The Impact of the Transportation Efficiency on the Tourism Eco-efficiency based on PVAR Model: A Case Study of the Yellow River Basin

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Abstract: Transportation and tourism are closely related, and transportation is an important factor that affects the tourism eco-efficiency. Based on the transportation data and the tourism data of 9 provinces in the Yellow River Basin from 2007 to 2019, we use the Super-SBM model and the Super-SBM model with undesirable output (Un-Super-SBM model) to measure the transportation efficiency and the tourism eco-efficiency. We use the PVAR model to analyse the panel data of the transportation efficiency and the tourism eco-efficiency, and discuss the impact of the transportation efficiency on the tourism eco-efficiency. As a result, the transportation efficiency and the tourism eco-efficiency of the whole Yellow River Basin are relatively high, but the transportation efficiency and the tourism eco-efficiency of Inner Mongolia need to be improved. The transportation efficiency has a positive impact on the tourism eco-efficiency, and the impact can reach its peak in the short term, but the impact is long-term. The impact of the tourism eco-efficiency on the transportation efficiency is not significant.

1 INTRODUCTION

In recent years, China's tourism industry has developed rapidly. According to the data from the National Bureau of Statistics, the number of tourists reached 6.072 billion in 2019, which has increased by more than 6 times in 18 years. Although affected by COVID-19 in 2020, the number of tourists has reached 2.88 billion. With the large-scale development of tourism activities, environmental pollution and resource consumption caused by tourism activities have also received extensive attention (Azam, et al., 2018). How to realize the coordinated development of ecological environment protection and tourism has become a research hot spot. Therefore, the concept of the tourism eco-efficiency has gradually formed. The tourism eco-efficiency's focus is the integration of tourism, ecology, and efficiency. It not only considers resource energy consumption and environmental pollution, but also measures the importance of the tourism economic output. The tourism eco-efficiency is often described as a variable in the relationship between the tourism input and output. While the economic output of tourism and the value of services increase, the carbon emissions are reduced during the tourism process. There are many measurement methods of the tourism eco-efficiency, mainly including the ratio method, the index system method, and the data envelopment analysis (DEA) method. In recent years, the DEA method have been widely used in the measurement of the tourism eco-efficiency. The Un-Super-SBM model is one of the most common DEA models used by researchers.

There are many factors influencing tourism eco-efficiency, and many researchers have conducted a lot of discussions on both the macro and micro perspectives. Looking at the existing literature on tourism eco-efficiency research, it is found that transportation has always been an important factor influencing the tourism eco-efficiency. For example, Gossling and Yao believe that the mode of transportation is one of the main factors affecting the tourism eco-efficiency (Gossling, et al., 2005), (Yao, Chen, 2015). However, there are few papers that can clearly explain the specific extent of the impact of

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transportation on the tourism eco-efficiency. The transportation efficiency is an index to evaluate the comprehensive transportation system of a region, and the most common method to measure the transportation efficiency is the DEA method.

The Yellow River Basin is a key area for ecological protection in China. In 2019, President Xi proposed a major national strategy for ecological protection and high-quality development in the Yellow River Basin. The green and high-quality development of the Yellow River Basin is one of China's important tasks in the future. A planning for the construction of the Yellow River National Cultural Park in 2020 is proposed. With the advancement of the construction of the National Cultural Park, the tourism industry in the Yellow River Basin will develop rapidly. The transportation infrastructure of the Yellow River Basin has been greatly improved in recent years. Therefore, this paper takes 9 provinces in the Yellow River Basin as case sites, and calculates the transportation efficiency and the tourism eco-efficiency based on the transportation data and the tourism data from 2007 to 2019 to form the panel data, and uses the panel vector autoregression (PVAR) model to study the impact of the transportation efficiency on the tourism eco-efficiency.

2 DATA AND METHODOLOGY

2.1 The Transportation Efficiency and the Tourism Eco-efficiency

In order to study the impact of the transportation efficiency on the tourism eco-efficiency in the Yellow River Basin, we choose 9 provinces' data in the Yellow River Basin from 2007 to 2019, and calculate the transportation efficiency and the tourism eco-efficiency of each province by the SBM model. The data in this article mainly come from the official website of the National Bureau of Statistics (http://www.stats.gov.cn/), Year Book of China Transportation & Communication, Yearbook of China Tourism Statistic, Yearbook of China Tourism, and the yearbooks of 9 provinces in the Yellow River Basin.

