The Impact of Science and Technology Innovation on Carbon Emission Reduction Efficiency

--Based on the input-output perspective

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Abstract. Using 30 provinces, municipalities and autonomous regions in China from 2013 to 2019 as the research objects, the dynamic benefits of emerging technologies and high technology on reducing carbon emission reduction efficiency was analyzed from the input-output perspective using the DEA-Malmquist method and by calculating the Malmquist index. Tobit regression analysis was also used to further investigate the factors influencing the differences in carbon emission reduction efficiency between different provinces and cities. The findings show that: i) science and technology innovation has a significant positive effect on reducing carbon emissions, and factors such as R&D funding have a positive effect on efficiency; ii) the regional tertiary industry share positively moderates this effect, while the regional Internet development level negatively moderates this effect. Finally, based on the results of the empirical study, we analyze the reasons for the changes of carbon emission reduction efficiency in each region and propose management suggestions to promote the improvement of carbon emission reduction efficiency.

Keywords: Innovation Management, Data Envelope Analysis, Carbon Emission Efficiency.

1. Introduction

The development of ecological civilization is now facing severe tests such as tightening resource constraints, ecosystem degradation and serious environmental pollution[1]. Promoting green development through scientific and technological innovation, as a combination of innovation-driven and green development strategies, is one of the core elements to boost the construction of ecological civilization, and has gradually become a hot spot of concern for all sectors of society [2]. Carbon dioxide emissions have an important influence on regional warming, precipitation changes and extreme weather [3-5], so carbon dioxide emissions are an important indicator of the green development of a region. It is of great interest to explore the role of science and technology innovation in promoting green development by analyzing the effect of science and technology innovation on the carbon dioxide emission situation.

The two areas of exploring the impact of high technology on carbon emissions and analyzing how to reduce the efficiency of carbon emissions have received extensive attention. In terms of the impact of science and technology innovation, Li Guifa and Wang Qiuyue constructed a spatial Durbin model based on panel data of Chinese provinces and found that increasing green R&D funding had a positive effect on carbon productivity improvement in the target region as well as the surrounding regions[6]. Xuefeng Zhang et al., constructed an empirical model of industrial carbon productivity based on the Heckman two-stage model for data related to 41 industrial sector subsectors in China in 2019, and studied that surface technology innovation can significantly improve industry carbon productivity[7].

In terms of reducing carbon emission efficiency, Ma Dalai et al. measured the carbon emission efficiency of Chinese provinces and cities, and investigated the regional variability and spatial autocorrelation of carbon emission efficiency among provinces[8]. Chenyao Qu et al. used a DEA model to measure the carbon emission efficiency of manufacturing industry segments in China and studied the influence of various factors on high, medium and low carbon emission efficiency industries[9]. Wang Hui et al., and Yang et al. explored the factors influencing China's carbon emission performance land from the perspectives of several, including policy and industry[10,11].

Existing studies on the ecological performance evaluation of STI have achieved some success, and most scholars have used theoretical analysis or regression analysis to study in depth the impact of STI on ecological environment[12,13], climate conditions, etc. [14,15]. However, most of the existing studies have focused on provinces, industries and specific economic zones, and few studies have investigated the impact of factors such as technological progress and economic development on carbon emission efficiency in China. In this paper, we conduct an empirical study on the level of science and technology innovation and carbon emissions in 30 Chinese provinces (autonomous regions and municipalities directly under the central government, later abbreviated as "provinces"), and analyze the impact and changes of science and technology innovation in depth. We also analyze the impact of science and technology innovation on carbon emission reduction from the perspective of input-output efficiency by using the DEA-based Malmquist productivity index, and analyze the related impact mechanisms and influencing factors in order to enrich the relevant research.

