Research on the Relative Efficiency of International Travel Agencies and Tourist Development Strategy：Linking the Balanced Scorecard with DEA models

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Abstract

In recent years, the tourism industry and the number of international travel agencies have grown extremely rapidly in China. This paper combines several analytical techniques, DEA models and the Balanced Scorecard （BSC） in order to shed new light on the relative efficiency of international tourism development. In the first stage, we use the canonical analysis model to investigate correlations. In the second stage, we adopt DEA models, including CCR, BCC and FDH, to analyze the relative efficiency of international travel agencies. In the third stage, we use BSC to construct a tourism development strategy. We analyze the overall efficiency, pure technique efficiency, and scale efficiency of international travel agencies. We also investigate the most productive scale size for international travel agencies in China. Finally, we provide some management suggestions and a development strategy for the tourist industry and international travel agencies in China.

keyword：International Tourism, Balanced Scorecard, DEA, SBM, FDH

1. Introduction

The Chinese government sees the tourism industry as an engine for economic growth and has taken various measures to support it. So far, statistics and information from the Ministry of Tourism show that China has designated 99 cities as famous historical and cultural cities of national caliber, and placed 750 cultural relics under key protection. There are also 119 national scenic and tourist resorts across the land. Nineteen Chinese scenes and sights have appeared on a UNESCO（United Nations Educational, Scientific and Cultural Organization） list of natural and cultural heritage sites. China’s venerated history and splendid culture have resulted in a land that is pockmarked with cultural relics and treasures. Not only is the Chinese tourism industry is rich in resources, but it also has come a long way in terms of transportation, service, accommodation, catering and shopping facilities, and recreation. Tourist facilities are being constantly improved, and so is service. The tourism industry and the number of international travel agencies have grown rapidly in China.

In this study, we measure the relative efficiency of international travel agencies in China. The purposes of this study are to measure and evaluate the productive efficiency of international travel agencies in a developing country. The methodology used to perform efficiency analysis of the international travel agencies is Data Envelopment Analysis（DEA）. DEA is a mathematical programming tool that is well suited to this type of research for several reasons. DEA is a linear programming-based technique that converts multiple input and output measures into a single comprehensive measure of productivity efficiency 【1】. One of its most important features is its ability to handle multidimensional inputs and outputs, unlike traditional performance indicators that generally use one input-one output measures. Moreover, it is non-parametric, and no preconceived relationships need to be established in order to construct a model of an enterprise. Unlike other frontier approaches that define input-output relationships by estimating a true production frontier, DEA uses actual input-output data to construct a best practice frontier. Once the models are determined, application of DEA in industry is relatively simple.

DEA is a mathematical programming approach developed to measure the relative efficiency of units in an observed group of similar units. DEA provides a relative efficiency measure for each unit based on a set of similar units or on best performers operating on the frontier. Since DEA was developed by Charnes, Cooper, and Rhodes【4】, it has been widely applied to such industries as finance【13】and medical care【7】. Recently, several studies have examined the performance and the efficiency of the tourism industry using DEA【3】. So far, no similar studies on the relative efficiency of the tourism industry or international travel agencies in China have been done. In this paper, we discuss the relative efficiency of inputs and outputs for international travel agencies in China.

Kaplan and Norton【12】have created a powerful new tool, the "strategy map," that enables companies to describe the links between intangible assets and value creation with a clarity and precision never before possible. We discuss tourism development strategies and construct a strategy map of efficient DMUs.

The rest of the paper is organized as follows. Section 2 presents a brief review of the DEA theorem and BSC related research. Section 3 describes the methodology, research frame, samples and input-output variables. Section 4 presents the results of empirical analysis, including correlation analysis, efficiency analysis, reference set analysis, and bilateral analysis. We also discuss the returns to scale, most productive scale size, and the relationship between the efficiency and size of provinces. In addition, we construct tourism development strategies and a strategy map of BSC. Finally, some concluding remarks and a summary are given in section 5.

2. Literature Review

2.1 Using Data Envelopment Analysis to Measure Operational Efficiency

This section introduces Data Envelopment Analysis (DEA). Farrell【6】introduced a framework for efficiency evaluation and measurement, which was subsequently studied by Charnes, Cooper, and Rhodes【4】, Banker, Charnes, and Cooper【5】and others. The linear programming approach is known as data envelopment analysis（DEA）. The DEA model assumes that the random error is zero so that all unexplained variations can be treated as reflecting inefficiencies. The linear programming approach is flexible. It can measure input or output efficiency under the assumption of various types of constant returns to scale（CRS）and variable returns to scale（VRS）.

Figure 1 shows the relationship between the CCR model and BCC model using a single input-single output scenario. The constant returns to scale envelopment surface （the CCR model）must pass through the origin and is, therefore, less restrictive than the envelopment surface of the BCC model. The BCC model reduces the size of the feasible production region by enveloping the data more tightly, and as expected, the number of efficient DMUs declared efficient increases as do the overall efficiency scores. It should be noted that constant returns to scale may exist in a data set if the frontier formed using the BCC model follows the same frontier formed by the CCR model. DEA is a non-parametric linear programming technique used to compare input and output data of production units, or Decision Marking Units（DMUs）,with input and output data of other similar DMUs. It is a technique used to measure and evaluate the relative performance of production units. DEA is commonly used to evaluate the efficiency of a number of producers. A typical statistical approach is characterized as a central tendency approach and it evaluates producers relative to an average producer. In contrast, DEA is an extreme point method and compares each producer with only the "best" producers.

