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Estimating the efficiency of a sustainable Chinese tourism industry using bootstrap technology rectification☆

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ABSTRACT

This paper estimates the efficiency of the Chinese tourism industry using traditional data envelopment analysis (DEA) and bootstrap-DEA. It also identifies the determinants of efficiency. The comprehensive and pure technical efficiency values estimated by DEA are higher than those estimated by bootstrap-DEA, indicating that the former method tends to overestimate efficiency. Further, the changes in comprehensive and pure technical efficiency are not significant, while some models display no efficiency. Additionally, economic development, urbanization, and the degree of opening up have positive effects. By regional division, the comprehensive technical efficiency declines from east to west and economic development is not significant in the eastern and central areas. Thus, the model is technically improved by adding environmental factors and adopting bootstrap technology to obtain more accurate efficiency values and decompose the rectified efficiency values. Finally, a panel Tobit model is used to analyze efficiency determinants.

1. Introduction

The sustainable development is relevant to the development of the global tourism industry. The damage to the environment by tourism is irreversible and the outdated environmental protection consciousness of tourists leads to a significant decline in the self-healing ability of the ecosystem. Hence, any evaluation of the tourism industry should include its negative impacts on the environment along with other determinants.

The tourism industry, having one of the widest development prospects in the 21st century, shows strong abilities for sustainable development and risk resistance. For instance, the ratio of the comprehensive final consumption of Chinese tourism to the total final consumption of the national economy from 2015 to 2017 exceeded 14%. The ratio of comprehensive tourism capital formation to the total national capital formation, as well as that of comprehensive tourism exports to total national exports were around 6% during 2015–2017. Therefore, while the development of the tourism industry is important for stimulating consumption, it has neglected protecting the ecological environment, resulting in a high wastage of resources and low economic output. This has greatly restricted quality and efficiency development in this industry. The concept of green tourism had started to gain attention even before the Chinese Tourism Development Committee put forward regulations in 2018 to ensure adherence to the rules of sustainable development and to promote green tourism. Therefore, estimating the efficiency of the tourism industry from the perspective of sustainable development and exploring its key determinants are of great significance to academic research.

Green tourism can be understood as a concept similar to the sustainable development of tourism and eco-tourism. Specifically, it refers to the rational use of resources and protection of the ecological environment, while providing products that ensure comfort, safety, and human health to society members. Green tourism incorporates the concept of sustainable development and runs on the idea of harmony between people and the environment. Therefore, green tourism means that tourism actors, including tourists, restaurants, scenic spots managers, travel agencies, and tour guides, must respect nature and protect the environment in all aspects of the entire tourism process. Green tourism is based on the premise of understanding nature, protecting nature, and not destroying the natural ecology balance. It is thus a comprehensive reflection of economic development, social harmony, and environmental values.

Previous studies have typically separated the ecological efficiency of tourism from its developmental efficiency when discussing environmental and resource issues in tourism. However, this study technically adjusts the input and output indexes of the tourism industry, adds

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ecological environmental factors to the evaluation of tourism efficiency, and observes changes in tourism efficiency from the sustainable development perspective. Moreover, bootstrap technology is used for rectifications when decomposing efficiency, to ensure a faithful representation of research conditions. Based on data on 31 provinces in China from 2011 to 2016, this paper uses the fixed asset investments of tourism enterprises, the number of class A and above scenic areas, tourism industry employment, and environmental governance investments as input indexes, and number of tourist arrivals at class A and above scenic areas, and revenues of tourism enterprises as output indexes. First, data envelopment analysis (DEA) is used to calculate the efficiency of the tourism industry in each of the 31 provinces in China, while considering environmental governance investments. Second, the model is optimized and bootstrapping is used to calculate more precise efficiency values. Finally, a Tobit model is employed to analyze the determinants of the tourism efficiency to identify the key factors and optimal paths for the sustainable development of tourism under the restriction of environmental protection.

The structure of the paper is as follows. The first section introduces the problems in the development of the Chinese tourism industry; the second reviews domestic and foreign studies on tourism industry efficiency and applications of bootstrapping technology; the third calculates the efficiency values of all decision-making units using the DEA method and employs the deviation rectification technology of bootstrap-DEA to provide more precise efficiency values; the fourth employs a Tobit model to empirically analyze the key determinants of comprehensive efficiency; and the final section summarizes the results and provides suggestions for the sustainable development of tourism. The sustainable use of resources in the context of development and externalities can thus be combined with tourism-related issues to aid the future development of Chinese tourism.

2. Literature review

The concept of sustainability has been extensively discussed in the various fields of social development (Fujii and Managi, 2013; Halkos and Managi, 2017; Kumar and Managi, 2010; Shoyama et al., 2013), while economic development efficiency has always been a research hotspot. Hence, tourism efficiency has become an important way to measure resource effectiveness and the overall development of the industry. Research by foreign scholars on the efficiency of the tourism industry started being conducted earlier than research on China. Their research objectives included the overall tourism industry and its related enterprises. For instance, at the macro level, Hadad et al. (2012) classified 105 countries and regions, calculated comprehensive efficiencies using the DEA method, and carried out a comparative analysis based on the calculated efficiency values. Ponjan and Thirawat (2016) studied the impact of Thailand's tourism tax cuts using the computable general equilibrium model. Eugenio-Martin and Inchausti-Sintes (2016) examined low-cost travel and tourism expenditures, estimated a system of simultaneous equations using the three-stage least squares method, and concluded that low-cost travel savings are transferred, at least partially, to higher tourism expenditure at the destination. Kiani Mavi et al. (2018) analyzed eco-efficiency and eco-innovation with common weights.

Further, most studies by foreign scholars focus on tourism enterprises. For instance, Assaf (2012) calculated the operating efficiency of tourism enterprises in Asia-Pacific using stochastic frontier analysis. Ben Aissa and Goaied (2016) analyzed hotel profitability in Tunisia using DEA and return on assets, and found that hotel size, level of indebtedness, exposure to crisis events, and level of managerial education are influential. Koroteeva et al. (2016) found that tourism enterprises in Russia could gain a strategic competitive advantage by providing higher quality services than those of their competitors. Fernández et al. (2018) studied the impact of tourism on airport efficiency. Mendieta-Peñalver et al. (2018) analyzed the relationship between tourist destinations and the competitiveness of international hotels using DEA and regulation mode methods, showing a positive correlation between destination and enterprise competitiveness.

In general, foreign studies' attention on the tourism industry is at the micro level. More research is based on the cost changes of tourism institutions, while there are fewer studies on environmental changes and the sustainable use of resources in tourism.

