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Dynamic efficiency assessment of the Chinese hotel industry ☆

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ABSTRACT

The paper introduces for the first time a totally dynamic two-stage approach to analyzing the hotel industry's technical efficiency at the sub-national level. The first stage uses data envelopment window analysis (DEWA) to assess regional hotel sectors' technical efficiency over time. Unlike previous studies, the second stage uses a dynamic Tobit model to investigate the impact of macro contextual factors on the hotel sector efficiency. The study chooses the Chinese hotel industry during the period 2001–2006 as its application setting. The findings of the investigation indicate that the Chinese hotel industry is approaching an efficient operation in general, recovering from a major dip in 2003 resulting from the Severe Acute Respiratory Syndrome (SARS) outbreak. In addition, the study introduces a novel two-dimensional efficiency-based matrix to assess the competitive advantage of different regions of the Chinese hotel sector. The paper presents strategic market implications for hoteliers, government decision-makers, and destination management organizations. The proposed methods are applicable for situations in which an exogenous event of a destabilizing impact (e.g., SARS) does occur.

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1. Introduction

As an economy in transition from a socialist to a market-based system, China is gradually opening its market to the world since the late 1970s. The past three decades witness the emergence of an increasingly matured Chinese hotel industry with rapid globalization and competition. The development of hotel joint ventures and cooperative management in the 1980s, the transformation of private ownership and stock ownership in the 1990s, and the recent diversification of hotel brands and types demonstrate the growth and change in the Chinese hotel industry (Yu, 2003). Zheng (2008) provides an excellent overview of the Chinese lodging industry between 1978 and 2006.

Following an earlier setback in 2003 (when the SARS outbreak occurred), both the 2008 Summer Olympics in Beijing and the 2010 World Expo in Shanghai mark the capacity of Chinese hotel industry in meeting the growing demand of domestic and international travelers. According to the classical theory of industrial organization economics, the structure of an industry and the conduct of its firms determine the industry's performance (McWilliams & Smart, 1993). The regression and progression of the Chinese hotel industry provide an ideal application setting for a dynamic approach that focuses on productivity assessment.

In China's increasingly competitive marketplace, hotel performance measurement is not only a powerful management tool for hoteliers but also a helpful source of information for administrators responsible for regional and national tourism planning and operations. Typically, industry evaluations of the performance of the hospitality industry are based on average occupancy rates and average room rates, by revenue per available room (Wassenaar & Stafford, 1991), or by breakeven room occupancy (Wijeysinghe, 1993). Such indicators, however, only give a single dimensional snapshot of the intricate hotel industry. Anderson, Fish, Xia, and Michello (1999) point out the difficulty of drawing conclusions about the relative productivity of the hotel industry without simultaneously considering the mix and nature of services provided. Thus, hospitality researchers should pay more attention to a relatively sensitive performance evaluation method.

As the Data Envelopment Analysis (DEA) is gaining importance in analyzing relative efficiency in the hospitality and tourism industries (Barros & Dieke, 2008; Wöber, 2002), the present study employs a totally dynamic approach of DEA to assess the relative technical efficiency at the regional hotel sector level in China. DEA is a non-parametric, multi-factor, productivity analysis tool that utilizes multiple input and output measurements to evaluate a number of relevant decision making units' (DMUs) relative efficiency. For the regional hotel sector, technical efficiency refers to a comparative measure of the effectiveness with

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which evaluators use a given set of inputs, such as labor and capital, to produce a targeted set of outputs, such as revenue and room occupancy. When explicitly taking into account the mix of service outputs produced, DEA is best suited to the comparison or benchmarking of a number of similar operational units (Donthu, Hershbergerb, & Osmonbekove, 2005).