The development of DEA methodology stems from the usual measure of productivity, a ratio of outputs to inputs. The formulation of a relative efficiency measure, or the ratio of weighted outputs to weighted inputs, was introduced to account for the existence of multiple inputs and multiple outputs.

(1) CCR Model

For any special DMUs , the CCR model with constant return to scale can be formulated as follows to obtain a score of technical efficiency：

Maximize $w_0 = \sum_r u_r y_{rj_0}$, (1)

Subject to $\sum_i v_i x_{ij_0} = 1$,

$$\sum_r u_r y_{rj} - \sum_i v_i x_{ij} \le 0, j = 1,\dots,n,$$

$$u_r \ge \varepsilon, r = 1,\dots,s,$$
$$v_i \ge \varepsilon, i = 1,\dots,m$$

（where m is the number of inputs, and s is the number of outputs）.

Using the duality in linear programming, we can derive an equivalent envelopment form for this problem. The envelopment form involves fewer constraints than the CCR formulation and is, thus, preferred for programming.

The dual can be formulated for any linear programming problem and can prove to be particularly useful to solve. The dual of the multiplier problem is the envelopment problem. The envelopment problem is often solved rather than the multiplier problem since it does not have nearly as many constraints as the multiplier form. The number of constraints in the multiplier form is equal to the number of DMUs plus one,（n+1）, the additional constraints that the sum of the inputs equal to a constant or one.

The dual model is constructed by assigning a dual variable to each constraint in the primal problem. The following model is the envelopment form of the CCR model（input-orientation）：

Minimize $z_0 = \theta - \varepsilon \sum_i s_i^- - \varepsilon \sum_r s_r^+$, (2)

Subject

to $\theta_{ij_0} - s_i^- - \sum_j x_{ij} \lambda_j = 0, i = 1,\dots,m,$

$$-s_r^+ + \sum_j y_{rj}\lambda_j = y_{rj_0}, r = 1,\ldots,s,$$

$$s_i^-, s_r^+, \lambda_j \geq 0$$

(where z_0 unconstrained, , m is the number of inputs, and s is the number of outputs).

The number of constraints in the envelopment form is reduced to the sum of the inputs and outputs. A unit is efficient only if w_0^* and z_0^* are equal to 1. In other words, if the optimal values θ^* for a unit is equal to 1, and the slack variables s_i^- and s_r^+ are both equal to 0, then a unit is considered to be efficient. The dual variables are identical to the shadow prices in the multiplier form; therefore, the λ_j 's are the shadow prices related to the constraints that limit the efficiency of each unit to be no greater than 1. In the multiplier, or primal, problem, if a constraint is binding, the shadow price will be positive, and when the constraint is non-binding, the shadow price will be 0. A positive shadow price in the primal or a positive value for the λ_j 's in the dual identify the inefficiency unit's peer group or the reference set.

The CCR model described above is limited to the following three restrictions:(1) constant returns to scales (CRS), (2) strong disposability of inputs and outputs, and (3) convexity of the set of feasible input-output combinations. Each restriction can be relaxed although the constant returns to scale restriction is most often relaxed. By relaxing the constant returns to scale constraint, we can achieve discrimination between departures due to pure technical inefficiency or to scale inefficiency can be made.

(2) BCC Model

The BCC model, named after Banker,, Charnes, and Cooper【5】,was developed by relaxing the CCR model or the constant returns to scale assumption on the envelopment surface. The constraint $\sum \lambda_j = 1$ is added to the above mathematical formulation of the CCR model. Because the constant returns to scale constraint is relaxed, the facets forming the envelopment surface are no longer forced to pass through the origin. As a result, projected points for inefficiency units are determined as convex combinations of efficient units rather than as linear combinations, as is the case with constant returns to scale envelopment surface. The following model is the envelopment form of the BCC model (input orientation):

$$\text{Min } z_0 = \theta_B - \varepsilon\left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\right), \qquad (3)$$

$$\text{s.t. } \theta_B X_{io} = \sum_{j=1}^{n} X_{ij}\lambda_j + s_i^-, \ i=1,\ldots m,$$

$$Y_{ro} = \sum_{j=1}^{n} Y_{rj}\lambda_j - s_r^+, \ r=1,\ldots s,$$

$$\sum_{j=1}^{n}\lambda_j = 1, \quad s_i^-, s_r^+, \lambda_j \geq 0$$

(where z_0 is unconstrained, , m is the number of inputs, and s is the number of outputs).

(3) Slacks-Based Measure (SBM Model)

Tone【15】has proposed a slacks-based measure (SBM),which is non-radial and deals with input/output slacks directly. The SBM returns an efficiency measure between 0 and 1, and gives unity if and only if the DMU concerned is on the frontiers of the production possibility set with no input/output slacks.

