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A stochastic frontier approach to assessing total factor productivity change in China's star-rated hotel industry

Abstract: Using a Stochastic Frontier Analysis (SFA) approach and a flexible translog production function considering neutral technological progress, this study assesses technical efficiency change, technological change, and scale change, and further measures the total factor productivity (TFP) change and its convergence of China's star-rated hotel industry in 31 provinces, municipalities and regions from 2001 to 2015. The results show that the TFP change of China's star-rated hotel industry was generally favorable and boosted by both the technical efficiency change and technical change; nevertheless, the scale change hindered and largely caused fluctuations in the TFP change. From a regional economic perspective, the TFP change of the star-rated hotel industry in most of the eight comprehensive economic regions examined was rather stable. While few comprehensive economic regions existed absolute convergence, all of the regions showed significant conditional convergence except for the Eastern Coastal region.

Key words: star-rated hotel, total factor productivity change, stochastic frontier analysis, efficiency, convergence analysis.

Introduction

China has experienced rapid growth in tourism in recent years and ranked second globally in terms of both its tourist arrivals and international tourism receipts, mainly due to its strong currency and economy (United Nations World Tourism Organization, 2016; China National Tourism Administration, 2016). In 2017 alone, China received 139.48 million inbound tourists and added US $123.4 billion in tourism receipts to the economy (National Bureau of Statistics of China (NBSC), 2018). Tourism development including the hotel industry is widely recognized as a positive way in promoting regional economic growth (Chou, 2013). To support a massive tourism industry and sustain its growth in China, a robust hotel industry is a prerequisite, as hotels, irrespective of their type or caliber, provide accommodation for tourists and business people alike for both international and domestic travel. Our study aims to assess the total factor productivity change and investigate the influential factors of China's star-rated hotel industry, so as to help it move forward in regard to contributing to tourism at large.

Star-rated hotels have been a major driver for the development of the hotel industry in China (Liu & Tsai, 2018) and the revenue generated has, on average, accounted for 74.8% of the whole hotel industry nationwide during 2005-2016 (NBSC, 2018). Besides, the Chinese government has deployed supply-side structural reforms, hoping to enhance the productivity of the service sector, including tourism (Xi, 2016). To sustain the star-rated hotel industry in regard to the supportive role it plays in tourism, identifying the determinants of total factor productivity change relevant to crucial economic factors (Chatzimichael & Liasidou, 2019), such as demand intensity, labor supply, capital investment, and technical progress, is necessary in establishing distinct productivity goals that facilitate the supply-side reform.

While tourism has exhibited positive effects on regional economic growth (Proenca & Soukiazis, 2008; Pratt, 2015), to what extent the role that tourism including the hotel industry has played over regional development in better addressing the issue of regions' developmental gaps is one most intricate research topic (Krakover, 2004; Li et al., 2016). As different provinces and regions possess varied tourism and economic characteristics and resources, how to improve their respective star-rated hotel industry performance in terms of productivity and further promote regional economic growth pertinently and precisely can be examined by assessing TFP change at a regional level.

This study applies a Stochastic Frontier Analysis (SFA) approach to assessing technical efficiency change, technological change, and scale change, and further measuring the total factor productivity (TFP) change and its convergence of China's star-rated hotel industry. On the basis of this, the determining factors of TFP change can be identified and relevant policy measures can be advanced to help the industry's structural reform in meeting the nation's economic agenda (Fernández & Becerra, 2015).

Frontier models can be applied to analyze the performance of businesses that fail to completely utilize existing technology due to the existence of different organizational factors, such as firm scale. Overall productivity changes are driven by both technical progress and technical efficiency changes. Policymakers can devise effective measures with which to improve the productivity of the star-rated hotel industry if the causes of variation in productivity growth are identified and measured. That is, a given policy could be used to move the production frontier upward by adopting innovation if undesirable technical progress impedes TFP growth, whilst another policy could be deployed to help enhance the course of learning-by-doing and managerial practices if fading technical efficiency hampers productivity growth. Therefore, the research goal of this study is to show hotel managers and provincial government officials the specific components of productivity that not only contribute to but also hinder growth, thereby allowing them to devise policies accordingly to help boost the productivity growth of the industry.

Literature review

Traditional non-frontier models measuring productivity generally treat observed output variables, such as revenue or profit, as performance measures, in order to identify the best practice of the subjects under evaluation (Baker & Riley, 1994). They thereby ignore the process or efficiency of turning resource inputs into production outputs. As a result, yield management research has gradually seen more applications of frontier modeling, which considers both inputs and outputs (Donaghy et al., 1995). Frontier models assume that businesses fail to completely utilize existing technology and resources, or they suffer from non-economies of scale, leading to inevitable inefficiencies in production (Kim, 2011). That is, frontier models recognize changes in efficiencies and scale as determinants of productivity growth. Two primary frontier models exist: data envelopment analysis (DEA) and stochastic frontier analysis (SFA).

DEA is a more common approach to analyzing hospitality firms' technical efficiency. It is a non-parametric, multivariate, and multiple linear programming technique that measures the efficiency of decision-making units (DMUs) by comparing the ratios of multiple outputs to multiple inputs (Charnes et al., 1978; Liu et al., 2018). In DEA, the measure of efficiency for any DMU is derived by comparing the distance between the points on the frontier with those that are below the frontier (Cooper et al., 2011). Efficiency is measured as a percentage or alternatively bounded between zero and one, with a value of one indicating a DMU's being efficient laying on the efficiency frontier whereas a value of less than one inefficient. This method is used to evaluate the efficiency of entities having complex or unexplored relations between multiple inputs and outputs because it does not require any parametric specifications and thus is not susceptible to specification error (Wu et al., 2018).