2. Model Construction

2.1. Data Envelopment Analysis

Data Envelopment Analysis (DEA), a model for dealing with complex problems with multiple input and multiple output indicators, has the advantages of not needing to know the specific form of the production function. We use DEA model to evaluate decision making units (DMUs) with constant payoffs of scale in a relatively efficient way. The efficiency evaluation index corresponding to each decision making unit (DMU) is:

$$h_k = \frac{u^T y_i}{v^T x_j} = \frac{\sum_{r=1}^{n} u_r \, y_{rj}}{\sum_{i=1}^{m} v_i \, x_{ij}} \tag{1}$$

We assume that there are a total of *t* provinces (t DMUs), *L* input indicators and *M* output indicators, and note that x_{jl} is the lth resource input for the jth province, and the corresponding y_{jm} is the mth output for the jth province (j=1,2,···,t; m=1,2,···,M). Then the output model based on constant returns to scale under the minimal axiomatic assumption for the 0th province can be expressed as:

$$\min\left[\theta - \varepsilon\left(\widehat{e^T} s^{\mp} e^T s^+\right)\right]$$

$$s.t.\begin{cases} \sum_{j=1}^{t} \lambda_j \, x_{jl} + s^- = \theta x_l^0 \\ \sum_{j=1}^{t} \lambda_j \, y_{jm} - s^+ = y_m^0 \\ s^-, s^+ \geq 0 \\ \lambda_j \geq 0, j = 1,2,\cdots,t \end{cases} \tag{2}$$

where λ_j is denoted as the weight variable, s^+, s^- are denoted as the positive and negative relaxation variables, respectively, ε is the Archimedean infinitesimal, $\theta \in [0,1]$, and for the final objective if $\theta = 1$, it is denoted as the combined efficiency optimum with respect to the inputs.

And under the scale invariant model, we can transform into a VRS scale variable model by adding the convexity assumption $\sum_{j=1}^{n} \lambda_j = 1$. In the case of scale variation, the actual output efficiency can be decomposed into pure technical efficiency and scale efficiency. For our research question, we choose to use output orientation, i.e., to study how to maximize carbon reduction efficiency without changing the input factors.

2.2. DEA-Malmquist method

Compared to the traditional DEA method, we consider that there are significant dynamic benefits in technological innovation, emerging technology inputs, and therefore it is difficult to judge the overall dynamic efficiency changes from a single assessment. Therefore, we introduced the DEA-Malmquist method, which has been mainly applied to the study of dynamic efficiency change trends, defining the Malmquist productivity index (tfpch) for two adjacent periods as[16]:

$$M_0(x_t, y_t, x_{t+1}, y_{t+1}) = \left[\frac{D_0^{t+1}(x_{t+1}, y_{t+1})}{D_0^{t+1}(x_t, y_t)} \times \frac{D_0^{t}(x_{t+1}, y_{t+1})}{D_0^{t}(x_t, y_t)}\right]^{1/2} \tag{3}$$

where $D_0^t(x_{t+1}, y_{t+1})$ represents the input distance function based on the production point in the same time period compared with the frontier technology.

Malmquist index can represent input-output efficiency by using the ratio of distance functions in different periods, and combined with DEA method, it can realize the cross-sectional comparison as well as the vertical analysis of input-output efficiency. malmquist index measures the dynamic index change of efficiency from period t to t+1, which can be decomposed into technical efficiency change index (EC) and technical progress change index (TC):

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Malmquist productivity index can be decomposed into these three items. A change in scale efficiency greater than 1 indicates an improvement in scale efficiency, a change in pure technical efficiency that is greater than 1 is an improvement in resource allocation efficiency; a change in technology greater than indicates an improvement in production technology; and a Malmquist productivity index greater than 1 which indicates an improvement in overall productivity. If the opposite is less than then it indicates a decrease in the corresponding efficiency.

2.3. Tobit regression model

Since the traditional OLS least squares regression, does not respond well to the constrained variables, to further explain the differences in the efficiency values of each DMU, we need to use the Tobit regression model to solve this problem. To further analyze the influencing factors that cause the differences in the efficiency of each DMU and to make suggestions for improving the efficiency. We constructed the following Tobit regression model by using the calculated DEA-Malmquist coefficient as the dependent variable and the level of Internet development and the share of tertiary sector in local i in period t as independent variables.

$$y_{it} = \beta_0 + \beta_1 Internet_{it} + \beta_2 Tertiary_{it} + \varepsilon_{it} \tag{5}$$

Where β_0 denotes the intercept term, β_1, β_2 denotes the regression coefficients of the corresponding variables, *i* denotes the region, and *t* denotes the year.

3. Model solving

3.1. Data and Sample

We obtained relevant data for 31 provinces and cities across China in the National Statistical Yearbook and the China Carbon Accounting Database (CEADs)[17-20], excluding the data sample of Tibet Province (which has too many vacant data values), and obtained panel data on STI and carbon emissions for 30 provinces and cities across China from 2013-2019.