In order to estimate the efficiency of a DMU（ x_0, y_0 ）,we formulate the following fractional program in λ , s^- ,and s^+ :

$$\text{Min } \rho = \frac{1 - \frac{1}{m}\sum_{i=1}^{m} s_i^- / x_{i0}}{1 + \frac{1}{s}\sum_{r=1}^{s} s_r^+ / y_{r0}}, \qquad (4)$$

s.t. $x_0 = X\lambda + s^-$,

$$y_0 = Y\lambda + s^-,$$

$$\lambda \geq 0, s^- \geq 0, s^+ \geq 0.$$

In this model, we assume that $X \geq 0$. If x_{i0}=0, then we delete the term s_i^- / s_{i0} in the objective function. If $y_{io} \leq 0$, then we replace it with a very small positive number so that the term s_r^+ / y_{r0} plays the role of a penalty.

(4) Free Disposal Hull (FDH Model)

In this section we take discussion with FDH（Free Disposal Hull）. The purpose of FDH is to measure and evaluate the performance of a producer. FDH is a mathematical programming technique, developed by Deprins, Simar and Tulkens【5】. FDH generalizes the more commonly used data envelopment analysis technique by relaxing the convexity assumption of the latter. The following model is the equation form of the FDH：

Let

$Y_0 = \{(x^k, u^k) | x^k \in R_+^I, u^k \in R_-^J, k = 1,2,\ldots,n\} \cup \{(O^I, O^J)\}$

Denote a set of n actually observed production plans, to which the origin of the input-output space is added by convention（ O^I and O^J are the $I-$ and $J-$dimensional null vectors）; for the sale of brevity, we call Y_0 the observations set or the data set. Also let $Y(Y_0)$ denote a reference production set constructed from Y_0. Then, a free disposal hull（FDH）reference production set（Y_{FDH}）constructed from Y_0 can be written as follows：

$$Y_{FDH}(Y_0) = \left\{ \begin{bmatrix} u \\ x \end{bmatrix} \in R_+^{I+J} \middle| \begin{bmatrix} u^h \\ x^h \end{bmatrix} + \sum_{i=1}^{I} u_i \begin{bmatrix} o^J \\ e_i^J \end{bmatrix} - \sum_{i=1}^{J} v_j \begin{bmatrix} e_j^J \\ o^I \end{bmatrix}, \right.$$

$$\left. (x^h, u^h) \in Y_0; u_i \geq 0; v_j \geq 0, \quad i = 1,2,\ldots, I; j = 1,2,\ldots, J \right\}$$

(5)

Where e_i^I denotes an I-dimensional zero vector with the i-th component equal to 1, and similarly, e_j^J denotes a J-dimensional zero vector with the j-th component equal to 1.

2.2 Using Balance Scorecard to Construct the Tourist Development Strategy

The Balanced Scorecard（BSC）was developed by Kaplan and Norton【8】, and includes four perspectives：the learning and growth perspective, internal process perspective, customer perspective and financial perspective.

The scorecard has been adopted by many companies and industries, and it appears to meet several management needs. The BSC is more than a collection of financial and non-financial measurements. It is a translation of the business unit's strategy into a linked set of measures that define both the long-term strategy objective and the mechanisms for achieving and obtaining feedback on those objectives【9】【10】【11】. Kaplan and Norton【12】have created a powerful new tool, the "strategy map," that enables companies to describe the links between intangible assets and value creation with a clarity and precision never before possible. We can use strategy maps to link those processes to desired outcomes; to evaluate, measure, and improve the processes most critical to success; and to target investments in human, informational, and organizational capital【12】.

3. Methodology and Data

3.1 Research Framework

Our goal using this model is to evaluate the performance and relative efficiency of international travel agencies in China, in order to provide an additional measure of efficient operations and development in China. We combine two analytical tools, the DEA model and Balanced Scorecard（BSC）, in the operating model. Referring to related research papers, we collect useful data to analyze and produce input-output items. In the first stage, we use the BSC management tool to decide on and to produce indicators of measurement perspectives, and in the second stage, we establish a modified DEA model. The operational performance model for BSC combined with DEA and research variables is shown in Figure 2.