Despite a wide variety of DEA applications existing in various contexts such as regional development (Dinc, Haynes, & Tarimcilar, 2003), the banking industry (Luo, 2003; Ward, 2009), and the higher education industry (Hsu, Chao, & James, 2009), Wöber (2006) conducts a comprehensive literature review related to the application of DEA technique in the tourism and hospitality fields, and he concludes that only a few recent studies start to raise attention among tourism researchers (Anderson, Fok, & Scott, 2000; Chiang, Tsai, & Wang, 2004). Recently, Chen (2009) also recognizes that the performance evaluation factors in the hospitality industry are multi-dimensional in nature and can hardly be aggregated using price or cost figures, and he acknowledges the usefulness of the DEA technique in the hospitality industry. Chen (2009) proposes a modified DEA model to measure the performance of a Taiwanese hotel chain. Similarly, Botti, Briec, and Cliquet (2009) apply the DEA method to examine French hotel chains, and they conclude that no specific organization form (e.g., plural forms versus franchise and company-owned systems) is more efficient than another. Motivation for the present study comes from the fact that the majority of DEA studies in the hospitality industry are static in nature, based mainly on cross-sectional data at the individual level of hotel entities. The present study assesses the hotel industry at the aggregate level of the regional hotel sector coupled with a dynamic analysis of DEA, monitoring technical efficiency and stability behavior over time. The study also identifies the critical antecedents of technical efficiency. Previous research focuses on the micro contextual factors (Hwang & Chang, 2003; Yang & Lu, 2006), however, the influence of macro socio-economic factors needs further consideration. The present study partially fills the gap by focusing attention on the antecedents of technical efficiency at the regional hotel sector level in China.

The purposes of the present study are threefold: to explore the dynamic technical efficiency of the Chinese hotel industry at the sub-national level; to provide a strategic framework for classifying regional hotel sectors that would be instrumental in the assessment of their competitive (dis)advantage; and to examine the impact of socio-economic variables on technical efficiency scores of the Chinese hotel industry.

The current study offers a unique methodological contribution to the tourism literature. Specifically, the study employs a data envelopment window analysis (DEWA) in conjunction with a *dynamic* Tobit model (unlike previous studies that use exclusively a *static* Tobit model) to examine antecedents of DMUs' relative efficiency over time using the Chinese hotel sector at its aggregate regional level as the application setting. Based on the obtained relative efficiency measures together with their fluctuations over time, the paper extends the DEA application within the literature by introducing a novel two-dimensional efficiency-based matrix to assess the competitive advantage of different regions of the Chinese hotel sector. The designated matrix serves not only as a tool for market segmentation, but also as a thoughtful basis for strategic decision-making and performance management that would be of help to government decision-makers, hoteliers/investors, and destination management organizations (DMOs). The methods of analysis mentioned above appear appropriate as the studied period (i.e., 2001–2006) includes an exogenous event of a destabilizing impact (i.e., SARS in 2003).

2. Literature review

2.1. DEA studies in the hotel industry

The initial relative efficiency analysis of Farrell (1957) is cast in terms of a ratio formulation by Charnes, Cooper, and Rhodes (1978). Technical efficiency comparisons can illustrate the extent of output expansions (or input reductions) available to firms of any given scale of operation from the adoption of available technology and management practices (Sun, Hone, & Doucouliagos, 1999). In the hotel sector, the level of a sector's technical efficiency is measured by its distance from the production frontier.

A growing pool of literature exists regarding technical efficiency (Lovell, 1993; Russell & Schworm, 2009). However, this section reviews only DEA studies relevant to the scope and purposes of the present study. A distinguishing feature of the DEA approach is that no priori assumption is required about the analytical form of the production function. More specifically, for each DMU, the study calculates a single relative ratio by comparing total weighted outputs to total weighted inputs for each unit without requiring any specific functional form. Wöber's (2002) book provides more details. Notably, applying the DEA technique at the spatial (national or sub-national) dimension is appropriate and represents a recent trend in the literature (Bosetti, Cassinelli, & Lanza, 2006; Hsu, Chao, & Luo, 2008). The present study focuses on technical efficiency estimation at the regional level for the Chinese hotel industry.

Table 1 identifies number of notable studies employing the DEA approach to measure efficiency in the hotel industry. The table classifies the studies as static (based on cross-sectional data) or dynamic (based on panel data) and highlights the inputs and outputs utilized in each study. Wöber's (2006) work offers an extensive literature review on DEA applications in the tourism and hospitality industry published between 1986 and 2006. Pulina, Detotto, and Paba (2010) also provide a review of notable DEA applications published between 2006 and 2009.

2.2. Questions unanswered in DEA literature for hospitality

As a whole, the body of literature on hotel operational efficiency leaves a number of questions unanswered. First, most DEA studies in the hospitality industry, including a recent study by Perrigot, Cliquet, and Piot-Lepetit (2009), focus on the performance of hotels at the cross-sectional level. Though the outcome may still be useful, a dynamic context sheds additional light on the trend of DMUs' relative efficiency. Trend analysis can give rise to a seemingly excessive use of resources intended to produce beneficial results in the future. As such, researchers should prefer panel data (i.e., balanced longitudinal data) over purely cross-sectional data in that they not only enable researchers to compare a DMU with its counterparts but also allow them to track an individual DMU over a period of time for movement in efficiency (Wöber, 2002).