Since Morey and Dittman (1995) first employed DEA to assess the efficiency of 54 hotels in the United States, scholars have widely applied DEA to assess the technical efficiency and productivity of the hotel industry in different regions. Tsaur (2001) measured the technical efficiency of 53 international tourist hotels in Taiwan. On the basis of DEA, Hwang and Chang (2003) estimated the Malmquist index and the efficiency changes of 45 hotels during 1994 - 1998 in Taiwan. Analogously, Hu and Cai (2004) adopted the method to measure hotel productivity in California. Sigala (2004) assessed the productivity of three-star hotels in the United Kingdom by employing stepwise DEA. Combining DEA with the Malmquist Index, Untong et al. (2011) estimated the change in managerial efficiency and management technology of hotels in Thailand from 2002 to 2006. Sun et al. (2015) measured and tested the spatial–temporal evolutionary characteristics of TFP in China's tourism industry from 2001 to 2009. Furthermore, Huang (2017) assessed inefficiency indices derived from manual and non-manual labor, and analyzed the influence of labor utilization on the productivity of 67 tourist hotels in Taiwan.

However, DEA allows for the absence of random fluctuations in the production frontier, in which deviations from the frontier are considered as inefficiency; such statistical inference possibly overestimates technical inefficiency, due to the ignorance of the statistical error (Chen, 2007). In contrast, the stochastic frontier production function views any deviation of the observed production as being attributable to purely random disturbances and inefficiency, which is reflected as a composite error term. In particular, the purely random component captures the influence of variables that are beyond the control of the production unit under evaluation (Ceolli, 1995). That is, the stochastic frontier approach can not only isolate the influence of factors other than those inefficient causes, but also correct the possible upward bias of inefficiency (Ceolli, 2005).

Because of these advantages, a number of studies have employed this approach to estimate the technical efficiency of hotels. For example, Anderson et al. (1999) used the approach to measure the efficiency of 48 hotels in the United States and found that the hotel industry performed relatively efficiently, with efficiency measures above 89%. Barros (2004) used a stochastic cost frontier model to analyze the technical efficiency of a Portuguese state-owned hotel chain from 1999 to 2001. Chen (2007) employed a generalized Cobb-Douglas cost frontier approach to measure the cost efficiency of Taiwan's international tourist hotels, and determined chain hotels to be significantly more efficient than their independent counterparts. Hu et al. (2010) used a stochastic frontier approach to estimate the cost efficiency of 66 international tourist hotels in Taiwan from 1997 to 2006, and found that their average efficiency was 0.912. Kim (2011) employed a stochastic frontier approach to evaluate the Malaysian hotel industry's TFP growth and found the hotels' average efficiency to be 41%; the average technical progress, technical efficiency change, and total factor productivity growth were 0.127, -0.057, and 0.070, respectively. Assaf and Magnini (2012) evaluated hotel efficiency using a distance stochastic frontier method and discussed the difference between efficiency scores with and without satisfaction as an output. Oliveira et al. (2013) further analyzed the efficiency of hotel companies in the Algarve (Portugal) based on a parametric method of the stochastic frontier approach using a production function, and found that hotel location and the existence of golf facilities played an important role in efficiency performance. Similar to Kim (2011), Chatzimichael and Liasidou (2019) also employed a stochastic frontier approach to evaluate the TFP growth of 25 European countries from 2008 to 2015, and found that hotel-sector productivity growth rates were indeed rather low in most European countries, which was partially caused by relatively slow improvements in efficiency.

Expanding this line of work, our study intends to estimate a stochastic production frontier to, first, evaluate the technical efficiency change, technological change, and scale change of the star-rated hotel industry at the provincial level in China. Second, the various change indices are then combined to derive TFP change. Furthermore, the current study proposes a novel two-dimensional TFP change rate and stability-based matrix diagram to measure the star-rated hotel industry's performance among the eight comprehensive economic regions possessing varied regional economic developmental orientations. Finally, based on a convergence framework, this study captures the spatial heterogeneity of the different economic regions in terms of their TFP change. Analyzing TFP change and its three components at both provincial level and economic regional level could further help to identify their respective impacts, so as to help industry stakeholders and managers devise measures to improve the TFP of the star-rated hotel industry.

Methodology

Stochastic frontier analysis and assumption tests

A stochastic production frontier function is defined as in Equation (1) below:

$$Y_{it} = X_{it}\alpha + V_{it} - U_{it}, i = 1, 2, \cdots, N; \quad t = 1, 2, \cdots, T \tag{1}$$

where

Y_{it} is the production of the *i*th hotel in the *t*th time period;

X_{it} is a k×1 vector of input quantities of the *i*th hotel in the *t*th time period;

α is a vector of unknown parameters, which is to be estimated;

V_{it} is the white noise;

U_{it} is the production loss due to hotel-specific technical inefficiency.