Figure 2: Model for combining BSC and DEA

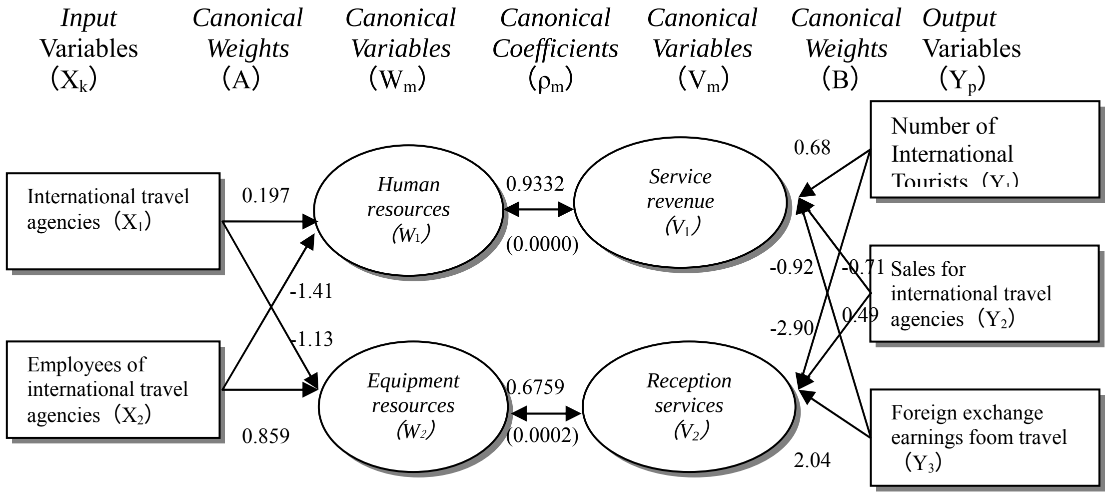


Figure 3 Canonical correlation

3.2 Data

Mainland China has 31 provinces, including autonomous regions and municipalities. Thirty provinces were subjected to empirical analysis in this study. Data from the China statistics database were used to determine the relative efficiency of the provinces in China. In this study, we chose 31 provinces in China. The data was collected in 2002. Thirty-one DMUs were subjected to empirical analysis in this study.

3.3 Selection of variables

In this research, international travel agencies provided two inputs, which produced the outputs. Table 1 shows a summary of the input and output statistics that were used to construct the DEA models. Constructing the models allowed us to investigate the relative efficiency scores for international travel agencies. The above three inputs have generally been used throughout the literature. The two inputs in the operational performance model are international travel agencies（x_1） and employees of international travel agencies（x_2）. Identifying the output of productive activities in general and of international travel agencies in particular presents difficulties for cost measurement and also production performance. The three outputs used here were reception of international passengers（y_1）, sales for international travel agencies（y_2）,and foreign exchange earnings from travel（y_3）.

Table 1 Summary of statistics for 31DMUs

	(1) International travel agencies	(2) Employees of international travel agencies	(3) Number of International Tourists	(4) Sales for international travel agencies	(5) Foreign exchange earnings from travel
Max	180.00	17027.00	240.37	1006665.60	4484.00
Min	7.00	13.00	0.57	4562.60	3.00
Average	42.25	2348.42	52.58	126246.54	515.12
SD	36.36	3064.98	58.87	223640.27	933.02

4. Empirical Results

4.1 Correlation Analysis

Table 2 shows the Pearson correlation coefficients for several of these variables. The main findings can be summarized as follows. The input variables（i.e., international travel agencies and employees of international travel agencies）have high correlation values with respect to the output variables（i.e., reception of international passengers, sales for international travel agencies, and foreign exchange earnings from travel）.These are highly positive correlation coefficients, and they indicate that there is a strong relationship between input and output. The correlation analysis results show a positive relationship between the input and output variables examined in this study.

Table 2 Pearson correlation analysis

	International travel agencies	Employees of international travel agencies	Number of International Tourists	Sales for international travel agencies	Foreign exchange earnings from travel
International travel agencies	1				
Employees of international travel agencies	0.8928355	1			
Number of International Tourists	0.9062734	0.8311577	1		
Sales for international travel agencies	0.9538764	0.9139242	0.9364889	1	
Foreign exchange earnings foom travel	0.9104411	0.9149782	0.9371624	0.96954248	1

4.2 Canonical Correlation Analysis

To quantify the associations between these two sets of variables, i.e., the strength of the two sets of variables, we used canonical correlation analysis（CCA）to reduce the dimension and investigate the correlations. The canonical correlation analysis revealed a significant correlation between the dynamics of the inputs and outputs variables. Canonical structure matrix generated the canonical variables,（W_1 ,V_1）and（W_2 ,V_2）,of shown in Table 3.The results of canonical correlation analysis revealed a canonical first correlation value 0.9332 (χ^2 = 71.774, P-Value=0.000), and a second correlation value of 0.6759 (χ^2 = 16.484, P-Value=0.002),as shown in Table 4. Figure 3 shows that the canonical first correlation revealed a significant correlation between human resources and service revenue (ρ_1＝0.9332) , and a significant correlation between equipment resources and reception services（ρ_2＝0.6759）.