Research on tourism efficiency by domestic scholars followed the research by foreign scholars as follows. In their study on the efficiency of tourist attractions, Cao et al. (2015) calculated the efficiency of scenic spots from 1992 to 2012 in China using DEA and a deviation rectification of the bootstrap-DEA method, concluding that the functions and influences of pure technical efficiency were higher than those of scale efficiency when considering generalized moment analysis. Cao et al. (2015) analyzed the effects of Chinese economic fluctuations on the efficiency of national scenic areas using DEA, empirical mode decomposition, and wavelet decomposition methods.

Domestic scholars have also focused on regional tourism. For example, Li et al. (2014) studied the efficiency and temporal and spatial characteristics of tourism in the four great coastal urban agglomerations since 2000 in eastern China, finding that the influence of pure technical efficiency on comprehensive technical efficiency was higher than that of tourism scale efficiency in the southern coastal areas, as opposed to the northern coastal areas. Leroux and Pupion (2017) focused on the hotel industry, and Liu et al. (2018) measured the environmental efficiency of the transportation industry based on large-scale data.

When environmental resource problems arise in tourism development, scholars first measure the eco-efficiency of tourism destinations in regional tourism. Chu et al. (2016) analyzed regional ecological efficiency in China using two-stage DEA and found that ecological benefits in most areas in China in 2013 were relatively low and the average ecological efficiency in the east was higher than that in the central and western areas. Huang et al. (2016) evaluated the environmental benefits of Taiwan's coastal tourism development using DEA, finding that the development of the tourism industry was closely related to the maintenance of the environment. Further, the conditions in west Taiwan were better than those in the east, with most areas having small populations, low income, and high energy consumption. Peng et al. (2017) created a comprehensive evaluation index system to analyze the characteristics and evolution of eco-efficiency for an individual tourism destination, the results indicating that eco-efficiency improved continuously. Tang et al. (2017) studied energy efficiency and carbon efficiency in the tourism industry. Song et al. (2018) studied the relationship between environmental regulations, staff quality, green technology, R&D efficiency, and profit in manufacturing. Chen and Zhao (2018) studied the relationship between eco-efficiency and tourism under new-type urbanization. Xie et al. (2018) analyzed the green efficiency of arable land use in China. Xie et al. (2019) studied the spatio-temporal disparities and determinants of the total-factor green use efficiency of industrial land in China.

In addition to calculating the efficiency of the tourism industry in previous studies, the use of DEA led to significant differences between calculated and actual efficiency values. Hence, the bootstrap-DEA model is a better method to calculate efficiency. A combination of bootstrap technology and DEA for the rectification of efficiency values during efficiency decomposition can effectively improve the accuracy of calculated efficiency values; these effects of rectification have already been proved by many applications. For instance, Halkos and Tzeremes (2013) researched the efficiency levels of the top 25 football clubs in Europe using two-stage double bootstrap-DEA. Song et al. (2013a) analyzed the current energy efficiency problem in China using this method. Song et al. (2013b) calculated and analyzed the energy efficiencies of BRICS using bootstrap-DEA based on a small sample. Finally, Li et al. (2014) used the bootstrap method for rectifications to study the efficiency of tourism development in the four large eastern coastal urban agglomerations in China.

Domestic scholars have studied tourism efficiency at both the micro and macro levels. Additionally, the environmental and ecological problems in tourism development have gradually become of interest to scholars over the past three years, ecological efficiency becoming their research focus. However, in the past, ecological problems were not combined with tourism efficiency, and protection of the ecological environment was not considered when calculating efficiency. From the perspective of output, most pollution comes from the waste discharged by secondary industries. It is thus not reasonable to include it in the model. Further, while selecting variables, few scholars have considered including environmental protection expenditure as an input variable, implying efficiency values were overestimated.

There have been numerous studies on the selection of input and output indexes for calculating tourism industry efficiency. For instance, Li et al. (2014) used employment per 10,000 persons in tertiary industries, number of 3A and above scenic spots, number of three-star and above hotels, and number of foreign and domestic travel agencies as input indexes, and total number of tourists and tourism revenue as output indexes for studying the efficiency of urban tourism development of the four large eastern coastal urban agglomerations in China since 2000. Chu et al. (2016) selected labor, capital stock, energy consumption, and pollution treatment investment as input indexes, and GDP as output index to estimate regional ecological efficiency in China. Chaabouni (2018) used the labor force and capital stock in the tourism industry as input indexes and tourist numbers and the GDP of the tourism industry as output indexes to study regional tourism efficiency in China. Peng et al. (2017) selected the average wage level of employees, new fixed asset investments, energy consumption, water consumption, and food and beverage consumption as input data and tourism revenue and garbage, sewage, and waste gas emissions as output data for measuring the eco-efficiency of Huangshan National Park. Combined with the literature, in the process of selecting input indicators, the amount of capital, quantity of labor, and scale of tourism are the factors considered in most studies, while output indicators ae typically the corresponding income and number of tourists, sometimes measuring ecological efficiency. Unexpected output is added when the model is applied. Therefore, if the theory of sustainable development is to be applied to tourism, adding environmental economic factors to the input indicators should be considered.

When analyzing determinants and based on their research objectives, scholars have selected different variables. Ben Aissa and Goaied (2016) selected the efficiency score, hotel size, age of hotel, debt-equity ratio, destination capability to attract international tourists, and manager's number of years of study after a bachelor's degree as determinants of hotel profitability in Tunisia. Peng et al. (2017) selected per capita tourism revenue, ratio of a hotel's revenue to total revenue, energy consumption per CNY 10,000 of tourism revenue, new fixed assets investment per CNY 10,000 of tourism revenue, and standard discharge rate of sewage as determinants of the eco-efficiency of Huangshan National Park. Based on the literature, the amount of capital, scale of the industry, degree of openness, and level of urban or regional development are variables that most scholars choose. Therefore, these variables were also chosen in the process of index selection in this paper. In areas with high levels of economic development, such as the eastern coastal provinces of China, the degree of urbanization is higher than inland, urban facilities are more complete, and the tourism management system is more mature. Attracting tourists can also attract large amounts of foreign capital. The region will increase its degree of openness and of opening up to further accelerate the development of tourism.