In order to measure the TFP change and its decomposition on the basis of the translog distance function methods described in Fuentes et al. (2001) and Orea (2002), a translog stochastic production frontier is thus considered and defined in Equation (2):

$$\ln y_{it} = \alpha_0 + \sum_{n=1}^{N} \alpha_n \ln \boldsymbol{x}_{nit} + \frac{1}{2}\sum_{n=1}^{N}\sum_{j=1}^{N} \alpha_{nj} \ln \boldsymbol{x}_{nit} \ln \boldsymbol{x}_{jit} + \sum_{n=1}^{N} \alpha_{tn}\, t \ln \boldsymbol{x}_{nit} + \alpha_t t + \frac{1}{2}\alpha_{tt} t^2 + v_{it} - u_{it} \tag{2}$$

where $v_{it} \sim N(0, \sigma_v^2)$ and $u_{it} \sim iidN^+(\mu, \sigma_u^2)$, v_{it} and u_{it} are independent of each other, and other parameters are the same as those in Equation (1). The parameter t represents the time trend in Equation (2), reflecting technological change interacting with input variables and allowing neutral technical changes (Färe et al., 1997). The parameter n represents different input resources.

According to Battese and Coelli (1992), technical inefficiency is specified as:

$$u_{it} = u_i \eta_{it} = u_i \exp(-\eta[t - T]) \tag{3}$$

where η is a parameter representing the change rate in technical inefficiency. A positive value of η denotes improving technical efficiency over time and a negative one otherwise.

The maximum-likelihood estimates for the parameters of the stochastic frontier model, as defined in Equations (2) and (3), can be obtained using a software program, FRONTIER 4.1, in which the variance parameters are expressed in terms of $\gamma = \sigma_u^2 / \sigma_s^2, \sigma_s^2 = \sigma_u^2 + \sigma_v^2$; the parameter γ should lie between 0 and 1. In particular, the deviation away from the production frontier is mainly attributable to white noise when γ equals zero or is attributable to inefficiency if γ equals one.

In this method, technical efficiency can be derived by subtracting statistical noise from a calculated total divergence between actual production and the production frontier. Nevertheless, this method is subject to specification error as it requires parametric specification. Moreover, the method is quite restrictive when analyzing entities having complex relationships between multiple inputs and outputs that defy functional specification.

Prior to further calculations, the assumptions underlying the production function form (i.e., Equation (2)) and the technical inefficiency function form (i.e., Equation (3)) should be tested for their appropriateness for adoption. In this study, five tests were performed. Test one assessed the significance of parameter γ to see whether or not a stochastic frontier production function is required and was hypothesized as follows:

H_0: a stochastic frontier production function is not required ($\gamma = 0$).

H_1: a stochastic frontier production function is required ($\gamma \neq 0$).

Test Two assessed the existence of quadratic-term parameters to see whether the Cobb-Douglas production form or a translog function form is more appropriate and was hypothesized as follows:

H_0: all the quadratic-terms are equal to zero and the production form is a Cobb-Douglas one ($\alpha_{nj} = \alpha_{tn} = \alpha_{tt} = 0$).

H_1: at least one of the quadratic-terms is not equal to zero ($\alpha_{nj} \cup \alpha_{tn} \cup \alpha_{tt} \neq 0$) and the production form is a translog one.

Test Three assessed the existence of parameters related to *t* to see whether or not technological change exists in the production function and was hypothesized as follows:

H_0: parameters related to *t* do not exist and the technological level remains every year ($\alpha_t = \alpha_{tn} = \alpha_{tt} = 0$).

H_1: at least one parameter related to *t* exists ($\alpha_t \cup \alpha_{tn} \cup \alpha_{tt} \neq 0$) and the technological level changed.

Test Four assessed the significance of parameters related to the interactive term between *t* and *x* to see whether or not technical change is Hicks-neutral and was hypothesized as follows:

H_0: the interactive term between *t* and *x* is equal to zero ($\alpha_{tn} = 0$) and the technical change is Hicks-neutral.

H_1: the interactive term between *t* and *x* is not equal to zero ($\alpha_{tn} \neq 0$) and the technical change is not Hicks-neutral.

Test Five assessed the significance of parameter η to see whether or not the technical efficiency is time-invariant and was hypothesized as follows:

H_0: parameter η is equal to zero and the technical efficiency is time-invariant.

H_1: parameter η is not equal to zero and the technical efficiency is not time-invariant.

In accordance with Coelli et al. (2005), the estimated parameters in the equations can be tested using the following likelihood ratio (LR) statistic:

$$LR = -2 * [\ln L_R - \ln L_U] \sim \chi^2(J) \tag{4}$$

where $\ln L_R$ and $\ln L_U$ respectively denote the maximized values of the restricted and unrestricted log-likelihood functions and J is the number of restrictions. The null hypothesis H_0 of the previous five tests should be rejected at the 100α% significance level when the *LR* statistic is greater than the critical value $\chi^2_{1-\alpha}(J)$.

After these tests have been conducted, technical efficiency, technical efficiency change, technical change, and scale change should be calculated as follows.

TFP change and its decomposition

The technical efficiency (TE) level of hotel *i* in year *t* can be determined as

$$\mathrm{TE}_{it} = \mathrm{E}(\exp(-u_{it})|e_{it}) \tag{5}$$

where $e_{it} = v_{it} - u_{it}$, TE_{it} can then be used to calculate the component of the technical efficiency change (TEC). That is,

$$\mathrm{TEC}_i^{s,t} = \mathrm{TE}_{it}/\mathrm{TE}_{is} \tag{6}$$

where *t* and *s* represent different years, and $t = 2, 3, \cdots, T; s = 1,2, \cdots, T-1$.