Second, differences in efficiency derive from a host of contributory factors (Barros & Dieke, 2008). A number of studies reveal that a substantial difference exists in hotel efficiency changes due to variations such as hotel location, source of customers, and management styles (Hwang & Chang, 2003; Yang & Lu, 2006). Do other macro contextual factors (e.g., richness of local tourism resource, international attractiveness, payment levels of employees, etc.) matter? The relationships between macro socioeconomic factors and the technical efficiency of the regional hotel sector warrant further examination.

Third, given consistent economic development in China over the past three decades, surprisingly, to the best knowledge of the authors, no previous research has studied the dynamic movement in the Chinese competitive hotel industry. The present study explores a dynamic Tobit regression model to examine the antecedents of regional hotel sectors' technical efficiency in China. Conceptually, researchers could regard a hotel sector in each of China's 31 regions as a unique decision-making unit. The findings can aid government decision-makers and DMOs in improving the performance of regional hotel sectors by benchmarking themselves against regions with a similar macro contextual environment.

Table 1
Literature survey of DEA studies in the hotel industry.

Authors	Method	Units	Inputs	Outputs
Static analysis with purely cross-sectional data				
Anderson et al. (2000)	DEA-CCR and DEA-BCC	48 hotels/motels in the United States, 1994	(1) average employee annual wage, (2) average price of a room, (3) average price of food and beverage operations, (4) average price of casino operations, (5) average price of hotel operations, (6) average price of other expenses.	Total revenues which consist of revenue from rooms, gaming, food and beverage, and other type.
Chiang et al. (2004)	DEA-BCC model and CCR model	25 four or five star hotels in Taipei 2000	(1) Number of hotel rooms, (2) food and beverage capacity, (3) number of employees, (4) total cost of the hotel.	(1) Yielding index, (2) F&B revenue, (3) miscellaneous
Haugland et al. (2007)	DEA-CCR model	101 hotels in Norway, 2005	(1) Number of hotel rooms, (2) number of employees.	(1) Sales revenue, (2) occupancy rate.
Dynamic analysis with panel data				
Barros (2005)	DEA-Malmquist productivity index	42 hotels of a Portuguese hotel chain, 1999–2001	(1) Full-time workers, (2) cost of labor, (3) book value of property, (4) external costs.	(1) Sales, (2) number of guests, (3) nights spent in the hotel.
Yang and Luu (2006)	DEA-Window analysis	46 international tourist hotels in Taiwan, 1997–2002	(1) Total operating expenses, (2) number of employees, (3) number of guest rooms, (4) total area of catering division.	(1) Total operating revenues, (2) average room rate, (3) average production value per employee in the catering division, (4) average production value of the catering division (per 36 square feet).
Pulina et al. (2010)	DEA-Window analysis	Hotels across 20 regions in Italy, 2002–2005	(1) Labor cost.	(1) Sales revenue; (2) value added.

Note. See Appendix A for an overview of DEA-CCR and BCC models.

3. Method

3.1. Research design

As in the recent study of Pulina et al. (2010), which examines the Italian hospitality industry in 20 regions, the hotel sector in a particular region of China is regarded as a decision making unit in the present study. A notable concern is that in formulating strategic management decisions, one must first measure the comparative performance of the entire industry before one may comprehend its advantages and disadvantages (Hwang & Chang, 2003). Therefore, unlike the study of Pulina et al. (2010), this study employs a two-step procedure to deduce a dynamic evaluation of technical efficiency within the Chinese hotel industry.

In the first step, annual data for the 31 geographical regions that make up China's hotel industry were collected for six years (from 2001 to 2006). Notably, the DEA window approach enables the identification of not only general trends in the efficiency of the Chinese hotel industry as a whole, but also individual patterns of relative efficiency variation at the regional level. The study uses an output-oriented DEA model (BCC model, named after Banker, Charnes, & Cooper, 1984), which identifies the relative technical efficiency with a focus on maximizing output of the analyzed DMUs, to evaluate the technical efficiency of the Chinese hotel industry (the appendix provides more details about the model).