The measurement of the transportation efficiency has not yet formed a unified index system. The impact of transportation on tourism is mainly reflected in the passenger transportation. So we mainly consider four transportation modes: railway, highway, waterway, and aviation. Therefore, we choose the railway operating mileage, the highway line mileage, the inland waterway mileage, the aircraft take-off and landing sorties, and the number of employees in the four modes as input indicators. And the passenger volume and passenger turnover of the four modes of transportation as output indicators. We use the Super-SMB model to measure the transportation efficiency. The SBM model is a data envelopment analysis (DEA) method proposed by Tone, which overcomes the shortcomings of ordinary DEA models that cannot effectively deal with slack variables (Tone, 2001). Tone put forward the Super-SMB model based on the SBM model to deal with the effective decision-making unit (DMU) in 2002 (Tone, 2002). We use X to represent the input vector and Y to represent the output vector. m and s represent the number of input variables and output variables, respectively. We consider n DMUs and define the matrices X, Y as follows:

$$X=\left[x_1,x_2,...,x_n\right]\in R^{m\times n} \tag{1}$$

$$Y=\left[y_1,y_2,...,y_n\right]\in R^{s\times n} \tag{2}$$

The equation of the Super-SBM model to calculate DMU (x_0, y_0) is as follows:

$$\rho=\min\frac{1/m\sum_{i=1}^{m}(\overline{x}_i/x_{i0})}{1/s\sum_{k=1}^{s}(\overline{y}_k/y_{k0})} \tag{3}$$

$$s.t.\ \ \overline{x}_i \geq \sum_{j=1,\neq 0}^{n}\lambda_j x_j,$$

$$\overline{y}_k \leq \sum_{j=1,\neq 0}^{n}\lambda_j y_j,$$

$$\overline{x}_i \geq x_{i0}, 0\leq \overline{y}_k \leq y_{k0}, \lambda_j \geq 0$$

where λ is the intensity vector and ρ is the efficiency value of the DMU.

At present, researchers prefer to use the Un-Super-SBM model to measure the tourism eco-efficiency. Based on previous papers, we take the number of tourism companies (including the number of star-rated hotels, the number of travel agencies, and the number of A-level scenic spots), the number of employees in the tourism industry, and the investment value of fixed assets in the tourism industry as input indicators. The number of tourists and the tourism income are used as desirable output indicators. The tourism carbon emissions are used as undesired output. And the tourism carbon emissions refer to the measurement method of Zha et al. (Zha, et al., 2020) The Un-Super-SBM model adds undesired output based on the Super-SBM model. We use X (1), Y (2) and Z (4) to represent the input vector, the desirable output vector, and the undesirable output vector. The equation of the Un-Super-SBM model to calculate DMU（x_0, y_0, z_0） is (5):

$$Z=(z_1,z_2,...,z_n)\in R^{w\times n} \tag{4}$$

$$\rho^*=\min\frac{1+\frac{1}{m}\sum_{i=1}^{m}\frac{s_i^x}{x_{i0}}}{1-\frac{1}{s+w}\left(\sum_{k=1}^{s}\frac{s_k^y}{y_{k0}}+\sum_{l=1}^{w}\frac{s_l^z}{z_{l0}}\right)} \tag{5}$$

$$s.t.\quad x_{i0}\geq\sum_{j=1,\neq 0}^{n}\lambda_j x_j - s_i^x,$$

$$y_{k0}\leq\sum_{j=1,\neq 0}^{n}\lambda_j y_j + s_k^y,$$

$$z_{l0}\geq\sum_{j=1,\neq 0}^{n}\lambda_j z_j - s_l^z,$$

$$s_i^x\geq 0, s_k^y\geq 0, s_l^z\geq 0, \lambda_j\geq 0$$

where m, s, and w are the number of input variables, desirable outputs variables, and undesirable output variables. And $\rho*$ is the efficiency value of the DMU. s^x, s^y, and s^z represent the slacks in input, desirable output, and undesirable output.

We use the software called MaxDEA Ultra to calculate the Super-SBM model and the Un-Super-SBM model. In the calculation process below, the transportation efficiency is abbreviated as TRE and the tourism eco-efficiency is abbreviated as TOEE.

2.2 Panel Vector Autoregression Model

In order to explore the impact of the transportation efficiency on the tourism eco-efficiency in the Yellow River Basin, the panel vector autoregression (PVAR) model established in this paper is as follows:

$$Y_{it}=\lambda_0+\sum_{j=1}^{k}\gamma_j Y_{it-j}+\alpha_i+\beta_t+\varepsilon_{it}, i=1,2,\ldots,T \tag{6}$$

$$Y_{it}=(TRE_{it},TOEE_{it})^T \tag{7}$$

where Y_{it} is a two-dimensional column vector. TRE and TOEE respectively represent the transportation efficiency and the tourism eco-efficiency. The k represents the lag order. α_i and β_t respectively represent fixed effect and time effect. γ_j represents the matrix of lag period coefficients to be estimated. λ_0 represents the 2×1 order intercept term vector. ε_{it} represents the random disturbance term vector. To avoid heteroscedasticity, we take the logarithm of both TRE and TOEE, namely lnTRE and lnTOEE.