Technical change (TC) between year *s* and *t* for the *i*-th hotel can be directly directly devised from the estimated parameters. That is, the partial derivatives of the production function with respect to time can be first evaluated by using the data of the *i*-th hotel in years *s* and *t*. Next, technical efficiency change between the adjoining years *s* and *t* is calculated as the geometric mean of these two partial derivatives. If a translog function is involved, we will have the exponential of the arithmetic mean of the log derivatives as shown below.

$$\mathrm{TC}_i^{s,t} = \exp\left\{\frac{1}{2}\left[\frac{\partial \ln y_{is}}{\partial s} + \frac{\partial \ln y_{it}}{\partial t}\right]\right\} \tag{7}$$

Furthermore, the TFP change may produce a biased measure if the productivity changes attributable to scale economies are not captured (Nishimizu & Page, 1982; Oh et al., 2012). One way of capturing scale change (SC) is to follow Orea's (2002) proposed approach, as follows:

$$\mathrm{SC}_i^{s,t} = \frac{1}{2}\sum_{n=1}^{N}[\varepsilon_{nis}SF_{is} + \varepsilon_{nit}SF_{it}]\ln(x_{nit}/x_{nis}) \tag{8}$$

where $SF_{is} = (\varepsilon_{is} - 1)/\varepsilon_{is}$, $\varepsilon_{is} = \sum_{n=1}^{N}\varepsilon_{nis}$ and $\varepsilon_{nis} = \frac{\partial \ln y_{is}}{\partial x_{nis}}$.

This scale change is equal to zero when the production technology has a constant return to scale (CRS) on which the scale elasticity (ε_{is}) equals one. Finally, according to Kumbhakar (2003), the TFP change (TFPC) can be calculated as:

$$\mathrm{TFPC}_i^{s,t} = \mathrm{TEC}_i^{s,t} + \mathrm{TC}_i^{s,t} + \mathrm{SC}_i^{s,t} \quad (9)$$

Convergence analysis approach

In this study convergence analysis is conducted to assess whether or not TFP change in the various regions approaches convergence (Martin & Mitra, 2001). In general, three types of convergence exist: σ convergence, absolute *β*-convergence and conditional *β*-convergence. An index representing the level of distribution such as standard deviation is adopted to conduct the σ convergence check, where a diminishing index with the passing of time implies a σ convergence form, and an increasing index denotes a divergence form. Specifically, in this study standard deviation was employed to measure σ convergence as follows:

$$\sigma_{\mathrm{t}} = \sqrt{\frac{1}{I-1}\sum_{i=1}^{I}(TFP_{\mathrm{i,t}} - \overline{T}FP_{\mathrm{t}})^2} \quad (10)$$

where $TFP_{\mathrm{i,t}}$ is the TFP of region *i* at time *t*, and $\overline{T}FP_{\mathrm{t}}$ is the mean of TFP of all the regions in period t. When σ convergence exists (i.e., $\sigma_{t+1} < \sigma_{\mathrm{t}}$), the distribution coefficient of TFP is condensing.

The absolute *β*-convergence presumes that all the regions have analogous economic environments and evaluate if the TFP of each region can attain the same steady change rate, and if the slow regions have an inclination to draw near the developed ones. The absolute *β*-convergence formula (Sala-i-Martin, 1995) can be shown as follows:

$$[\ln(TFP_{\mathrm{i,t}}) - \ln(TFP_{\mathrm{i,0}})]/T = \alpha + \beta \ln(TFP_{\mathrm{i,0}}) + \varepsilon \quad (11)$$

α is a constant and $\ln(TFP_{\mathrm{i,0}})$ is the log of TFP's beginning value in period $t=0$ in the region *i*, and β is its coefficient. The absolute *β*-convergence form is present if β is notably negative, signifying slow regions' inclination in drawing near the developed ones' TFP.

Lastly, the conditional β-convergence analysis will take regional economic features into consideration in assessing if the each region's TFP change could converge to its own steady level, implying the possibility of a lasting gap between the slow and developed regions. The current study adopted a panel data fixed effects model to assess the conditional β-convergence (Miller & Upadhyay, 2002). The formula is expressed below:

$$\ln(TFP_{\mathrm{i,t}}) - \ln(TFP_{\mathrm{i,0}}) = \alpha + \beta \ln(TFP_{\mathrm{i,t-1}}) + \varepsilon \quad (12)$$

where α is the fixed effects term of the panel data, matching the steadiness conditions of the various regions. The conditional β-convergence form is present if the estimated β value is significantly negative, signifying the ith region's TFP change will converge to its own steady level.

Data and Variables

In this study, the TFPC, TEC, TC, and SC of the star-rated hotel industry of the 31 provincial-level regions in China were measured between 2001 and 2015. The data represent a balanced panel consisting of 465 time-series observations. To estimate the production function, total operating revenue (y) was selected to represent hotel production output. Input variables were selected to reflect labor and capital resource inputs deployed in producing revenue (Zhou et al., 2008; Huang et al., 2012). Thus, two inputs in terms of the number of employees and the volume of fixed assets were selected to signify human resources and capital investment (Kim, 2011). The above input and output variables were also used by Barros and Dieke (2008) and Kim (2011).

According to the input and output variables, the data used for this study were obtained from Statistical Yearbook of China and the CEIC Database. Supplementary Table 1 shows the average annual value of the input and output variables used for parameter estimation and TFPC, TEC, TC, and SC assessment.