In the second step, a dynamic Tobit regression model, designed to relate technical efficiency scores along with a number of macro contextual variables, is used to identify the influential efficiency antecedents.

3.2. DEWA

Initiated by Charnes, Clark, Cooper, and Golany (1984), the data envelopment window analysis (DEWA) is a time-dependent version of typical DEA. DEWA works on the principle of moving averages (Charnes, Cooper, Lewin, & Seiford, 1994) and is useful for detecting performance trends of a DMU over time. Indeed, Kumbhakar and Lovell (2000, p. 10) argue that "panel data provide more reliable evidence on their performance [than what cross-sectional data could offer], because they enable us to track the performance of each producer through a sequence of time periods."

The basic plan is to regard each DMU as being a different DMU in each of the reporting dates. Each DMU is not necessarily compared with the whole data set, but instead only with alternative subsets of panel data. To formalize, consider N DMUs ($n=1, \ldots, N$) which are observed in T periods ($t=1, \ldots, T$) and each utilizes r inputs to produce s outputs. The sample thus has $N \times T$ observations, and an observation n in period t, DMU_t^n has an m-dimensional input vector $x_t^n=(x_{1t}^n, x_{2t}^n, \ldots, x_{mt}^n)'$ and an s-dimensional output vector $Y_t^n=(y_{1t}^n, y_{2t}^n, \ldots, y_{st}^n)'$.

The window starting at time k, $1 \le k \le T-w+1$ and of width w, $1 \le w \le T$, is denoted by k_w and has $N \times w$ observations. The matrix of inputs for the window analysis is given by

$$X_{kw} = \left(x_k^1, x_k^2, \ldots, x_k^N, x_{k+1}^1, x_{k+1}^2, \ldots, x_{k+1}^N, \ldots, x_{k+w}^1, x_{k+w}^2, \ldots, x_{k+w}^N\right),$$

and the matrix of outputs is

$$Y_{kw} = \left(y_k^1, y_k^2, \ldots, y_k^N, y_{k+1}^1, y_{k+1}^2, \ldots, y_{k+1}^N, \ldots, y_{k+w}^1, y_{k+w}^2, \ldots, y_{k+w}^N\right).$$

The present study contrasts the hotel sector of a certain region in a particular period with its own performance in other periods as well as the performance of other regions. Data from 31 ($N=31$) regions in China over six ($T=6$) yearly periods are the subject of analysis. Following the original work of Charnes et al. (1984), a three-year window width ($w=3$) is adopted. As such, each region is represented as a different unit for each of the three successive years in the first window (2001, 2002 and 2003), thus a total of 93 DMUs ($N \times w = 31 \times 3$) are analyzed to obtain sharper and more realistic efficiency estimates. The window is then shifted one year at a time, and an analysis is performed on the subsequent three-year panel (2002, 2003 and 2004) of the next 93 DMUs. In general, one performs $T-w+1$ separate analysis, where each analysis examines $N \times w$ regions.

4. Data

4.1. Defining input–output indicators

The authors based the selection of input and output indicators on two criteria: the literature survey (Table 1) and the availability of reliable data sources. According to studies presented in Table 1 (e.g., Anderson et al., 2000; Barros, 2005), input resources for the hotel industry include variables such as staff, capital and equipment. These resources produce tangible and intangible services through front office and back office operations (Yasin, Czuchry, & Dorsch, 1996). The present study employs three input indicators: (1) total number of full-

time employees in a regional hotel sector; (2) total number of guest rooms in a region; (3) total fixed assets in a regional hotel sector. Outputs are often concrete measurements that an organization uses to see if its objectives are met (Hwang & Chang, 2003). Thus, the analysis includes the following output indicators: (1) total revenue comprised from the revenue generated by room occupancy, food and beverage service, and other sources such as laundry, night clubs, and service fees; (2) average occupancy rate calculated by taking total occupied room-nights as a percentage of total available room nights. Haugland, Myrtveit, and Nygaard (2007) employ two input variables (i.e., number of hotel rooms and number of employees) and two output variables (i.e., sales revenue and occupancy rate) to calculate efficiency scores among 101 Norwegian hotels. More recently, Pulina et al. (2010) employ one input variable (i.e., labor costs) and two output variables (i.e., sales revenue and generated value added) to obtain efficiency scores among 20 Italian hospitality regions. The fact that four out of five variables used in the current study are the same as the parameters used in Haugland et al.'s (2007) article and two out of the three variables considered in Pulina et al.'s (2010) paper are used in this research paper indicates that the input and output measures of the present study are in accordance with recent DEA research in the hotel industry. Table 2 includes the descriptive statistics of all the variables utilized in the DEWA-BCC model.