This paper adjusts the input indexes of the tourism industry at the technical level and adds ecological environmental factors to the evaluation of tourism efficiency. The proposed model can well offset the problems arising in tourism efficiency calculations after technical adjustment. It also includes environmental governance investment as an input variable. First, traditional DEA is used to calculate efficiency values for the tourism industry. Second, bootstrap-DEA is used to rectify the calculated efficiency values. Finally, a Tobit model is used to explore the determinants of the tourism efficiency as to provide better suggestions for green tourism.

3. Methods and data

3.1. The DEA model

DEA was first proposed by operational research experts, Charnes and Cooper, in 1978 (Charnes et al., 1978). It is a relative efficiency evaluation method that can study the multi-inputs and multi-outputs of multiple decision-making units. Its results are not related to dimensions. As this model has been widely used in numerous fields, its basic principles and computation processes will be briefly introduced here (Wei, 2000).

Assume there are decision-making units $DMU_j(j = 1, 2, \ldots, n)$ and each DMU_j has m input elements x_j and s output elements y_j, for which $x_j = (x_{1j}, x_{2j}, \ldots, x_{mj})^T$ and $y_j = (y_{1j}, y_{2j}, \ldots, y_{mj})^T$. $v = (v_1, x_2, \ldots, x_m)^T$ stands for the weight of each input element and $u = (v_1, x_2, \ldots, x_m)^T$ refers to weight of each output element. Therefore, DMU_{j_0} can be expressed as per the following linear programming formula:

$$\begin{cases} max\, h_0 = \dfrac{\sum_{r=1}^{s} u_r y_{rj_0}}{\sum_{i=1}^{m} v_i x_{ij_0}}, \\ s.\ t.\ \dfrac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \le 1,\ j = 1,\ 2, \ldots, n, \\ u_r \ge 0,\ v_i \ge 0,\ r = 1,\ 2,\ \cdots s,\ i = 1,\ 2, \ldots, m. \end{cases}$$

The form of duality is:

$min\theta$,

$s.\ t. \begin{cases} -y_i + y\lambda \ge 0 \\ \theta x_i - x\lambda \ge 0 \\ \lambda \ge 0 \end{cases}$, where θ is the efficiency value of the DMU.

When the value range of θ is [0,1], the above formula is a CCR model; when the formula contains constraint $A\lambda = 1$, the above formula is transformed into a DEA model with variable returns to scale, that is, a BCC model.

3.2. The bootstrap-DEA model

The bootstrap-DEA model makes up for the shortcomings of the traditional DEA method. A sample distribution obtained by the bootstrap method can simulate the distribution of the original sample estimators and rectify efficiency value deviations. Additionally, it can provide confidence intervals for efficiency calculations, so that the errors of efficiency evaluation and statistical testing problems of the traditional DEA model can be avoided (Simar and Wilson, 1999; Song et al., 2013b).

The basic idea of the bootstrap-DEA method is the numerical simulation of original data and calculating the DEA efficiency of the simulated data (Simar and Wilson, 2000). The specific operating steps can be found in the literature (Simar and Wilson, 1998) as follows:

(1) For each DMU(X_k, Y_k), $k = 1, \ldots, n$, X_k and Y_k respectively refer to the input and output of the kth DMU. By using DEA, we obtain efficiency value $\hat{\theta}_k = \min\{\theta \mid Y\lambda \ge Y_k; \theta X_k \ge X\lambda; \lambda \ge 0\}$, where θ is a scalar and λ is a $n \times 1$ constant vector;
(2) Using efficiency value $\hat{\theta}_k$, $k = 1, \ldots, n$ based on n DMUs, the bootstrap method is used to generate random efficiency values $\theta_{1b}^*, \ldots, \theta_{nb}^*$ with scale n. b refers to using the b^{th} iteration of the bootstrap method and θ_{kb}^* to the k^{th} random value among $\hat{\theta}_1, \ldots, \hat{\theta}_n$ and $k = 1, \ldots, n$;
(3) Calculate the simulation sample (X_{kb}^*, Y_k), in which

$X^*_{kb} = (\widehat{\theta}_k/\theta^*_{nb}) * X_k$, $k = 1, \ldots, n$;

(4) For each simulation sample, we use the DEA method to calculate efficiency value $\widehat{\theta}_{bk}$, $k = 1, \ldots, n$;

(5) By repeating steps (2) to (4) B times, we obtain a group of estimated values $\widehat{\theta}_{bk}$, $b = 1, \ldots, B$;

To guarantee the coverage of the confidence interval, considering sample sizes, this paper sets the B of the sample dataset as 1000 (Hall, 1986).

3.3. Data sources and variable selection

The data used in this study was obtained from the China Statistical Yearbook 2012–2017, China Environment Yearbook 2012–2017, and China Tourism Statistics 2011–2017 (Editing Committee of China Environment Yearbook, 2017; National Bureau of Statistics PRC, 2017; National Tourism Administration of The People's Republic of China, 2017).

Efficiency in tourism is an important index for measuring the level and quality of tourism development. Usually, different input and output variables are selected based on research requirements. Although research on tourism efficiency has become more insightful, there are still disputes on the choice of variables. Investment in environmental governance protects and improves environmental quality and prevents the deterioration of the ecological environment. It is the relevant investment entities of the society that use social accumulation funds and various compensation funds and consumption funds in terms of currency and labor. The investments in environmental protection by factors such as machinery and equipment will eventually form an environmental capital stock. In the narrow sense, this includes pollution control investment and operating costs of pollution control facilities; in a broad sense, it also includes environmental protection research investment, ecological construction investment, and environmental protection institution capacity building. To a certain extent, the total investment in environmental governance reflects the overall level and intensity of social environmental protection, being an environmental and economic embodiment of sustainable industrial development that can relatively accurately reflect the economic expenditures of the tourism industry for environmental protection. Therefore, this paper improves traditional models by introducing environmental protection investment as an input index to express the relationship between environment and economy, further including sustainability factors in the analysis.

However, the wide coverage of the tourism industry makes data selection difficult. Therefore, based on research requirements and data availability, this study limited the selection of indicators to enterprises that are representative of the current tourism industry and selected the number of class A and above scenic spots as the input indicator to describe the scale of tourism development in each region, employment figures in the tourism industry as the input index for the labor factor, fixed asset investments of tourism enterprises and environmental governance investment as input indexes for capital, and total tourist arrivals at class A scenic spots and revenues of tourism enterprises as output indexes.

3.3.1. Input indexes

(1) Number of class A and above scenic spots: The number of scenic spots is an important index to measure the current development level of the tourism industry. This study uses the number of class A and above scenic spots in every province during 2011–2016 as input index for industry scale.