We refer to Shisai Ge et al. in their study of green innovation performance in the Yangtze River Delta using three waste emissions, R&D personnel, and funding as the main input indicators, and selecting indicators such as local green space per capita as the output performance[21]. For our input indicators, we selected data on local R&D input costs, the number of R&D personnel, and other scientific research in each province and city, and for output indicators, we selected carbon emissions, air quality, and GDP values, the number of patent applications and R&D projects. The descriptive statistics of the data are shown in Table I

Table 1. Variable descriptive statistics

Variable	vars	n	mean	sd	se
year	1	210	2016	2	0.14
RD_fulltime	2	210	92116.03	124258.8	8574.67
RD_items	3	210	13576.92	19220.85	1326.36
RD_funds	4	210	3688904	4664022	321848.1
patent	5	210	105213.8	140429.7	9690.57
airquality	6	210	250.8	63.84	4.41
GDP	7	210	26474.54	20679.96	1427.05

3.2. Analysis of green innovation efficiency by province

By selecting the load prediction results of 403 and 411 lines. We can see that the actual values of the lines basically match the predicted values, but there are also some errors, especially in the peak period of electricity consumption, as shown in Table.1.

Table 2. Average Green Innovation Efficiency by Province, 2014-2018

province	tfpch	effch	pech	techch	sech
Anhui	0.966970	0.906924	0.969982	1.065849	0.949008
Beijing	1.121517	1.000000	1.000000	1.121517	1.000000
Fujian	1.069790	0.944917	1.002405	1.128345	0.943151
Gansu	1.091943	1.012249	1.018288	1.083078	0.995786
Guangdong	1.102004	0.964727	1.000000	1.149314	0.964727
Guangxi	1.074506	0.951732	1.000000	1.125924	0.951732
Guizhou	0.996129	0.923038	1.003232	1.085223	0.922089
Hainan	1.117699	1.002234	1.000000	1.115641	1.002234
Hebei	1.020467	0.954516	0.938025	1.083856	1.031545
Henan	0.997138	0.920465	1.000000	1.087221	0.920465
Heilongjiang	1.078598	0.991275	1.012389	1.090174	0.982931
Hubei	1.070452	0.948470	1.043938	1.129340	0.927822
Hunan	1.006751	0.909522	0.957178	1.115995	0.955733
Jilin	1.061728	1.069095	0.990833	1.053084	1.080338
Jiangsu	0.948597	0.860645	1.000008	1.111241	0.860685
Jiangxi	1.060065	0.946588	0.958945	1.125772	0.995354
Liaoning	1.043907	0.915699	0.906352	1.142503	1.042091
Neimenggu	0.984928	1.000241	1.003965	1.023214	0.994899
Ningxia	1.012702	0.896940	0.886832	1.138446	1.017672
Qinghai	1.076895	1.000000	1.000000	1.076895	1.000000
Shandong	1.102371	0.930927	1.000000	1.185754	0.930927
Shanxi	1.016904	0.971338	0.947026	1.104933	1.019915
Shaanxi	1.081151	0.986570	1.000900	1.104279	0.981217
Shanghai	1.131638	0.985585	1.073843	1.153430	0.952183
Sichuan	0.969671	0.880247	1.000000	1.106792	0.880247
Tianjin	1.140586	1.035835	1.047506	1.107702	0.991404
Xinjiang	1.119688	1.010631	1.000000	1.132195	1.010631
Yunnan	0.969250	0.863835	1.000000	1.129719	0.863835
Zhejiang	0.972056	0.906597	0.977491	1.070595	0.926973
Chongqing	0.945085	0.845876	0.966011	1.116318	0.947429

By conducting DEA analysis and Malmquist index calculation for each province, we obtained the average green innovation efficiency of each province in China from 2013 to 2019 (Table 2). From Figure 1 we can find that most of the provinces in the country had better output levels in STI inputs during 2014 to 2018, and individual provinces and municipalities (Liaoning, Shanxi, Inner Mongolia, Zhejiang, Chongqing, Anhui) had a decrease in output levels from 2016 to 2017. Most of the provinces have a Malmquist index below 1 during 2018-2019, i.e., a decreasing trend in efficiency compared to the previous period.