Table 1: The results of the transportation efficiency.

Year	SX	IM	SD	HN	SC	SH	GS	QH	NX
2007	1.31	1.14	1.85	1.57	1.83	1.76	1.27	1.13	1.82
2008	1.37	1.07	2.17	3.60	1.94	1.64	1.45	1.79	1.91
2009	1.21	1.07	2.12	1.57	1.75	2.09	1.28	1.87	1.90
2010	1.27	1.06	2.07	1.64	1.61	1.90	1.27	1.92	2.10
2011	1.28	1.04	1.89	1.33	1.75	2.59	1.33	1.99	2.06
2012	1.24	1.16	1.88	1.45	1.52	1.90	1.44	2.27	1.96
2013	1.27	1.25	2.03	1.48	1.62	1.95	1.45	3.19	2.31
2014	1.26	1.25	1.60	1.42	1.61	1.84	1.36	1.34	2.28
2015	1.26	1.22	1.58	1.47	1.80	1.93	1.40	2.64	2.34
2016	1.26	1.37	1.61	1.47	1.47	1.86	1.31	1.22	2.48
2017	1.25	1.33	1.62	1.61	1.39	1.78	1.42	1.18	2.50
2018	1.25	1.34	1.60	1.52	1.57	1.68	1.25	1.20	2.33
2019	1.29	1.07	1.63	1.47	1.68	2.13	1.28	2.78	2.40

Table 2: The results of the tourism efficiency.

Year	SX	IM	SD	HN	SC	SH	GS	QH	NX
2007	1.06	0.54	1.13	1.41	1.12	0.64	0.32	1.12	1.35
2008	1.08	0.52	1.15	1.68	1.05	0.60	0.30	1.48	1.32
2009	1.10	0.58	1.15	1.44	1.07	0.82	0.32	1.70	1.33
2010	1.06	0.53	1.21	1.32	1.16	0.81	0.40	1.64	1.37
2011	1.10	0.53	1.20	1.21	1.15	0.95	0.52	1.58	1.27
2012	1.07	0.45	1.15	1.08	1.23	1.05	0.51	1.60	1.24
2013	1.07	0.44	1.13	1.19	1.19	1.04	0.59	1.66	1.32
2014	1.11	0.50	1.10	1.23	1.28	1.06	0.69	1.52	1.30
2015	1.28	0.41	1.08	1.18	1.30	1.01	0.61	1.33	1.44
2016	1.36	0.48	1.05	1.05	1.30	1.04	0.57	1.23	1.27
2017	1.45	0.38	1.09	1.05	1.13	1.06	0.73	1.14	1.49
2018	1.36	0.41	1.10	1.03	1.07	1.07	0.72	1.06	1.67
2019	1.38	0.44	1.06	1.04	1.06	1.05	1.06	1.13	1.54

3 RESULTS

3.1 The Results of the Transportation Efficiency and the Tourism Eco-efficiency

The Super-SBM model and the Un-Super-SBM model are used to evaluate the transportation efficiency and the tourism eco-efficiency of 9 provinces in the Yellow River Basin. The results are shown in Table 1 and Table 2.

It can be found from Table 1 that each transportation efficiency in the Yellow River Basin is greater than 1.00, indicating that the overall transportation efficiency of the Yellow River Basin is relatively high. The transportation efficiency of Shandong (SD), Shaanxi (SH), Ningxia (NX) and Sichuan (SC) is higher than that of other provinces. Inner Mongolia (IM), Gansu (GS) and Shanxi (SX) have lower transportation efficiency. Qinghai's (QH) transportation efficiency is unstable and fluctuates greatly.

It can be found from Table 2 that, except for Inner Mongolia, Shaanxi and Gansu, the tourism eco-efficiency in other provinces is relatively higher (greater than 1.00). However, the tourism eco-efficiency in Shaanxi and Gansu has shown an upward trend, and has exceeded 1.00 in recent years. The tourism eco-efficiency in Henan (HN) and Inner Mongolia has a downward trend.

3.2 Empirical Analysis of PVAR Model

3.2.1 Stationarity Test

In order to prevent the spurious regression caused by non-stationary variables and ensure the validity of the estimation results, we use LLC test to test the stationarity of lnTOEE and lnTRE. The results are shown in Table 3. The results show that both series are stationary.

Table 3: The results of LLC test.

	T Statistics	P-value
lnTRE	-6.6648***	0.0000

*** stands for the significance level of 1%.

3.2.2 Determining the Optimal Lag Order

We choose the maximum lag order at 3 and use three information criteria (AIC, BIC and HQIC) to determine the optimal lag order. The calculation results of the information criteria are shown in Table 4. According to the results of the three information criteria, the optimal lag order is selected as 3.