(2) Employment in the tourism industry: The tourism industry is labor-intensive, with human capital playing an indispensable part. This paper uses employment per 10,000 people in the tourism industry in every province during 2011–2016 as an input index representing labor.

(3) Fixed asset investments of tourism enterprises: The continuous investment growth of tourism enterprises can facilitate the expansion of the tourism industry. Therefore, we use the fixed asset investments (in CNY million) of tourism enterprises in every province during 2011–2016 as an input index for measuring capital.

(4) Environmental governance investment: Sustainable development concern coordination between the economy, environment, and other factors. The environment cannot be neglected in relation to the development of the tourism industry. Hence, the scale and development level of tourism in a province are closely related to environmental quality, where better environmental quality implies thorough pollution treatment and more tourists. The environmental governance investment is a necessary input for maintaining a favorable environment. Although there is no mention of this index in previous studies, this paper selects the environmental governance investment (in CNY million) of every province during 2011–2016 as an input index for capital.

3.3.2. Output indexes

(1) Tourist arrivals at class A scenic spots: The number of tourist arrivals reflects the attraction and scale of the local tourism industry. This paper uses the total number of tourist arrivals per 100 million people at class A scenic spots of every province during 2011–2016 as an output index.

(2) Revenues of tourism enterprises: The revenues of tourism enterprises are an important indicator for measuring the economic output of the tourism industry. It reflects the economic benefits of the tourism industry: the higher the revenues of tourism enterprises, the higher is the level of development of the tourism industry. This paper uses the revenues of tourism enterprises (in CNY 100 million) of every province during 2011–2016 as an output index.

To avoid the influence of price changes and to make the data comparable, year 2011 is used as the base period. The fixed asset investments of tourism enterprises and environmental governance investments are deflated using the fixed assets price index of each province. The revenues of tourism enterprises are deflated using the household consumption price index in each province. As the fixed assets price index of Tibet is not complete, the national fixed assets price index is used instead. The descriptive statistics are shown in Table 1.

Table 1
Descriptive statistics of input and output indexes.

	Variable	Unit	Sample quantity	Mean value	Standard error	Min	Max
Input index	Fixed assets investment	CNY 100 million	186	184.96	176.19	24.07	822.84
	Employment figure	10,000 people	186	7.33	5.69	0.43	27.86
	Number of scenic spots		186	238.47	160.18	29	1054
	Environmental governance investment	CNY 100 million	186	228.19	167.84	26.20	686.29
Output index	Total tourists received	100 million people	186	1.07	0.92	0.01	5.14
	Revenue of tourism enterprises	CNY 100 million	186	177.45	198.30	8.07	796.11

Table 2
Efficiency values of every province during 2011–2016 and rectified efficiency values.

	2011				2012			
Province	OE	Boot-OE	PTE	Boot-PTE	OE	Boot-OE	PTE	Boot-PTE
Beijing	1.000	0.771	1.000	0.867	0.925	0.787	1.000	0.847
Tianjin	1.000	0.811	1.000	0.881	0.757	0.711	0.961	0.915
Hebei	0.662	0.592	0.745	0.706	0.509	0.479	0.532	0.509
Shanxi	0.563	0.524	0.669	0.638	0.565	0.529	0.671	0.632
Inner Mongolia	0.544	0.513	0.703	0.678	0.560	0.536	0.700	0.672
Liaoning	1.000	0.899	1.000	0.917	0.523	0.470	0.574	0.537
Jilin	0.400	0.370	0.567	0.537	0.481	0.421	0.548	0.503
Heilongjiang	0.528	0.490	0.658	0.624	0.686	0.606	0.688	0.632
Shanghai	1.000	0.751	1.000	0.880	1.000	0.736	1.000	0.830
Jiangsu	1.000	0.892	1.000	0.867	1.000	0.910	1.000	0.829
Zhejiang	1.000	0.882	1.000	0.911	1.000	0.876	1.000	0.831
Anhui	0.920	0.844	0.942	0.889	0.949	0.877	1.000	0.869
Fujian	1.000	0.914	1.000	0.931	1.000	0.904	1.000	0.915
Jiangxi	1.000	0.932	1.000	0.944	0.979	0.916	1.000	0.951
Shandong	0.845	0.781	0.863	0.809	0.715	0.653	0.737	0.675
Henan	1.000	0.819	1.000	0.883	0.928	0.829	1.000	0.858
Hubei	0.804	0.759	0.841	0.811	0.829	0.788	0.850	0.817
Hunan	1.000	0.854	1.000	0.903	1.000	0.913	1.000	0.928
Guangdong	1.000	0.822	1.000	0.872	1.000	0.856	1.000	0.828
Guangxi	0.763	0.719	0.801	0.765	0.751	0.706	0.786	0.748
Hainan	0.874	0.756	1.000	0.868	0.948	0.840	1.000	0.827
Chongqing	0.973	0.893	1.000	0.948	0.942	0.890	1.000	0.956
Sichuan	0.972	0.874	1.000	0.938	0.807	0.691	1.000	0.855
Guizhou	0.724	0.679	1.000	0.937	0.812	0.767	1.000	0.946
Yunnan	1.000	0.873	1.000	0.912	0.747	0.680	0.778	0.731
Tibet	0.252	0.223	1.000	0.858	0.266	0.239	0.977	0.877
Shaanxi	0.754	0.688	0.791	0.747	0.790	0.731	0.798	0.747
Gansu	0.547	0.494	0.781	0.733	0.536	0.493	0.660	0.611
Qinghai	0.415	0.385	1.000	0.879	1.000	0.720	1.000	0.816
Ningxia	0.413	0.384	1.000	0.889	0.405	0.378	1.000	0.822
Xinjiang	0.480	0.444	0.584	0.560	0.445	0.406	0.532	0.502
Average	0.788	0.698	0.901	0.825	0.769	0.688	0.864	0.775