[Insert Supplementary Table 1 here]

Analysis and Discussion

Hypothesis testing

According to our research framework, as described in the methodology section, hypothesis testing related to Equations (2) and (3) was performed by assessing the LR statistic. The results are presented in Supplementary Table 2. In the first test, the null hypothesis (H_0) was rejected because an LR of 275.94 is greater than $\chi^2_{1-0.01}(k)$ (i.e., 10.501), which means that the inefficiency item u_{it} exists. That is, the stochastic frontier production function should be adopted. In the second test, H_0 was rejected because an LR of 73.58 is greater than $\chi^2_{1-0.01}(k)$ (i.e., 10.501), which means that the translog function form, Equation (2), is more suitable than the Cobb-Douglas production form. In the third test, H_0 was rejected because an LR of 68.82 is greater than $\chi^2_{1-0.01}(k)$ (i.e., 10.501), which means that there existed technical change. Since technology could change over time, H_0 in the fourth test was accepted because an LR of 3.12 is smaller than $\chi^2_{1-0.01}(k)$ (i.e., 10.501), indicating that technical change is irrelevant to any input resource and thus was Hicks-neutral. Finally, H_0 in the fifth test was rejected because an LR of 8.4 is greater than $\chi^2_{1-0.01}(k)$ (i.e., 8.273), meaning that technical efficiency did change over time. That is, the change in technical efficiency should be considered in TFP decomposition.

[Insert Supplementary Table 2 here]

Parameter estimates

After the above testing, maximum-likelihood estimations of the parameters in the translog stochastic frontier production function defined in Equations (2) and (3) were carried out. The calculated results are presented in Table 1.

[Insert Table 1 here]

The estimated value of γ (i.e., 0.802) is statistically significant at the 1% level, signifying the presence of technical inefficiency, which is in accordance with the results of the first hypothesis test. The estimated value of η (i.e., 0.024) is positive and statistically significant at the 1% level, implying that ascendant technical efficiency existed throughout the study period.

The coefficients, also known as elasticities, associated with fixed assets (α_1) and labor (α_2), are 0.41 and 0.359, respectively. Both are statistically significant at the 1%

level. The sum of these two production elasticities equals 0.769, suggesting that the returns to scale of the star-rated hotel industry in China decreased at the sample's mean data point. The coefficient of time (α_t) (i.e., 0.028) is statistically significant at the 1% level, indicating that a mean technological progress of 2.8% per year was observed from 2001 to 2015. Furthermore, the coefficient of time squared (α_{tt}) (i.e., -0.007) is statistically significant at the 1% level, showing that the star-rated hotel industry's technological progress rate decreased very mildly throughout the study period. The coefficients of time, interacting with fixed assets ((α_{t1})) and with labor input ((α_{t2})) variables, are -0.012 (significant at the 10% level) and 0.015 (significant at the 5% level), respectively, implying that technological progress was slightly fixed assets-oriented and labor-saving, in line with the Hicks-neutral hypothesis test result. On the basis of this, the effect of technological progress on the elasticities of fixed assets and labor can be ignored.

TFP change and decomposition

According to our research framework, the values of TC, TEC, and SC year-on-year were calculated and then summated to derive the TFPC. That is, the TFPC can be partitioned and explained by the three components of TC, TEC, and SC, respectively. Supplementary Table 3shows the calculated results of these indexes; a positive number indicates an increase in the index, while a negative number shows otherwise.

[Insert Supplementary Table 3 here]

It can be seen that, while the TFPC values of the star-rated hotel industry were generally positive between 2001 and 2014, indicating favorable TFP change, the value was negative between 2014 and 2015, showing an unfavorable TFP change. The favorable performance in terms of the star-rated hotel industry's TFP was mainly attributable to both TEC (all years) and TC (mainly prior to 2009). TEC represents the efficiency level achieved as a result of management effort, and TC shows the difference in maximum productivity achievable adopting contemporary technology between time periods t and s (Liu & Tsai, 2018). From the results of the above, it is evident that management effort plays an important though somewhat descending role in TFP progression. The average values of TEC and TC were 1.967 and 2.824, respectively, reflecting the way in which technical efficiency increases at an average rate of 1.97% per annum and technology progressed at an average annual rate of 2.82%. These two factors led to a remarkable TFP change in the star-rated hotel industry at an average rate of 3.519% per annum. It is worth noting that the SC values during the study years had been, in general, negative and decreased at an average annual rate of 1.27%, offsetting the TFP change.

The TEC, TC, SC, and TFPC trends are further depicted in Figure 1. Even though TEC shows a rather stable trend, contributing to the TFPC, the latter fluctuates downward, largely due to declining TC, coupled with unfavorable SC. As analyzed in the earlier parameter estimation, the coefficient of time is positive ($\alpha_t = 0.028$), indicating technological progression, and the coefficient of time squared is negative ($\alpha_{tt} = -0.007$), implying a deteriorating technological progression rate, corresponding to the trend performance of TC in Figure 1. Although TEC shows a slightly declining trend, technical efficiency keeps increasing (i.e., TEC > 1), which echoes a positive value of η (0.024), indicating ascendant technical efficiency. Finally, while the sum of the two production elasticities of the two inputs suggests that the mean returns to scale, the star-rated hotel industry was decreasing between 2001 and 2015. The scale efficiency shows an ascendant trend, indicating that the returns to scale improved (Coelli et al, 2005). From the above analysis, it can be seen that the various indexes calculated from Equations (6)-(9), as shown in Supplementary Table 3, are consistent with the estimations of the various parameters shown in Table 1.