Table 3 Canonical Structure Matrix

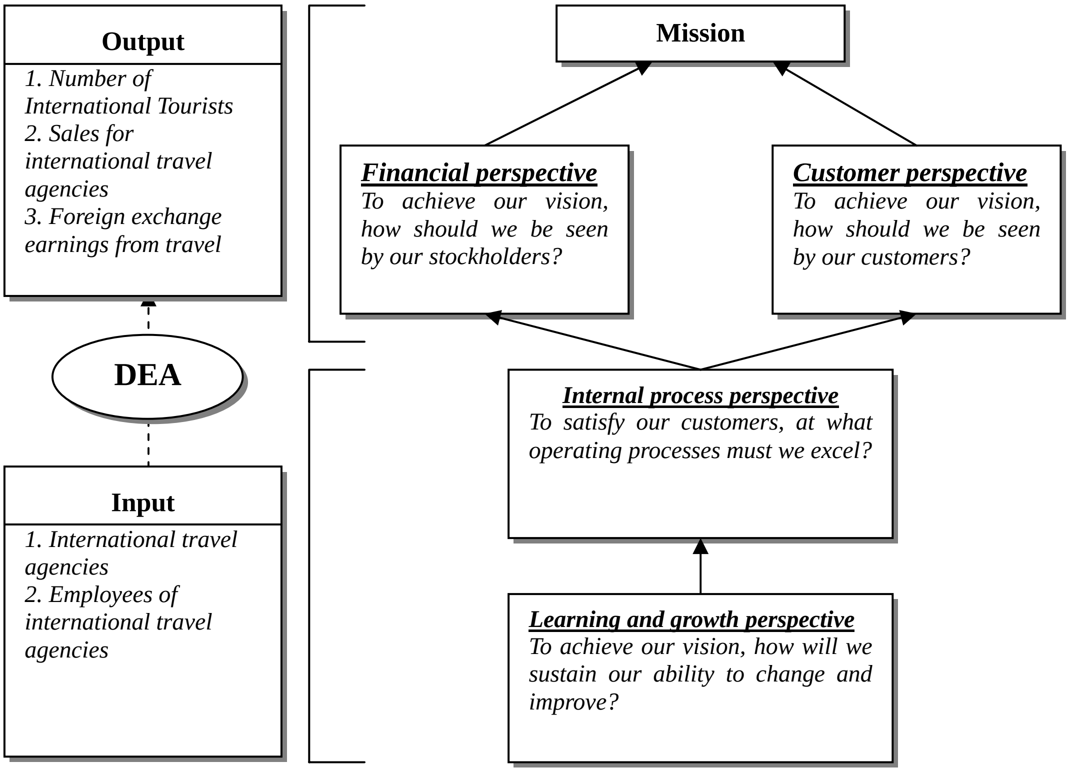
Input Canonical Variables	*Human resources（W_1）*	*Equipment resources（W_2）*
International travel agencies（X_1）	-0.6055*	-0.7958*
Employees of international travel agencies（X_2）	-0.9903*	-0.1388
Output Canonical Variables	*Service revenue（V_1）*	*Reception services（V_2）*
Number of International Tourists（Y_1）	-0.8457*	-0.5273*
Sales for international travel agencies（Y_2）	-0.9039*	-0.2457
Foreign exchange earnings foom travel（Y_3）	-0.9090*	-0.2004

Note：”” Canonical Loadings>0.5*

Table 4 Canonical Correlation

	Canonical Coefficients（ρ_m）	df	χ^2	P-Value
Canonical Correlation（ρ_1）	0.9332***	6	71.774	0.0000
Canonical Correlation（ρ_2）	0.6759***	2	16.484	0.0002

Note： * *Significant at the 0.01 level.*
** *Significant at the 0.05 level.*
*** *Significant at the 0.1 level.*



4.3 Efficiency Analysis

In this research, the DEA analysis models included CCR, BCC, the Slacks-Based Measure （SBM）, and FDH. DEA provides a comprehensive evaluation of overall performance. The results for each DEA model are summarized in Table 5. Table 6shows the Pearson correlation coefficients for the DEA models. The results for each DEA model are shown in Table 7.

Table 5 Summary statistics for efficiency measures（N=31）

	CCR	BCC	SBM	FDH
Mean	0.518	0.658	0.474	0.964
S.D	0.253	0.200	0.249	0.081
Max.	1	1	1	1
Min.	0.100	0.381	0.091	0.621
No. of efficient DMUs	3 （9.67％）	5 （16.12％）	3 （9.67％）	23 （74.19％）

First, an elementary insight is obtained by considering the dichotomous classification of DMUs as either efficient or inefficient. The number of efficient DMUs resulting from the use of different reference technologies is shown in the last row of Table 5. Clearly, and consistent with expectations, the FDH model turns out to be no better than the other reference technologies. It results in 74.19％ efficient DMUs, compared with 9.67％ for the CCR model, 16.12％for the BCC model, and 9.67％ for the SBM model. It is interesting to consider the extent to which the different methodologies agree on this basic dichotomous classification. All of the DMUs that are efficient for CCR, BCC, and SBM are efficient for FDH also. Of 24 efficient DMUs for FDH, only 3（9.67％）are efficient for CCR and SBM, and 5（16.12％）are efficient for BCC. In addition, Table 5 contains some descriptive statistics for each of the five

DEA models. The FDH-based index exceeds all others in terms of average mean efficiency scores.

Table 6 Correlation analysis of DEA models

	CCR	BCC	SBM	FDH
CCR	1			
BCC	0.73**	1		
SBM	0.99**	0.73**	1	
FDH	0.36**	0.48**	0.34	1

Note： * *Significant at the 0.01 level.*
** *Significant at the 0.05 level.*
*** *Significant at the 0.1 level.*

Table 6 shows the Pearson correlation coefficients for several of these DEA models, including CCR, BCC, SBM and FDH. The correlation analysis results show a positive relationship among the DEA models investigated in this study.