	2013				2014			
Province	OE	Boot-OE	PTE	Boot-PTE	OE	Boot-OE	PTE	Boot-PTE
Beijing	1.000	0.843	1.000	0.856	0.968	0.837	1.000	0.840
Tianjin	0.753	0.717	0.948	0.904	0.731	0.695	0.946	0.895
Hebei	0.489	0.464	0.525	0.503	0.492	0.468	0.526	0.503
Shanxi	0.573	0.537	0.698	0.661	0.572	0.528	0.705	0.663
Inner Mongolia	0.542	0.518	0.697	0.671	0.552	0.524	0.718	0.690
Liaoning	0.536	0.495	0.573	0.543	0.513	0.484	0.536	0.508
Jilin	1.000	0.878	1.000	0.893	0.517	0.459	0.570	0.516
Heilongjiang	0.489	0.463	0.655	0.623	0.519	0.477	0.637	0.604
Shanghai	1.000	0.761	1.000	0.848	1.000	0.744	1.000	0.827
Jiangsu	1.000	0.891	1.000	0.858	1.000	0.874	1.000	0.832
Zhejiang	1.000	0.851	1.000	0.840	1.000	0.849	1.000	0.832
Anhui	1.000	0.848	1.000	0.867	0.969	0.875	1.000	0.895
Fujian	1.000	0.916	1.000	0.919	1.000	0.925	1.000	0.923
Jiangxi	1.000	0.839	1.000	0.879	1.000	0.816	1.000	0.845
Shandong	0.723	0.664	0.723	0.675	0.675	0.627	0.675	0.624
Henan	1.000	0.861	1.000	0.894	0.889	0.792	0.943	0.869
Hubei	0.826	0.785	0.844	0.807	0.830	0.788	0.846	0.803
Hunan	1.000	0.906	1.000	0.920	1.000	0.894	1.000	0.907
Guangdong	1.000	0.873	1.000	0.848	1.000	0.869	1.000	0.826
Guangxi	0.773	0.724	0.803	0.758	0.767	0.713	0.820	0.781
Hainan	1.000	0.892	1.000	0.851	1.000	0.874	1.000	0.827
Chongqing	0.931	0.884	0.994	0.951	0.939	0.890	1.000	0.951
Sichuan	1.000	0.816	1.000	0.857	1.000	0.817	1.000	0.834
Guizhou	0.857	0.806	1.000	0.932	0.992	0.921	1.000	0.918
Yunnan	0.747	0.674	0.806	0.750	0.737	0.668	0.803	0.755
Tibet	0.478	0.444	1.000	0.833	0.302	0.263	1.000	0.808
Shaanxi	0.840	0.774	0.855	0.809	0.829	0.772	0.830	0.780
Gansu	0.674	0.606	0.729	0.671	0.642	0.581	0.670	0.618
Qinghai	1.000	0.865	1.000	0.832	1.000	0.772	1.000	0.818
Ningxia	0.421	0.386	1.000	0.865	0.501	0.452	1.000	0.875
Xinjiang	0.475	0.432	0.542	0.507	0.440	0.399	0.537	0.506
Average	0.811	0.723	0.884	0.794	0.786	0.698	0.863	0.770

(*continued on next page*)

Table 2 (*continued*)

	2015				2016			
Province	OE	Boot-OE	PTE	Boot-PTE	OE	Boot-OE	PTE	Boot-PTE
Beijing	1.000	0.857	1.000	0.846	1.000	0.843	1.000	0.795
Tianjin	0.757	0.698	0.998	0.950	0.737	0.687	0.991	0.913
Hebei	0.498	0.467	0.530	0.503	0.522	0.458	0.557	0.522
Shanxi	0.578	0.528	0.715	0.674	0.585	0.528	0.725	0.668
Inner Mongolia	0.561	0.535	0.702	0.667	0.557	0.524	0.715	0.652
Liaoning	0.521	0.470	0.563	0.527	0.644	0.568	0.666	0.545
Jilin	0.463	0.411	0.659	0.609	0.470	0.423	0.605	0.561
Heilongjiang	0.546	0.495	0.669	0.628	0.653	0.545	0.750	0.702
Shanghai	1.000	0.739	1.000	0.840	1.000	0.726	1.000	0.823
Jiangsu	1.000	0.815	1.000	0.846	1.000	0.807	1.000	0.835
Zhejiang	1.000	0.827	1.000	0.835	1.000	0.813	1.000	0.796
Anhui	0.978	0.901	0.999	0.930	0.918	0.899	1.000	0.920
Fujian	1.000	0.916	1.000	0.924	1.000	0.878	1.000	0.936
Jiangxi	1.000	0.860	1.000	0.877	0.982	0.831	0.985	0.855
Shandong	0.688	0.633	0.688	0.637	0.801	0.724	0.819	0.726
Henan	0.849	0.764	0.873	0.814	0.765	0.712	0.837	0.786
Hubei	0.824	0.782	0.838	0.799	0.832	0.735	0.834	0.776
Hunan	1.000	0.894	1.000	0.913	1.000	0.882	1.000	0.902
Guangdong	1.000	0.858	1.000	0.841	1.000	0.835	1.000	0.869
Guangxi	0.767	0.720	0.785	0.742	0.795	0.711	0.796	0.739
Hainan	1.000	0.843	1.000	0.837	1.000	0.816	1.000	0.862
Chongqing	0.940	0.887	1.000	0.952	0.948	0.869	1.000	0.946
Sichuan	1.000	0.800	1.000	0.846	1.000	0.784	1.000	0.933
Guizhou	1.000	0.819	1.000	0.853	1.000	0.804	1.000	0.856
Yunnan	0.736	0.661	0.789	0.739	0.735	0.679	0.795	0.722
Tibet	0.242	0.216	1.000	0.827	1.000	0.665	1.000	0.874
Shaanxi	0.820	0.738	0.846	0.788	0.819	0.728	0.833	0.745
Gansu	0.803	0.709	0.908	0.838	0.757	0.689	0.813	0.775
Qinghai	0.619	0.562	1.000	0.839	0.537	0.497	1.000	0.856
Ningxia	0.545	0.485	1.000	0.835	0.470	0.418	1.000	0.881
Xinjiang	0.443	0.397	0.549	0.512	0.482	0.422	0.562	0.498
Average	0.780	0.687	0.875	0.783	0.807	0.694	0.880	0.783

Note: OE, PTE, Boot-OE, and Boot-PTE represent comprehensive, pure, rectified comprehensive, and rectified pure technical efficiencies, respectively.

4. Efficiency analysis

Deap2.1 software is utilized to calculate comprehensive and pure technical efficiency values based on the data from 31 provinces in China during 2011–2016 using the traditional DEA model. Subsequently, MaxDEA software is used on the same data to obtain bootstrap rectified values. The results of the two models are shown in Table 2.

Figs. 1 and 2 show the results of the two models. Comparatively, the efficiency value of every province using the bootstrap-DEA model is significantly different from that under the traditional DEA model and all deviated values exceed 0. This indicates that the traditional DEA model relies on original sample data and overestimates efficiency values. It also indicates that the rectification effect of the bootstrap technology was satisfactory to expectations, which could be a reference for the future calculations of tourism industry efficiency.