[Insert Figure 1 here]

Regional performance analysis

In analyzing the star-rated hotel industry's TFPC and its components, we regarded hotels in China's 31 individual provinces and municipalities as 31 separate decision-making units. Based on the report of Development Research Center of the Chinese State Council, the 31 provinces and municipalities can be categorized into eight comprehensive economic regions considering their respective geographical locality and economic features, as shown in Supplementary Table 4. As a result, the level of TFPC, TEC, TC, and SC of the star-rated hotel industries in the eight regions can be further examined.

On the basis of regional divisions, the TFPC was re-calculated and listed in Supplementary Table 5. It can be seen that all of the annual average values (the last line in Supplementary Table 5) in different regions were positive, which is in accordance with the performance of annual average TFPC nationwide, as shown in the last line regarding TFPC in Supplementary Table 3. Although the TFP had seen increases in different regions, the change rates were somewhat different.

[Insert Supplementary Table 4 here]

[Insert Supplementary Table 5 here]

The tourism industry including hotels in the different regions of China have contributed to their regional economies to various extents (Pratt, 2015). Some of the eight regions, such as the Eastern Coastal region, are economically developed, while others, such as the Northwest region, are undeveloped. Those more economically-developed regional economies are likely to experience greater economic benefits as a result of better development in the tourism industry (Li *et al.*, 2016). The eight regions had had different levels and forms of economies and undergone different developments. As shown in Supplementary Table 4, only the Southwest and Northwest regions were characterized as tourism-affiliated, which should better facilitate the development of the star-rated hotel industry in their respective regions. Nevertheless, the TFPC performance in the Southwest and Northwest regions in general had underperformed as compared to other regions. Furthermore, the Southwest and Northwest regions had experienced more years of negative TFPC than the other regions. These two regions are situated in southwest China, and their performances in regard to economic development (in terms of GDP) and the added value of the tertiary industry were the worst among all the regions. Furthermore, the added value of hotels and restaurants in these two regions were below the average. According to Li *et al.* (2016), tourism development contributes significantly to the reduction of regional inequality, which means that the development of the hotel industry in these two undeveloped regions could facilitate regional economic development in a faster pace. In fact, the two regions' performances in terms of their respective TFPC did not reflect their partial economic positioning of being tourism affiliated.

As shown in Supplementary Table 4, the annual average GDPs, added values of the tertiary industry, and added values of hotel and restaurants in Eastern and Southern Coastal regions (especially the former) far outperformed those of the other regions. The developed economies of these two regions are inclined to participate in business and international trade, which require support with accommodation due to the foreseeable tourist arrivals. This has a direct influence on hotel sales and profitability (Chen, 2011), further triggering TFP increases without necessary input growth.

It is noted that the Northeast region, featuring heavy equipment manufacturing, showed the highest average TFP change rate of 4.78%. However, this region also displayed unfavorable performance in terms of the added value of hotels and restaurants. The Northern Coastal region, featuring new technology research, demonstrated a rather impressive average TFP change rate of 3.78%. However, the added value of hotels and restaurants was disappointing. Such figures suggest that the TFPC had a somewhat weak positive correlation with the added values of hotel and restaurants, and some output growth could only be explained by input growth (Kim, 2011).

To better illustrate the underlying relationship between TFP change and its annual fluctuations, the eight regions were plotted onto a two-dimensional matrix with the X-axis denoting TFP change rate and the y-axis denoting the stability of the change rate.

[Insert Figure 2 here]

As noted in Figure 2, we classified each region into a quadrant according to: (1) whether the mean TFPC of a region is greater or less than the grand mean of all the eight TFPC values; and (2) whether the standard deviation of a region's TFPC is greater or less than the mean standard deviation of the eight regions. Consequently, each of the eight regions fell into one of four quadrants, according to its TFPC characteristics.

Quadrant A – fast growth and high stability: Star-rated hotels in the Northeast, Northern Coastal, Southern Coastal and Middle Yangtze River regions operated consistently, with fast TFP change representing the best practice benchmark. Hotels in this quadrant should continue doing so by maintaining their operational advantages, leading to fast and stable growth. Note that all the featured economies of the four regions in this quadrant are not closely related to tourism, but are rather strongly associated with manufacturing and business. It could be inferred that business travelers likely contribute more to the local star-rated hotel industry than their leisure counterparts.

Quadrant C – slow growth but high stability: Star-rated hotels in the Eastern Coastal and Middle Yellow River regions operated consistently at a relatively slow level of TFP change and are clearly behind the other regions in terms of their TFP change. This quadrant accounts for much of the underperformance of China's star-rated hotel industry over time. Hotels in these two regions need to examine the underlying problems associated with slower TFP change and find a way to surpass their better-performing counterparts.

Quadrant D – slow growth and low stability: Star-rated hotels in the Southwest and Northwest regions operated with slow and relatively unstable TFP change over time. The economies of these two regions, situated in the southwest of China, rely on tourism. However, natural disasters occur frequently in this part of China. Although many tourist resources have been gradually developed alongside the vast developments of the western region of China, some tourist spots could be temporarily closed at any particular time, due to natural disasters. For example, Jiuzhaigou Valley in Sichuan, where the film *Crouching Tiger, Hidden Dragon* was shot, has been temporarily closed to tourists since June 2018, due to debris flow. Leisure tourists who were attracted to this location would have opted to visit other destinations instead, leading to instability in the performance of star-rated hotels in this region to some extent in different years.