Table 7 Efficiency scores of DEA models for 31 DMUs

DMU	CCR	BCC	Scale	SBM	FDH
1Beijing	1	1	1	1	1
2Tianjing	0.818	0.956	0.855	0.716	1
3Hebei	0.728	0.768	0.947	0.626	1
4Shanxi	0.261	0.469	0.556	0.220	0.916
5Inner Mogolia	0.774	0.785	0.985	0.669	1
6Liaoning	0.556	0.597	0.931	0.478	1
7Jilin	0.397	0.490	0.810	0.343	0.871
8Heilongjiang	0.524	0.569	0.920	0.452	1
9Shanghai	1	1	1	1	1
10Jiangsu	0.726	0.749	0.969	0.721	1
11Zhejiang	0.575	0.621	0.925	0.573	0.981
12Anhui	0.293	0.400	0.732	0.245	1
13Fujian	0.621	0.695	0.893	0.580	1
14Jiangxi	0.219	0.514	0.426	0.180	1
15Shandong	0.551	0.571	0.964	0.475	1
16Henan	0.418	0.546	0.765	0.368	1
17Hubei	0.493	0.645	0.764	0.379	1
18Hunan	0.309	0.431	0.716	0.297	1
19Guangdong	0.895	1	0.895	0.764	1
20Guangxi	0.410	0.455	0.901	0.388	1
21Hainan	0.289	0.410	0.704	0.277	0.621
22Chongqing	0.665	0.835	0.796	0.649	1
23Sichuan	0.337	0.422	0.798	0.303	0.804
24Guizhou	0.242	0.672	0.360	0.237	1
25Yunnan	0.558	0.632	0.882	0.463	1
26Tibet	1	1	1	1	1
27Shaanxi	0.603	0.677	0.890	0.579	1
28Gansu	0.251	0.464	0.540	0.224	0.863
29Qinghai	0.100	0.661	0.151	9.13E-02	1
30Ningxja	0.165	1	0.165	0.146	1
31Xinjiang	0.287	0.381	0.753	0.242	0.851

Table 7 presents the CCR efficiency scores under constant returns-to-scale, BCC technical efficiency scores, scale efficiency scores, slacks-based measure efficiency scores, and FDH efficiency scores. As items for measuring efficiency, we used international travel agencies（x_1）and employees of international travel agencies（x_2）as inputs, and number of international tourists（y_1）, sales for international travel agencies（y_2）, and foreign exchange earnings from travel（y_3）as outputs. The main findings can be summarized as follows. The CCR efficiency score analysis results show that 3 provinces（i.e., Shanghai, Tibet, and Beijing）are relatively efficient, based on the same scale efficiency scores and SBM efficiency scores. Their efficiency scores are all equal to 1. This shows that resource utilization for these provinces is excellent. On the other hand, 28 provinces were found to be inefficient because their efficiency scores were less than 1.

The scale efficiency scores as defined by the ratio CCR/BCC show large differences between the two groups. The average scale efficiency score was0.7739. Of the 31 provinces, 21（Hebei, Shanxi, Inner Mongolia, Liaoning, Jilin, Heilongjiang, Jiangsu, Zhejiang, Anhui, Fujian, Shandong, Henan, Hubei, Hunan, Guangxi, Hainan, Sichuan, Yunnan, Shaanxi, Gansu, and Xinjiang）have low BCC efficiency scores and relatively high scale efficiency scores, meaning that the overall inefficiency of these provinces as shown in the CCR column is caused by inefficient operations rather than scale inefficiency.

Of the 31 provinces, 2（Guangdong and Ningxja）have BCC efficiency scores equal to 1 and relatively low scale efficiency scores. This suggests that the CCR inefficiency scores can be mainly attributed to disadvantageous conditions.

Another model which has received a considerable amount of research attention is FDH（Free Disposal Hull）. The FDH results show that of the 31 provinces, 23（74.19％）are efficient. These results cannot distinguish efficient provinces from inefficient provinces correctly, compared with the CCR, BCC, and SBM models.

4.4 Reference set Analysis and Benchmarking Analysis

The reference set and their frequencies for the 31 provinces are given in Table 8. The most frequent reference province was found to be Shanghai. The results also show that Shanghai, Tibet, and Beijing are efficient and are in the reference set of all of the other provinces.