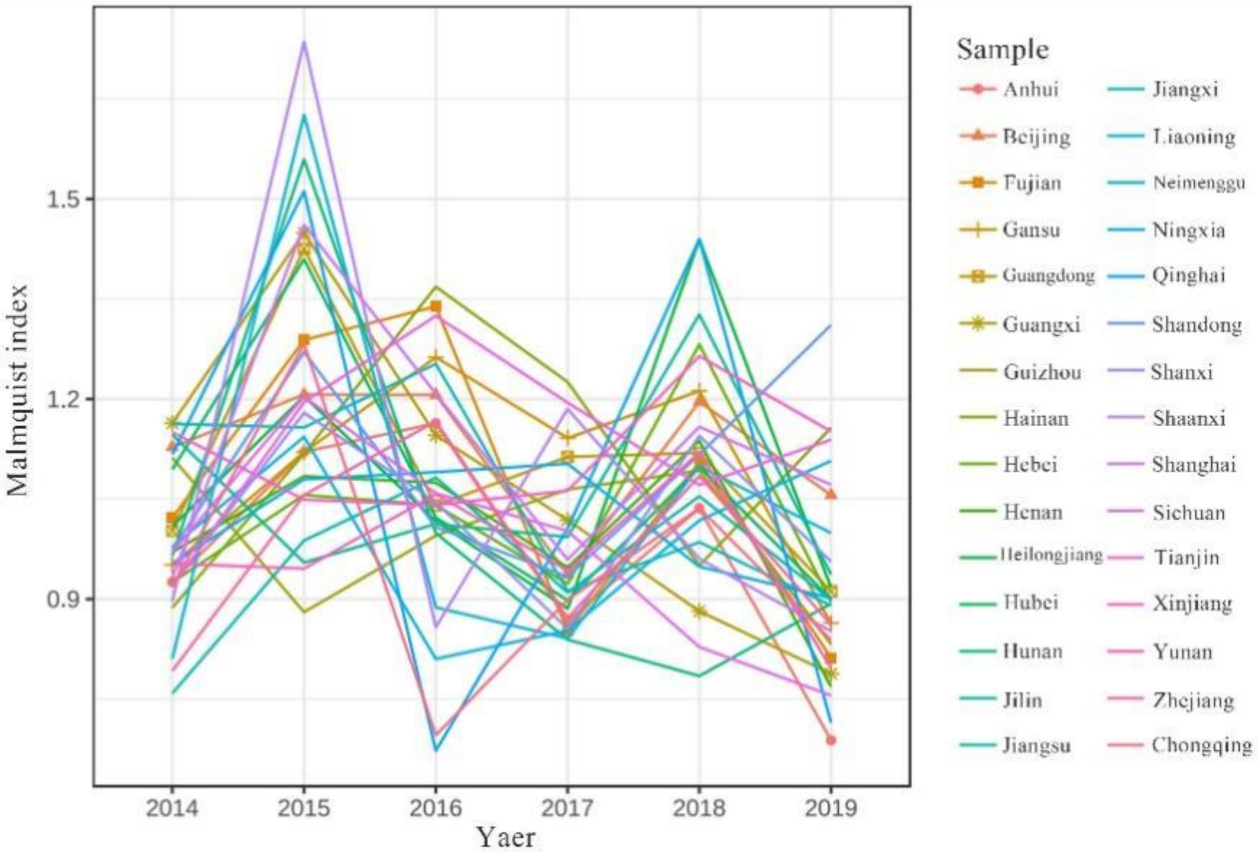

Figure 1. Change in Malmquist Index by Province, China, 2014-2019

From the comparison between prediction data and actual data, the BP neural network has better prediction performance and relatively small error, which can meet the demand completely, and has fast prediction speed and convenient operation.

3.3. Analysis of Green Innovation Efficiency in China

Table 3. Malmquist Index and Decomposition Means for 30 Provinces in China, 2013-2019

Year	MI	EC	TC	PTEC	SEC
2013-2014	0.984	0.89	1.113	0.983	0.908
2014-2015	1.225	0.967	1.271	0.989	0.99
2015-2016	1.065	1.053	1.032	0.99	1.08
2016-2017	0.975	0.986	0.992	1.031	0.959
2017-2018	1.1	0.92	1.201	0.975	0.952
2018-2019	0.922	0.89	1.044	0.972	0.92
Mean	0.976	1.088	1.044	0.988	1.03

As we can see in Table 3, the mean value of Malmquist index for 2013-2019 is 0.976 and the mean value of the improvement in the level of green development due to technological change is 0.988. In terms of the overall changes in the country, the green innovation efficiency is lower during 2016-2017, which is consistent with the results obtained from the analysis of green innovation efficiency in each province.