The average TFPC of each region is further decomposed into TC, TEC, and SC, from which TFP change can be studied more precisely. The decomposition results are depicted in Supplementary Figure 1.

[Insert Supplementary Figure 1 here]

The best and worst performers in terms of TFPC were the Northeast and Northwest regions, respectively. While the TC values appear to be rather comparable among all eight regions, the scale changes show otherwise, as does the TEC. The scale change in the Northwest region was the worst, seriously undermining the TFP change in this region. Furthermore, scale changes were negative in all regions except for the Northeast region. Analogously, while the TEC in the Eastern Coastal region underperformed that in the other regions, it was still a positive value, indicating an increase in technical efficiency. While TFP change was the slowest and scale efficiency seriously declined, the performance of TEC for the Northwest region outperformed those in other regions. As depicted in Figure 1, the TFPC and other indexes in different economic regions show various characteristics, which deserve further investigation.

Convergence analysis

The result of σ convergence analysis is presented in Supplementary Table 6.

[Insert Supplementary Table 6 here]

The values of standard deviation of TFP change overall trend downward during 2001-2015, despite there was some transitory fluctuation during 2006-2009, signifying the presence of a σ convergence form of the TFP change overall. Regionally speaking, while generally the first standard deviation values in 2001-2002 were large, the later values for all regions show a descending trend of fluctuation except for the Northwest region, indicating the convergence of the TFP change in those regions during 2001-2006, and then present some stability after short fluctuation in 2010-2011. The TFP change for the Northwest region exhibits some divergence trend after 2008. Besides, the results signify that the TFP change of the star-rated hotel industry overall existed a catching-up effect before 2008. That is, the slow regions showed an inclination of catching up with those better developed ones. Nonetheless, we should note that the provincial dissimilarities in the TFP change had widened between the Northwest region and other regions. Such differences could be attributed to a weakening effect of the diffusion of advanced production technology in the Northwest region and a rather stable trend of the production technology and management in the other regions in the later period of the sampling year.

The results of absolute β-convergence and conditional β-convergence estimation are shown in Table 2.

[Insert Table 2 here]

The regression coefficient of absolute β-convergence overall (-0.071, significant at the 5% level) signifies the presence of such convergence, meaning that the star-rated hotel industry's TFP change overall converged to a steady state. Regionally speaking, the regression coefficients of absolute β-convergence in the Northern coastal, the Middle Yangtze River and the Northwest comprehensive economic regions are -0.080 (significant at the 10% level), -0.027 (significant at the 1% level) and -0.074 (significant at the 10% level), respectively, indicating their TFP change of the star-rated hotel industry converged to a steady level. The regression coefficients of absolute β-convergence in the Northeast, Southern coastal, Middle Yellow River, and Southwest comprehensive economic regions are -0.070, -0.067, -0.052 and -0.073, respectively, however none of which is significant. It is worth noting that the regression coefficients of absolute β-convergence in the Eastern Coastal comprehensive economic region, which has been the most developed region in China, is 0.092, indicating a widening gap of the TFP change between the Eastern Coastal and other regions.

While the absolute β-convergence analysis is performed on condition that the operational environment for hotels in every region is analogous, in realty environmental heterogeneity in connection with economic disparities exists across all the regions. Consequently, the regional convergence analysis ought to be assessed conditionally (Beenstock & Felsenstein, 2008). As presented in Table 2, the estimated value of conditional β-convergence overall is -1.078 (significant at the 1% level), and those for all the regions are also negative (significant at either the 1% or 5% level with the exception of the Eastern Coastal region). In comparison to the previous absolute β-convergence analysis results, the star-rated hotel industry's TFP change in each region exhibits a tendency of conditional convergence, meaning that the TFP change in each region except for Eastern Coastal comprehensive economic region converged to its own stable level. The TFP change of the star-rated hotel industry in the Northern coastal, Middle Yangtze River, and the Northwest comprehensive economic regions showed both absolute and conditional β-convergence noticeably, signifying not only that the star-rated hotel industry's TFP change in the regions converged to their own steady levels but also that the dissimilarities in the TFP change among these regions were condensing. On the contrary, the star-rated hotel industry's TFP change in other regions (except for the Eastern Coastal) only exhibited conditional β-convergence; the star-rated hotel industry's TFP change in these regions only converged its own steady level and the regional disparities in terms of TFP change will persist.

Implications

The empirical findings of this study query the seemingly promising development and performance momentum of the star-rated hotel industry in China. While improved performance could be achieved by improving the industry's productivity growth, as has been commended by Barros (2006), Assaf et al. (2010), Chen (2010), and Liu and Tsai (2018), vigorously developing star-rated hotels but ignoring issues related to productivity and efficiency enhancement will doubtlessly cause resource waste and mediocre performance in the future.

Accordingly, the study findings elucidate how hotel managers and regional hotel sectors could pay attention to shaping ideal development strategies and devising effective policy measures. First, at the micro-level, to improve integral competitive strength and productivity for the star-rated hotel industry in China, practitioners and managers should take measures to prevent technological progression and technical efficiency changes from continuous stagnation or even regression. For example, hotel owners and management companies should take notice of initiating and adopting advanced production technology and service equipment that have been proven to be beneficial in enhancing hotel productivity (Melián-González & Bulchand-Gidumal, 2016). Furthermore, hotel managers could also develop and train employees to enhance their service awareness and skills, which would in turn help to improve hotel productivity. Meanwhile, given the observed fact of decreasing returns to scale in the star-rated hotel industry, both the amount of fixed assets and number of employees of the industry should be closely monitored. Hotel owners and government officials responsible for hotel development ought to contemplate confining and scrutinizing the volume of fixed asset investment in star-rated hotels in China to help enhance economic efficiencies of scale. Instead, measures taken by stakeholders in the star-rated hotel industry should aim to enhance management skills and adopt advanced production technology.