Table 8 Reference set Analysis and Returns to scale

DMU	CCR	Reference set	Reference Frequency	Ranking	Returns to scale
1Beijing	1	Beijing	14	1	CRS
2Tianjing	0.818	Shanghai, Tibet	0	5	IRS
3Hebei	0.728	Shanghai, Tibet	0	7	IRS
4Shanxi	0.261	Beijing, Shanghai, Tibet	0	26	IRS
5Inner Mogolia	0.774	Shanghai, Tibet	0	6	IRS
6Liaoning	0.556	Shanghai, Tibet	0	14	DRS
7Jilin	0.397	Shanghai, Tibet	0	20	IRS
8Heilongjiang	0.524	Shanghai, Tibet	0	16	DRS
9Shanghai	1	Shanghai	27	1	CRS
10Jiangsu	0.726	Beijing, Shanghai	0	8	IRS
11Zhejiang	0.575	Beijing, Shanghai, Tibet	0	12	IRS
12Anhui	0.293	Beijing, Shanghai, Tibet	0	23	DRS
13Fujian	0.621	Shanghai	0	10	IRS
14Jiangxi	0.219	Beijing, Shanghai, Tibet	0	29	IRS
15Shandong	0.551	Shanghai, Tibet	0	15	DRS
16Henan	0.418	Beijing, Shanghai, Tibet	0	18	IRS
17Hubei	0.493	Shanghai	0	17	IRS
18Hunan	0.309	Beijing, Shanghai, Tibet	0	22	IRS
19Guangdong	0.895	Shanghai	0	4	DRS
20Guangxi	0.410	Beijing, Shanghai, Tibet	0	19	IRS
21Hainan	0.289	Beijing, Shanghai	0	24	IRS
22Chongqing	0.665	Beijing, Shanghai	0	9	IRS
23Sichuan	0.337	Shanghai	0	21	IRS
24Guizhou	0.242	Beijing, Shanghai, Tibet	0	28	IRS
25Yunnan	0.558	Shanghai	0	13	IRS
26Tibet	1	Tibet	20	1	CRS
27Shaanxi	0.603	Shanghai, Tibet	0	11	IRS
28Gansu	0.251	Shanghai, Tibet	0	27	IRS
29Qinghai	0.100	Beijing, Shanghai, Tibet	0	31	IRS
30Ningxja	0.165	Beijing, Tibet	0	30	IRS
31Xinjiang	0.287	Beijing, Shanghai, Tibet	0	25	IRS

4.5 Returns to scale and most productive scale size

We will discuss the returns to scale of the 31 provinces in this section. Let (x_0, y_0) be a point on the efficient frontier. If we employ a CCR model in envelopment form to obtain on optimal solution ($\lambda_1^*,...,\lambda_n^*$) , then the returns to scale at this point can be determined based on the following conditions（Cooper et al.,2000）:

(Ⅰ) If $\sum_{j=1}^{n}\lambda_j^* = 1$ in any alternate optimum, then constant returns-to-scale prevails.

(Ⅱ) If $\sum_{j=1}^{n}\lambda_j^* > 1$ in any alternate optimum, then decreasing returns-to-scale prevails.

（Ⅲ）If $\sum_{j=1}^{n}\lambda_j^* < 1$ in any alternate optimum, then increasing returns-to-scale prevails.

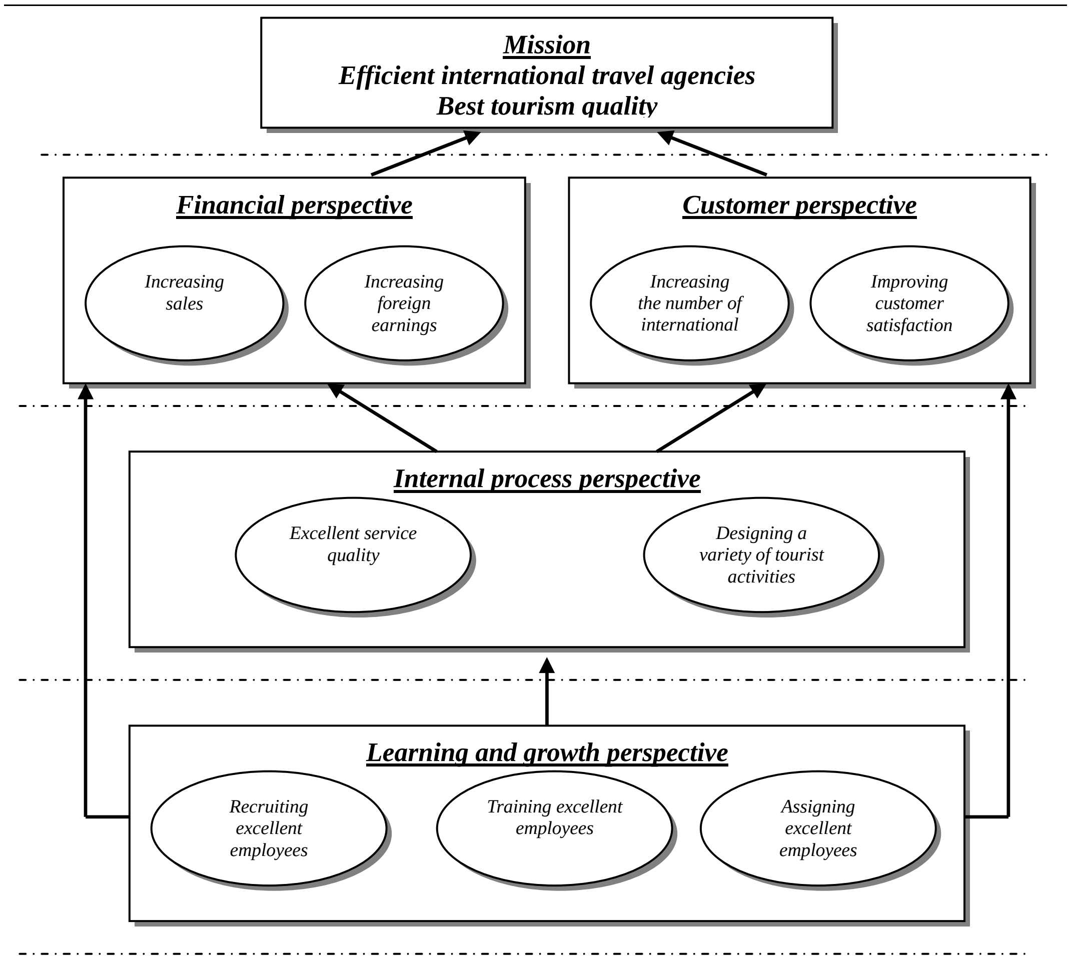
Thus, a DMU_0 found to be efficient for a CCR model will also be found to be efficient for the corresponding BCC model, and constant returns-to-scale means that DMU_0 is the most productive scale size 【1】.