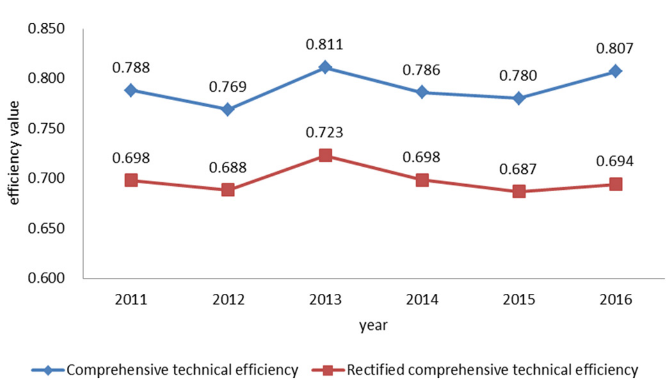

Fig. 1. Comparison of national comprehensive technical efficiency values and rectified values.

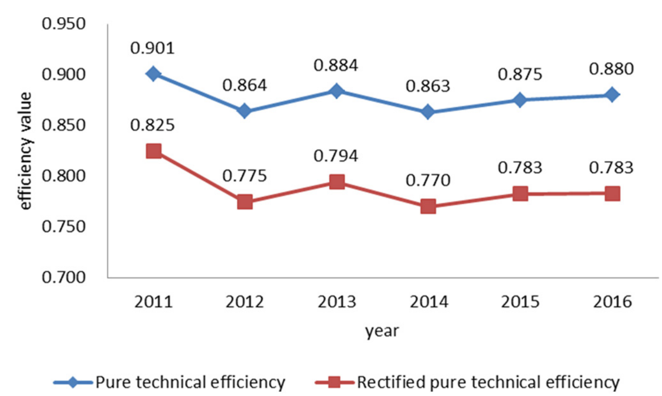

Fig. 2. Comparison of national pure technical efficiency values and rectified values.

For the entire country, the average values of the comprehensive technical efficiency during 2011–2016 ranged between 0.687 and 0.723 after rectification. The changes in the values in consecutive years were not large and there was no significant ascending or descending trend. During 2011–2016, the comprehensive technical efficiency reached a maximum value of 0.723 in 2013. One possible reason is that China focused more on developing its tourism industry in 2013 and passed the Tourism Law to expand tourism consumption and achieve a healthy development of the tourism industry. The rectified national pure technical efficiency registered average values between 0.770 and 0.825, and the changes were similar to those in the comprehensive technical efficiency values, registering a peak value of 0.825 in 2011 when China made efforts to develop rural and red tourism. Operating input and the quality of tourism enterprises in China improved and characteristic tourism villages were constructed, which promoted an increase in the pure technical efficiency of the Chinese tourism industry.

The comprehensive and pure technical efficiency values of individual provinces have displayed different trends over the six analyzed years. The comprehensive technical efficiency values increased significantly in seven provinces, decreased in six provinces, and remained stable in nine other provinces. Among the remaining nine provinces, high values that differed greatly for consecutive years were registered in 2011, 2013, and 2012, in Liaoning, Jilin, and Heilongjiang, respectively, because this was the period of the China—Russia Exchange and these three northeastern provinces of China are closest to Russia. Yunnan had a high efficiency value in 2011 because of the rectification and reformation of the tourism industry there, while Sichuan had an unprecedented low efficiency value in 2012 because its government ignored real problems in the development of the tourism industry. The efficiency of the tourism industry in the Tibet Autonomous Region remained low because of its remote geographical location on one hand and the existence of few policies and inputs related to the tourism industry on the other. The pure technical efficiency values increased significantly in three provinces, decreased in 13 provinces, and remained stable in 11 provinces. The varied trends of pure technical efficiency values in Liaoning, Jilin, and Yunnan were the same as those of their comprehensive technical efficiency values. However, the pure technical efficiency values of Gansu declined at first and subsequently increased, which was most likely related to the large investment in the tourism industry by the Gansu government as part of the 12th Five-Year Plan. This was accompanied by a comprehensive promotion of the Belt and Road Initiative strategy and the construction of Chinese civilization inheritance and innovation areas, leading to the development of the cultural tourism industry and growth of the tourism economy.

This study divides the 31 provinces in China into three regions—eastern, central, and western—according to the divisions used by the National Bureau of Statistics of China. As per Table 3, the comprehensive technical efficiency values of the eastern region range from 0.7 to 0.8 during 2011–2016, being higher than the average national value. This indicates that the east contributed to a large share of the national tourism industry and improved it. The reason may be that its geographical advantages attracted large investments that accelerated the development of tourism enterprises and construction of tourism facilities. Further, the rapid maturation of the tourism industry in the eastern region made it more stable than in the other regions. Moreover, the government sectors in the east adopted the concept of sustainable development earlier and published relevant policies and paid attention to environmental issues, which made the east a sustainability leader. The comprehensive technical efficiency in the both the central and western regions first increased and then decreased. The values for the central area ended up being close to the national averages, while the values for the west were much lower. Possible reasons are the unfavorable geographical location, insufficient publicity, and lower emphasis of the governments on tourism. Specifically, the existing tourism resources were not well used to attract foreign investments and the concept of sustainable development was not introduced in the development of the tourism industry timely. Over time, comprehensive technical efficiency declined from the east to the west every year. Regarding pure technical efficiency, the trend was different: efficiency values for the east declined and failed to reach national averages, except in 2011 and 2016; those of the central area declined in 2013 after reaching 0.8 and were also lower than the national averages; while the efficiency values for the west were higher than the national averages. The reason is that tourism demands little in terms of technology, meaning underdeveloped areas could utilize the experience and technology of developed areas over the short term to achieve a relatively high development level.

The analysis shows that the accuracy of the modified model is higher than that of the traditional one, indicating technical transformation met expectations. The inclusion of environmental governance investment ensures that the model considers environmental externalities and the sustainable use of resources when calculating efficiency. For constant output, the amount of investment required for environmental protection increases the value of the original input capital factor, resulting in a lower efficiency value. By comparing efficiency values before and after rectification, provinces with higher economic development levels, such as Beijing and Shanghai, had larger value deviations after rectification, while provinces with low levels of economic development, such as Guangxi and Qinghai, did not. Possible reasons are the randomness of sample generation during rectification and mutual influences of unknown factors, which could be identified in future research.

5. Analysis of determinants

5.1. Explanation for variables and modeling

The objective of calculating the efficiency of the tourism industry is to better judge the differences among different areas and to identify its determinants.