The results of this study also shed light on the macro-level. A fluctuating and downward trajectory of hotel productivity growth rate calls for prudent policies directing to reinforce the competitiveness of the star-rated hotel industry. The provincial government could set up policies such as tax credit/deduction measures to encourage hotels to introduce advanced technology and service equipment in their operations. Since the scale of the star-rated hotel industry should not be increased, developing the inventory quantity advantage of the industry is of high importance. Managers and practitioners could train employees to adopt advanced production technology (such as the use of mobile technology in receiving and responding to guests' housekeeping requests or room service orders) and improve asset utilization by, for example, tackling low room occupancy rates. The result showing that the scale change causes TFP change fluctuations indicates that the government should be sensitive to changes in market conditions and establish policy measures in time to ensure the stable development of the star-rated hotel industry.

Finally, the government has played an important role in promoting hotel industry growth at the regional level (Dwyer et al., 2009) and should implement measures that are closely integrated with regional economic development orientation to prevent productivity decline in the star-rated hotel industry. For example, in regions relying on economies related to business and manufacturing, such as the Eastern Coastal and Southern Coastal regions, star-rated hotel managers should focus more on the needs of business tourists. Hotels in regions positioned as tourism-related could pay particular attention to leisure travelers. It is worth noting that, while both the Southwest and Northwest regions were geared toward tourism development, their TFP performance in terms of growth rate and stability were rather disappointing, especially in regard to scale change. That is, their tourism scales in terms of sightseeing resources could be enhanced so that regional star-rated hotels can better utilize their resources in providing accommodation support to tourists, while simultaneously improving productivity and economy of scale. Furthermore, Pratt (2015) and Li et al. (2016) pointed out that compared to international tourism, domestic tourism contributed greater to the economy. Accordingly, regional star-rated hotel stakeholders including the government and hoteliers could consider cooperating with those in other regions to attract more domestic tourists, such that the star-rated hotel industry in the regions could collectively contribute more to economic development. Finally, in addition to learning from each other's individual developmental edges, different regions ought to embark on mutual cooperation among different regions to enhance the complementarity of tourism resources in different regions, and to advocate the overall productivity of the star-rated hotel industry.

Conclusion

The significance of this study lies in its broad assessment of the star-rated hotel industry in China from the perspective of TFP change and various efficiency component changes. The TFP performance of the star-rated hotel industry in China during the sample period was generally favorable, with an annual average growth rate of 3.52% (even though the growth had slowed down). While both TEC and TC helped boost TFP change, the scale change hindered and caused fluctuations in the TFP change. While TC and TEC show a downward trend, SC shows an upward trend.

By analyzing the development rate of TFP change in the star-rated hotel industry in the eight economic regions under study, the results indicate that, while the star-rated hotel industry's TFP increased during the study period, the growth rates have seen declines in all the regions studied. From the matrix analysis, we can see that star-rated hotels' TFP change in regions with development orientations that were not closely related to tourism were more stable than those in the Southwest and Northwest regions, the development orientations of which were closely related to tourism. In Table 1 and

Supplementary Figure 1, it can be seen that economies of scale in the Southwest and Northwest regions dropped the fastest, which was the main factor causing decreasing returns to scale in the star-rated hotel industry nationwide during the study period. Finally, the star-rated hotel industry's TFP change for all the regions except for the Eastern Coastal region converged to their own steady level and those for the Northern Coastal, Middle Yangtze River and Northwest comprehensive economic regions converged to each other.

Four major contributions are evident in this study. First, unlike previous hospitality and tourism studies, which have majorly applied nonparametric models, such as the Malmquist index model, the present study adopted an SFA approach to both test the validity of adopting the production function and to examine TFP change and technological progress and changes using various efficiency indices. Whilst previous studies have normally assessed hotel productivity with regard to relative efficiency, this study expands the scope of productivity assessment to the macro socio-economic environments of the eight economic regions in China. Second, our study proposes an innovative two-dimensional TFP change rate and stability-based matrix diagram with which to evaluate the performance of the star-rated hotel industry amongst China's eight different economic regions, with different regional economic development orientations. Third, the current study investigated the level of convergence for star-rated hotel industry's TFP change in different regions, which contributed to analysis related to regional differentiation in terms of star-rated hotel industry's TFP change. Lastly, the implications derived from the present study enable regional government officials to offer policy guidelines that will help improve the star-rated hotel industry TFP according to regional development orientations from a macro perspective.

However, the limitations are to be noted for the study. First, the study findings are limited to the collected sample and data. Therefore, the results and measures should be interpreted with caution. Second, the results of the study are limited to a regional/macro perspective. On the basis of the study results, further investigations should be carried out on a micro-level, to devise sub-regional measures with which to improve the respective hotel industries' TFP. Third, the specific factors related to star-rated hotels considered in this study were not exhaustive. Other factors could be considered for inclusion in explaining the components of total factor productivity in future studies.

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