion of import and export trade, is markedly positive, representing that the fierce competition in the process of import and export has prompted exporting countries to actively acquire technological spillovers through learning and business contacts, stimulating enterprises to increase their own exports through independent innovation. The competitiveness in trade, which in turn reduces carbon emissions and achieves higher economic returns, thus promotes the improvement of CEE and is beneficial to the development of a low-carbon economy.

On the contrary, the energy structure, industrial structure, fixed asset investment level and foreign direct investment have a significant negative impact on CEE, and the degrees of impact decrease in turn. The regression coefficient of the energy structure, that is, the proportion of coal consumption, is significantly negative, indicating that the proportion of coal consumption has a significant negative impact on CEE. The governments of the nine western provinces should take positive efforts to reduce the proportion of coal use in an orderly manner, actively develop new energy sources, and vigorously support the use of clean energy, thereby improving CEE and achieving low-carbon economic development. The regression coefficient of the industrial structure, that is, the proportion of the secondary industry, is significantly negative, indicating that the proportion of the secondary industry has a significant negative impact on the efficiency of carbon emissions. The development of a low-carbon economy in the nine western provinces cannot be over-reliant on the secondary industries with

high energy consumption and high carbon emissions. It is necessary to rationally adjust the industrial structure, carry out industrial upgrading, and appropriately increase the proportion of the tertiary industry. The fixed asset investment and foreign direct investment refer to the proportion of fixed assets investment and foreign direct investment in local GDP, respectively, and their regression coefficients are significantly negative. This is because fixed asset investment and foreign investment are mainly concentrated in high-emission and high-energy-consuming fields such as industry and real estate, which has a significant inhibitory effect on the improvement of CEE.

#### 4. Conclusions and Policy Implications

In this paper, the super-efficiency DEA method was used to calculate the CEE of the nine western provinces along the "Silk Road Economic Belt" from 2000 to 2015, and the Malmquist Index was carried out for its dynamic and static analysis. Then the global Moran's I index was applied to test the spatial auto-correlation between the provinces. Finally the Tobit regression model was constructed to analyze the factors affecting CEE. The specific research conclusions are summarized as follows.

(1) The overall average level of CEE in the nine western provinces from 2000 to 2015 is not high, and the fluctuation is small. The inter-provincial differences of CEE are significant as well as the obvious differences in economic development levels, displaying that the provinces with higher levels of economic development have a higher CEE. The above conclusions can be explained mainly from two aspects. For one thing, the proportion of the secondary industry in the nine western provinces is too high and the production methods are relatively extensive, which greatly increased CO<sub>2</sub> emissions per unit of output value. For another thing, the nine western provinces lack cooperation in technological innovation, environmental governance and capital investment, and thus cannot play a synergistic effect in the development of a low-carbon economy. Among them, due to the vast territory and good regional advantages, Xinjiang has a high export trade quota and a relatively low proportion of the secondary industry. Thus, its overall average value of CEE ranks first, and the annual CEE from 2000 to 2015 is greater than 1. In contrast, Qinghai, with a higher proportion of the secondary industry and lowest level of economic development in the nine western countries, ranks last in terms of the overall average CEE, which is in a relatively serious stage of diminishing returns to scale. Therefore, it is necessary for the nine western provinces to carry out more extensive strategic cooperation in technological innovation, talent exchange, and environmental protection. This will result in greater synergy and jointly achieve the goal of low-carbon economic development and narrowing the development gap between the western, eastern and center regions.

(2) On the whole, the average value of TFP in the nine western provinces from 2000 to 2015 is greater than 1, and the overall TFP has increased by 15.5%. The growth rate gaps between provinces do not exceed 5%. In addition, the average growth rate of EC and the average growth rate of TC were 0.3% and 15.1%, respectively. The value of TFP is mainly determined by TC and has the same trend with TC. With respect to TC, the main sources

are technology introduction and technological innovation. In the process of seeking higher CEE, the authorities of the nine western provinces should pay more attention to introducing supporting incentive policies so as to facilitate technology introduction and independent innovation, thereby improving the value of TFP.

(3) The test results of global Moran's I index imply that the CEE values of the nine western provinces are not spatially dependent, that is, there is no spatial agglomeration effect in the nine western provinces, which is totally contrary to the test results of the national or eastern regions. In addition, the regression results of Tobit model indicate that the impacts of R&D investment, energy-saving technology, urbanization and openness on CEE are significantly positive, and the degrees of influence decrease in turn. Therefore, the governments of the nine western provinces should improve CEE on the basis of following suggestions. Firstly, increasing R&D investment to promote the technological innovation and development, especially the energy-saving technology. Secondly, by promoting urbanization, high-tech industries can gain more opportunities for development. Thirdly, encouraging import and export trade so as to reduce high-emissions commercial transactions. The impacts of government expenditure, energy structure, industrial structure, fixed asset investment and foreign direct investment on CEE are significantly negative and the degrees of their influences decrease in turn. First of all, the authorities of nine western provinces should formulate a reasonable government expenditure plan and appropriately increase the proportion of environmental protection expenditures. Then, reducing the proportion of coal use and increasing the scale of clean energy use. Meanwhile, increasing the proportion of the tertiary industry and promoting the coordinated development of the three major industries. Further, reducing the proportion of fixed assets investment and strictly selecting the foreign investors to avoid excessive investment in high-energy and high-emission industries. Among them, R&D investment has the greatest positive impact on the CEE of the nine western provinces, while the government expenditure has the most negative impact on the CEE of the nine western provinces, which is worthy of more attention.

(4) To establish the carbon emissions trading market and to make the market play an automatic adjustment role. In addition to setting strict carbon emission targets, the authorities should also be encouraged to effectively control carbon emissions through carbon emissions trading, using external markets to regulate carbon emissions. Furthermore, carbon emissions trading will encourage companies to improve the CEE by introducing technology and technological innovation, which is conducive to saving energy consumption and trading the remaining carbon emission indicators in order to obtain additional income. The income from carbon emissions trading in turn will also stimulate enterprises to increase investment in technology research and development, thus forming a virtuous cycle of technology research and development.

## Acknowledgments

The authors sincerely thank the anonymous referees for their meaningful suggestions on a previous draft. This work was jointly supported by the National Social Science Foundation of China

(No.14CMZ034, No.15BMZ078) and National Natural Science Foundation of China (No.71874101).

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