4.2. Data collection

According to the administrative division in China, the country has 31 regions, which include 22 provinces (e.g., Guangdong, Yunnan), five autonomous regions (e.g., Guangxi, Xinjiang) and four autonomous municipalities (e.g., Beijing, Shanghai). Hong Kong and Macao are excluded from the analysis due to their exposure to foreign competition long before China opened its market to the world in 1978.

Annual data from 2001 to 2006 were collected from *The Yearbook of China Tourism Statistics*, an official publication by the China National Tourism Administration, 2002–2007. The number of years included in the current study appears to be appropriate for the DEWA framework (Yang & Chang, 2009). The study employs relevant input–output indicators of 31 regional hotel sectors, including three input indicators and two output indicators depicted above. To arrive at the DEWA results, the study uses a specialized DEA software package (DEASolver) to analyze the data.

5. Results

5.1. Efficiency trends of the Chinese hotel industry

A major decline in the average aggregate efficiency of the Chinese hotel industry occurred in 2003, when the SARS outbreak devastated Asian tourism. The World Travel and Tourism Council (WTTC, 2003) estimates that up to three million people in the tourism industry lost their jobs in the four most severely affected Asian economies (China, Hong Kong, Singapore and Vietnam) and that the cost of the outbreak to these four economies was over $20 billion in lost GDP. Tourism fell dramatically across China, and revenue from the Chinese hotel industry, public transportation and travel agency industry slid sharply in 2003. The average aggregate technical efficiency scores of the Chinese hotel industry turned out to be relatively high (above .85) in the ensuing years, indicating a rebound in the wake of SARS.

The efficient frontier representing best performance is made up of the regional hotel sectors in every window. Table 3 breaks down the average efficiency scores for each region by years, clarifying the trends and indicating which regions contribute to the decline and rebound in general efficiency levels during that period. The regions with efficiencies equal to one (1) are DMUs at the frontier, the optimal level of efficiency. Table 3 also indicates that the mean of all efficiency scores is .85 and the mean of their standard deviation is .06.

Table 4 presents a two-dimensional matrix to further illustrate the underlying relationship between technical efficiency and its fluctuation. The table classifies each region into a quadrant according to (1) whether the mean efficiency is greater or less than .85 (the mean of all efficiency scores) and (2) whether the standard deviation is greater or less than .06 (the mean of all standard deviations). Consequently, each of the 31 DMUs fall into one of four quadrants according to its technical efficiency characteristics:

A. *Zone of high efficiency and high stability*, where the regional hotel sector is operating consistently at high efficiency. The nine regions in the quadrant are the hospitality flagships: Shanghai, Guangdong, Zhejiang, Jiangsu, Henan, Guizhou, Chongqing, Hunan and Anhui. Hotel sectors in these regions are on the right track. They should maintain their stability and efficiency advantage, and seek to make further improvements. Note that the top tourist attractions (namely national 4A grade tourist attractions) located in these nine regions account for approximately 40% of all of China's top tourist attractions, indicating that these regions possess relatively more attractive tourism resources. The tourist attraction factor contributes to inducing domestic and foreign tourists, thus creating a stable market for the local hotel sector.
B. *Zone of high efficiency but low stability*, where the regional hotel sector is currently operating at high efficiency but is relatively inconsistent over time. Five DMUs (i.e., Beijing, Shanxi, Jiangxi, Qinghai, and Ningxia) are found in the quadrant. These five regional hotel sectors need to investigate the factors influencing the variability of their efficiency so that they may improve stability and maintain a secure efficiency advantage over time.
C. *Zone of low efficiency and low stability*, where the regional hotel sector is operating at low efficiency and is relatively inconsistent over time. The quadrant includes eight DMUs, consisting of Tibet, Shannxi, Yunnan, Gansu, Hainan, Shongdong, Tianjin and Heilongjiang. Unique trends are observed within this group. Specifically, Tibet, Shannxi, Yunnan and Hainan exhibited deteriorating behavior during the period of 2001–2006, while Shongdong, Tianjin and Heilongjiang exhibited improving performance, and Gansu showed a mixed performance of improvement and deterioration over time.
D. *Zone of low efficiency but high stability*, where the regional hotel sector is operating consistently at a relatively low level of technical

Table 2
Variables utilized in the DEWA model.