3.4. Analysis of the factors affecting the efficiency of linkage innovation

According to the above measure of efficiency, it is found that there are large differences in carbon emission reduction efficiency among different regions, so we use Tobit regression to further investigate the relevant factors that regulate the effect of STI investment on carbon emission reduction efficiency.

Table 4. Tobit regression results of factors influencing green innovation efficiency by province

Dependent variable	value
tertiary_industries	0.015 (0.014)
internet	−0.156* (0.092)
Constant	1.021*** (0.019)
Observations	180
Log Likelihood	53.454
Wald Test	4.252(df=2)

Note: *p<0. 1; **p<0.055; ***p<0.01

From the regression results in Table IV we can see that the development of the local level of Internet can have an impact on output efficiency at the 10% level, and this impact coefficient refers to the -0.15 standard deviation reduction for output efficiency at each standard deviation level increase in the level of Internet development, and this finding is significantly different from the existing studies. And the impact coefficient of the tertiary sector is positive but not significant.

4. Conclusions

According to the results of the DEA model empirical analysis we can see that most regions have a higher level on the green output of science and technology innovation in 2013-2018, and the input-output efficiency of science and technology development is very high for reducing carbon emissions. Individual provinces and municipalities (Liaoning, Shanxi, Inner Mongolia, Zhejiang, Chongqing, Anhui) had a decrease in output levels from 2016 to 2017, which is mainly related to the decrease in R&D funding in these provinces (cities) from 2016-2017. Most provinces have Malmquist index less than 1 during 2018-2019, i.e., there is a significant downward trend in STI for carbon emission reduction efficiency compared with the previous period, and we believe that the reduction in carbon emission reduction efficiency may be related to the spread of severe neocoronavirus pneumonia (Covid-19), and the global epidemic has caused R&D funding and the number of R&D projects, etc. in most regions compared with the previous The global epidemic may have reduced the efficiency of R&D staff and limited the development of the real economy, making it less efficient to translate STI into real products and use them to reduce carbon emissions. Therefore, we can see that science and technology innovation has a significant positive effect on improving the efficiency of carbon emission reduction, and factors such as R&D funding have a positive effect on the efficiency.

In the Tobit regression analysis, we can see that the level of local Internet development is significantly negatively correlated with carbon emission reduction efficiency, which is contrary to the conclusion of many existing literatures, and we believe that this is a result of the agglomeration effect of talents squeezing out the communication convenience brought by the Internet under the current development status in China, as most of the talents in China are concentrated in areas such as Yangtze River Delta, Pearl River Delta, and Bohai Sea Economic Belt, and technological innovation is Therefore, the concentration of talents leads to a different level of Internet development from our common sense perception, and the level of Internet development in provinces and cities does not give good play to the convenience of Internet communication to enhance the level of innovation and promote the efficiency of carbon emission reduction through communication; instead, Internet development leads to problems such as a significant increase in electricity consumption, which makes regional carbon emissions increase. The impact of local tertiary industry share is not significant, but the coefficient is still positive. The increase in the share of tertiary industry indicates that the proportion of high pollution and high carbon emission industries such as primary industry and secondary industry decreases compared to tertiary industry, which also has a positive effect on the improvement of carbon emission reduction efficiency.

Finally, we believe that provinces should increase investment in R&D, improve R&D funding, and continue to strengthen the construction of universities to improve education and research strength, and bring scientific and technological innovation with more research funding and research projects, so as to improve the carbon emission efficiency of their provinces and cities. Meanwhile, optimizing the industrial structure and promoting the transformation of industrial structure is also an important way to reduce carbon emissions, lowering the proportion of primary and secondary industries and raising the proportion of tertiary industry production. At the same time, provinces need to balance the relationship between the level of Internet development and carbon emissions, reduce the high carbon emissions brought about by Internet development through technological innovation while balancing the development speed and the proportion of development funds, adjust part of the balance of funds to scientific research and innovation, and focus on promoting the development of the real economy.

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