Of the 31 provinces investigated in this study, 3（9.67％）showed constant returns-to-scale, 5（16.12%）showed decreasing returns-to-scale, and 23 （74.19 %） showed increasing returns-to-scale.

When an province exhibits decreasing returns-to-scale ($\sum_{j=1}^{n}\lambda_j^* > 1$), it is likely that the performance of the program can be improved by decreasing its size. In general, the proportion of provinces showing increasing returns-to-scale has increased over time, and the average size of provinces in the sample has increased monotonically over time, which suggests changing technology over time. On the other hand, when a province exhibits increasing returns-to-scale ($\sum_{j=1}^{n}\lambda_j^* < 1$), it is likely that the province can improve its performance by increasing its size. Table 8 shows that Shanghai（Ⅰ）, Tibet（Ⅱ）, and Beijing（Ⅲ） have the most productive scale sizes （as shown in Figure 4）.

4.6 Balanced Scorecard Strategy Map analysis and Tourism Development Strategies

The results for the Balanced Scorecard strategy map of international travel agencies are shown in Figure 5. According to the canonical correlation analysis results, the canonical first correlation revealed a significant correlation between human resources and service revenue, and a significant correlation between equipment resources and reception services. We can thus construct a strategy map of international travel agencies and tourism development strategies. In the Balanced Scorecard strategy map of international travel agencies, as items for measuring the learning and growth perspective, we use employees of international travel agencies as an input variable and use *recruiting excellent employees, training excellent employees, and assigning excellent employees* as strategies. As items for measuring the internal process perspective, we use international travel agencies as an input variable, and use *excellent service quality and designing a variety of tourist activities* as strategies. As items for measuring the customer perspective, we use international passengers as an input variable and *increasing the number of international passengers* as a strategy. As items for measuring the financial perspective, we use sales for international travel agencies and foreign exchange earnings from travel as input variables, and *increasing sales and increasing foreign earnings* as strategies. Finally, we can create efficient international travel agencies using the Balanced Scorecard strategy map.



5. Conclusion

In this study, we have used nonparametric DEA methods to analyze the efficiency of international travel agencies in 31 provinces. The main findings can be summarized as follows.

First, the canonical correlation analysis revealed a significant correlation between the input and output variables. The CCR efficiency score analysis results show that 3 provinces are relatively efficient, and the results were for scale efficiency and SBM efficiency. The results of FDH analysis cannot distinguish between efficient and inefficient programs correctly, compared with the CCR, BCC, and SBM models. Of the 31 provinces investigated in this study, 3 exhibit constant returns-to-scale,and 5 exhibit decreasing returns-to-scale. These provinces can improve their performance by reducing the number of employees and their budgets. Of the 31 provinces, 23 exhibit increasing returns-to-scale. These provinces can improve their performance by increasing their size. Of the 31 provinces, 3 have the most productive scale sizes. Finally, we can create efficient international travel agencies using the Balanced Scorecard strategy map.

Throughout the study, special emphasis has been placed on quantifying and discussing the impact of model choice on the results. For this purpose, we have also introduced a framework for model comparison and used several simple techniques to analyze the results. The results of this research can help those involved in managing these programs understand their relative operating performance and, therefore, respond by appropriately regulating the levels of the input and output items.

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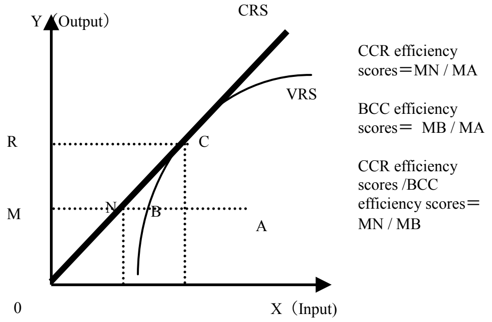

Figure 1 Envelopment Surfaces