Based on previous research and the current conditions in China, this paper divides determinants into the economic development level, urbanization level, and degree of opening up in terms of nature and culture. The main explanatory variables are as follows. (1) The level of economic development represents regional economic power, as areas with strong economic power are often capable of providing more capital inputs so that the maturation of the tourism industry is faster; GDP per capita in 2011 is adopted as the base for the level of regional economic development (measured in CNY 10,000/person) and its impact is anticipated to be positive. (2) The level of urbanization and development of tourism promote each other; hence, with increasing urbanization levels, restrictions on tourism development are reduced and more people participate in the industry so that its efficiency can be improved. As such, the proportion of urban population is selected to represent the level of urbanization and its impact is anticipated to be positive. (3) Finally, the degree of opening up represents the possibility and speed of transmission of advanced technologies and experience in

Table 3
Average regional efficiency values of the tourism industry after rectification, 2011–2016.

	Comprehensive technical efficiency						Pure technical efficiency					
	2011	2012	2013	2014	2015	2016	2011	2012	2013	2014	2015	2016
East	0.799	0.744	0.758	0.746	0.737	0.739	0.856	0.774	0.784	0.768	0.777	0.815
Central	0.678	0.713	0.737	0.684	0.686	0.675	0.768	0.762	0.802	0.755	0.768	0.770
West	0.594	0.600	0.669	0.654	0.628	0.656	0.840	0.786	0.801	0.786	0.803	0.809
Entire country	0.698	0.688	0.723	0.698	0.687	0.694	0.825	0.775	0.794	0.770	0.783	0.783

Note: The east includes Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Guangxi, and Hainan; the central region includes Shanxi, Inner Mongolia, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, and Hunan; and the west includes Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang, and Tibet.

Table 4
Descriptive statistics of determinants.

Variable	Symbol	Unit	Sample number	Mean value	Standard error	Minimum	Maximum
Comprehensive technical efficiency of the tourism industry	OE	–	186	0.698	0.178	0.216	0.932
Actual GDP per capita	ECON	CNY 10000/person	186	4.860	2.250	1.641	12.228
Proportion of urban population	UL	–	186	0.550	0.135	0.227	0.896
Aggregate investment of foreign-invested enterprises	OPEN	USD 100 million	186	1230.26	1793.88	7.26	8798.68

China, as areas with higher degrees of openness have more opportunities to attract foreign investments so that the construction and improvement of tourism enterprises can be accelerated. The aggregate investment of enterprises with foreign investments is used to represent the degree of opening up (measured in USD 100 million) and its impact is anticipated to be positive.

This paper uses rectified comprehensive technical efficiency values as explained variables and sets up the following panel model by using the above explanatory variables to estimate efficiency:

$OE_{it} = \beta_{0i} + \beta_{1i}ECON_{it} + \beta_{2i}UL_{it} + \beta_{3i}OPEN_{it} + \varepsilon_{it}$,where OE refers to the comprehensive technical efficiency value of the tourism industry; ECON, UL, and OPEN stand for level of economic development, level of urbanization, and the degree of opening up, respectively, as factors that affect comprehensive technical efficiency in the tourism industry; β_{1i}, β_{2i}, and β_{3i} are the coefficients on the explanatory variables, ECON, UL, and OPEN, respectively; β_{0i} is the constant term; ε_{it} the random error term; and subscripts i and t represent province and time, respectively. The descriptive statistics of these variables are shown in Table 4.

5.2. Empirical estimation and result analysis

Since comprehensive technical efficiency of the tourism industry is a limited dependent variable, whose value ranges from 0 to 1, a traditional estimation may lead to deviations in estimation results. Therefore, this paper employs the Tobit model (Tobin, 1956) to estimate the determinants of comprehensive technical efficiency in the tourism industry. After the Hausman test is run on the panel data, the fixed effect is greater than the random effect, but the fixed-effect Tobit model usually does not generate consistent or unbiased estimators, and as the random effects model is better, we chose to use a mixed regression Tobit model for analysis. The results obtained by using Stata 14 software are shown in Table 5.

The estimation results show differences in the regression fit for the entire country and individual regions. The results can be summarized as follows:

(1) Estimates for the level of economic development were as expected in all four models, with the eastern and central regions showing no significance. The results indicate that an increase in the level of economic development level will lead to an increase in tourism efficiency. As economic development in the eastern and central regions is relatively mature, the influence of regional economic development on improving the comprehensive efficiency of the tourism industry was minimal. Conversely, the efficiency of the tourism industry in the west was significantly influenced by the level of economic development. Due to the small amount of tourism resources effectively developed and utilized in the west and the "rich area" in tourism resources in the west, a "low valley area" of tourism development and the "poor area" of tourism economy are formed. In addition, the uneven development between regions and the unbalanced market structure are common problems in the tourism industry in the underdeveloped areas in the west, and are the bottlenecks restricting the development of tourism in the west. Therefore, the influence of the level of economic development on tourism in economically developed areas is small, but significant in economically underdeveloped areas.

(2) The significance of the level of urbanization was high for the entire country, as well as the central and west regions. With a gradual improvement in urban facilities, the influence of the level of urbanization on tourism decreases. However, when the level of urbanization reaches a certain stage, city modernization can provide a better environment for tourism, but cannot fundamentally improve the development efficiency of the tourism industry. This is one restriction that hinders the breakthrough of tourism development in the east. The signs of the coefficient in the regression equations for the entire country and the eastern and western regions, were as expected, indicating that the level of urbanization will improve the comprehensive efficiency of the tourism industry. However, the sign of the coefficient for the central region was different from what we anticipated, and a possible reason may be that there are great industrial provinces such as Shanxi, Jilin, and Heilongjiang in this region, and the existing problems regarding the environment and unbalanced industrial structure cause the impact of the level of urbanization on the comprehensive efficiency of the tourism industry to be negative. That is, the higher the urbanization level, the more serious are the existing problems.

(3) The signs of the coefficient on the degree of opening up in the four equations were as expected, indicating a positive influence of the degree of opening up on the comprehensive efficiency of the tourism industry. However, it also indicates that the influence of this variable on tourism efficiency was significant and increasing the degree of opening up is a key path to improving the comprehensive efficiency of the tourism industry. Tourism has the characteristics of foreign-related, communication, comprehensive, and linkages, and opening up has promoted the flow of people, finances, and goods across borders, across regions, across time and space, and directly promoted the increase tourism and related industries. Further, prosperity drives GDP growth and introduces the latest changes in the tourism industry and related technologies and related technologies. The purpose of opening up to the outside world is to break local protection and restrictions under the conditions of economic globalization and increasing competition, integrate international and domestic resource markets, and establish a coordinated economic system to make the tourism industry have a broader development space and promote it better.