Table 4: The results of the optimal lag order.

Lag	AIC	BIC	HQIC
1	-2.37741	-1.80072	-2.14408
2	-2.87812	-2.15595*	-2.5869
3	-2.94468*	-2.05785	-2.58887*

* stands for the optimal lag order determined by the AIC, BIC and HQIC information criteria.

3.2.3 Granger Causality Test

We use the optimal lag order to perform Granger Causality Test on lnTOEE and lnTRE. The results shown in Table 5 suggest that lnTRE is the granger cause of lnTOEE, but lnTOEE is not the granger cause of lnTRE. It shows that the transportation efficiency can affect the tourism eco-efficiency.

Table 5: The results of granger causality test.

Equation	Excluded	Chi2	P-value
h_lnTOEE	h_lnTRE	10.2480**	0.017
h_lnTRE	h_lnTOEE	2.0791	0.556

** stands for the significance level of 5%.

3.2.4 Impulse Response Function

The impulse response function (IRF) can analyse the impact of an endogenous variable on other variables, that is, how current value and future value of the variable will be affected when the model is impacted or the random error term changes. There are four response graphs of lnTOEE and lnTRE, including response graphs of these two variables to itself and the mutual response graphs of them. According to the results of the Granger Causality Test, we mainly analyse the IRF of lnTOEE to lnTRE. Figure 1 is the graph of IRF of lnTOEE to lnTRE. lnTOEE has a positive response to the impact of lnTRE. After being impacted by lnTRE by one standard deviation, lnTOEE reaches its peak in the first period, and then gradually decreases. And it lasts a long time.

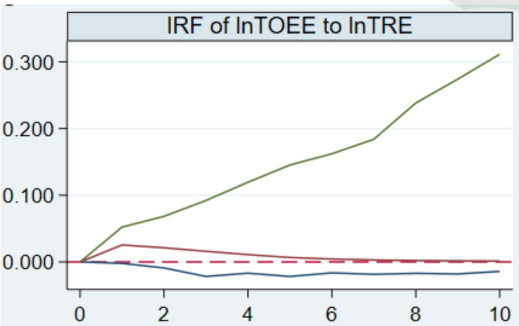

Figure 1: The impulse response function.

3.2.5 Variance Decomposition

We use variance decomposition to measure the proportion of lnTOEE impacted by lnTRE (the variance contribution rate of lnTRE to lnTOEE) to further explore the impact of the transportation efficiency on the tourism eco-efficiency. Figure 2 is the graph of the variance decomposition results for 20 forecast periods. In the first forecast period, lnTOEE is not affected by lnTRE. In the second prediction period, the variance contribution rate of lnTRE to lnTOEE increases rapidly to 9.1%. And then the growth rate gradually slows down. The variance contribution rate reaches the maximum value of 13.5% in the fifth period, and remains until the seventh forecast period, after which the variance contribution rate falls to 13.4% in the eighth period and remains unchanged for a long time. It shows that the transportation efficiency can affect the tourism eco-efficiency, and this impact will exist for a long time.

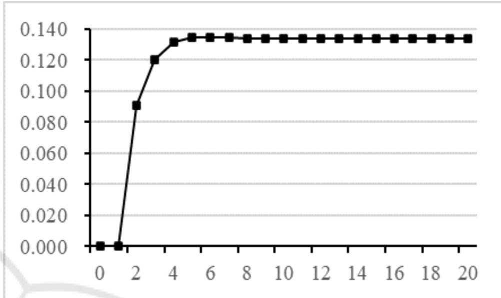

Figure 2: The results of the variance decomposition.

4 CONCLUSIONS

Based on the transportation data and the tourism data of 9 provinces in the Yellow River Basin from 2007 to 2019, we use Super-SBM model and Un-Super-SBM model to measure the transportation efficiency and the tourism eco-efficiency. The PVAR model is used to explore the impact of the transportation efficiency on the tourism eco-efficiency.

Except for Inner Mongolia, the transportation efficiency and the tourism eco-efficiency of the other provinces in the Yellow River Basin are at a higher level. The transportation efficiency and the tourism eco-efficiency of Inner Mongolia need to be improved.

From 2007 to 2019, the transportation efficiency of the 9 provinces in the Yellow River Basin has a positive impact on the tourism eco-efficiency, but the tourism eco-efficiency has no significant impact on the transportation efficiency. The impact of the transportation efficiency on the tourism eco-efficiency reaches the peak (13.5%) in the fifth forecast period, but drops to 13.4% after maintaining three forecast periods and remains unchanged for a long time. The impact of the transportation efficiency on the tourism eco-efficiency can be seen in the short term, but the impact is long-term.

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