(4) The influence of the three explanatory variables was most significant in the central and western regions, and smallest in the

Table 5
Regression results of the determinants of tourism industry efficiency.

Variable	Entire country	East	Central	West
ECON	0.0542**	0.0184	0.000388	0.147***
	(0.0224)	(0.0157)	(0.0210)	(0.0354)
UL	0.851*	0.326	−2.036***	1.560***
	(0.432)	(0.338)	(0.673)	(0.338)
OPEN	3.87e-05***	2.14e-05***	0.000401***	0.000439***
	(9.70e-06)	(7.84e-06)	(7.11e-05)	(0.000130)
Constant	0.445***	0.606***	1.577***	0.316***
	(0.144)	(0.163)	(0.289)	(0.103)
Observations	186	72	54	60

Note: *, **, and *** respectively refer to significance at the 10%, 5%, and 1% significance levels.

eastern one. The differences between the comprehensive efficiency of the tourism industry in the east and west were intuitive. Differences in economic development and social facilities construction cause large gaps in tourism industry development between developed and underdeveloped areas. Moreover, other factors, such as policy and geographical location, enlarge such gaps gradually so that regional differentiation appears.

6. Conclusions

Considering environmental governance investment, this paper analyzed the efficiency in the tourism industry in 31 Chinese provinces. The number of class A and above scenic spots, employment in the tourism industry, fixed asset investments of tourism enterprises, and environmental governance investment were used as input indexes, while total tourist arrivals at class A scenic spots and revenues of tourism enterprises were used as output indexes. The traditional DEA approach was first used to derive comprehensive and pure technical efficiency values of the tourism industry in each area, and then bootstrap technology was used to rectify these values and obtain more accurate ones. Subsequently, the efficiency values for the tourism industry during 2011–2016 for each province in China were analyzed from spatial and temporal perspectives. Finally, a panel Tobit model was set up to identify the determinants of tourism industry efficiency in China. The main conclusions are as follows.

Compared with the traditional DEA model, the bootstrap-DEA model can solve the problem of overestimation of efficiency values. A comparison between the comprehensive and pure technical efficiency values shows that none of the efficiency values of the 31 provinces reached effective results. Generally, efficiency values fluctuated around 0.8 with no significant increasing or declining trends. By region, the comprehensive technical efficiencies of the eastern, central, and western regions declined, while pure technical efficiencies were slightly higher in the central and western regions than in the eastern one. The regression results of the determinants showed that economic development, urbanization, and the degree of opening up had positive effects on tourism industry efficiency. Hence, improving urbanization and the degree of opening up could significantly improve the comprehensive technical efficiency of the tourism industry. The significance of these influences decreased successively from west to east, indicating that when the tertiary industries mature gradually and tourism develops to a certain degree, the degree of influence from external factors on tourism efficiency will decrease and any further development of the industry will depend on its own breakthroughs.

Based on the above conclusions, this paper makes the following proposals. As a labor-intensive industry with high resource consumption and low economic output, tourism will play an increasingly important role in the future social economy. Hence, capital investment in tourism-related enterprises should be increased, their examination enhanced, the development of tourist scenic spots quickened, and relevant preferential policies targeting tourism improved. Further, tourists' awareness of environmental protection should be strengthened and investment in environmental protection from the source should be reduced; under the premise of continuous economic development, modest investments should be made, so that capital can be fully utilized. The level of urbanization needs to be directionally promoted according to the current status of the region. Similarly, with respect to the degree of openness, it is necessary to highlight the characteristics of the regional tourism landscape to attract foreign investment and promote its maturity. Regarding the different regions analyzed in this study, the western one should improve facilities construction and strengthen publicity, the central region should adjust its industrial development structure in a timely manner while promoting urbanization to realize the transition from the secondary to the tertiary industries, and the eastern one needs to start from the scale angle, such as developing new tourism routes to find a way to break through bottlenecks. In the meantime, enhancing environmental pollution treatment and creating a favorable environment to attract tourists and adhere to green tourism are benign and healthy ways for the development of tourism.

For the future development of China's tourism industry, this paper identified the following points:

(1) If we want to improve the efficiency of tourism across China, it is important to reduce regional differences. The efficiency value of the western region is lower than the average, but in fact, tourism resources are the most abundant in the three regions, but have not been properly planned and developed, so the tourism industry in the eastern and central regions is stable. This is one way to improve tourism efficiency in the western region by developing and utilizing its rich tourism resources as much as possible and attracting tourists to increase its income.
(2) Stable economic development is the basis for the industry to mature. Before the development of tourism, it is necessary to first improve the regional economic status, adjust the industrial structure according to its own situation, and not blindly develop the tertiary industry. Economic strength will increase the involvement of the government. It is easier to improve the construction of related facilities by having capital for tourism investment and development.
(3) The development progress of urbanization should conform to the actual situation. For example, if the central region does not change its industrial structure first, complete the industrial transformation, and blindly carry out urbanization, the result is that economic development will slow down and not lead to tourism development. A good social environment means its each region still needs to analyze the impact of the current urbanization level on tourism, so that the level of urbanization and industrial development matched.
(4) Opening to the outside world means the opening to domestic and international markets and two types of resources, and the simultaneous opening and closing of both domestic and foreign markets. Therefore, the tourism industry should improve bilateral and multilateral cooperation mechanisms, take enterprises as mainstay, implement market-oriented operations, and promote multi-disciplinary and all-round pragmatic cooperation with relevant countries and regions to create a domestic two-way open link between the east and west. As such, a new development pattern, further expanding regional openness, promoting China's foreign economic cooperation and exchanges with the development of tourism, implementing a more proactive tourism opening and upgrading strategy, and improving the open tourism economy are strategies that are mutually beneficial, win-win, balanced, safe, and efficient. An open area for tourism forms foreign economic cooperation and competition.

The limitations of this paper are as follows. (1) Considering data availability, this paper only used data for 2011–2016 for analyzing tourism efficiency. Additionally, considering the wide coverage of the tourism industry, environmental governance investment was not classified by industry. Thus, the precision of the research process could be further improved. (2) The study considered three potential determinants but could not analyze the practical conditions in each area. Hence, more variables should be included in future research to analyze the individual conditions in each area more accurately.

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