Variables	Units	Range (2001–2006)	Mean	S. D.
Inputs				
Number of employees (X1)	Number	1,441–184,788	43,883	35,682.55
Guest rooms (X2)	Number	1,808–150,967	36,215	28,686.15
Fixed assets (X3)	10,000 RMB	31,661.62–6,109,022	1,010,105.75	1,096,903.12
Outputs				
Total revenue (Y1)	10,000 RMB	8147–2,731,874.44	360,705.86	462,277.05
Average occupancy rate (Y2)	Percentage	31.92–75.03	57.20	7.46

Note. RMB denotes China's official currency.

Table 3
Results of DEWA-BCC model (window length = 3).

		2001	2002	2003	2004	2005	2006	Mean	S. D.
R1	Beijing	.92	.91	.77	.96	.94	.98	.90	8.12%
R2	Tianjin	.77	.75	.71	.87	.92	.86	.81	8.62%
R3	Hebei	.79	.90	.81	.76	.79	.75	.80	5.26%
R4	Shanxi	.83	.83	.81	.89	.95	.99	.88	6.53%
R5	Inner Mongolia	.93	.87	.83	.83	.82	.84	.85	3.57%
R6	Liaoning	.86	.81	.72	.81	.85	.87	.80	5.46%
R7	Jilin	.91	.83	.77	.87	.77	.82	.82	5.19%
R8	Heilongjiang	.61	.82	.77	.83	.82	.85	.80	6.56%
R9	Shanghai	.95	1.00	.90	1.00	1.00	.97	.97	4.53%
R10	Jiangsu	.85	.89	.87	.93	.90	.92	.90	2.91%
R11	Zhejiang	.96	.99	.95	.96	.92	.95	.96	2.28%
R12	Anhui	.89	.89	.83	.91	.95	.92	.89	4.50%
R13	Fujian	.75	.83	.83	.79	.80	.77	.80	3.13%
R14	Jiangxi	.72	.94	.91	.93	.90	.92	.91	6.48%
R15	Shangdong	.83	.80	.75	.86	.89	.95	.83	6.56%
R16	Henan	.93	.89	.88	1.00	.94	.92	.93	5.22%
R17	Hubei	.92	.77	.73	.75	.79	.79	.77	5.43%
R18	Hunan	.92	.94	.97	.99	1.00	1.00	.97	3.06%
R19	Guangdong	.96	.93	1.00	1.00	.94	.92	.97	3.53%
R20	Guangxi	.87	.85	.76	.82	.79	.80	.81	4.29%
R21	Hainan	.96	.89	.83	.78	.79	.77	.83	6.44%
R22	Chongqing	.94	.94	.89	.89	.87	.87	.90	3.31%
R23	Sichuan	.82	.82	.76	.80	.82	.83	.80	3.15%
R24	Guizhou	1.00	.96	.89	.96	1.00	.96	.95	4.89%
R25	Yunnan	.85	.84	.76	.62	.73	.74	.74	8.62%
R26	Tibet	1.00	.87	.54	.69	.61	.57	.68	16.34%
R27	Shaanxi	.88	.89	.88	.67	.68	.65	.78	11.30%
R28	Gansu	.80	.85	.85	.69	.77	.85	.79	7.52%
R29	Qinghai	1.00	.94	.78	.91	1.00	1.00	.91	12.88%
R30	Ningxia	.92	.80	.99	1.00	1.00	1.00	.96	7.83%
R31	Xinjiang	.82	.77	.73	.81	.80	.83	.78	4.01%

Note. The value of technical efficiency ranges between zero (0) and one (1). The entry related to each year represents the average technical efficiency of a region over all windows for which the region is a member. For Beijing as an example, each of the entries .77 and .96 represents an average of three computed efficiency values. Each of the entries .91 and .94 represents an average of two values. Each of the entries .92 and .98 represents a single value. Therefore, the overall mean efficiency for Beijing (.90) and the standard deviation (8.12%) are computed based on 12 efficiency values (1 + 2 + 3 + 3 + 2 + 1).

efficiency. Nine DMUs belong to the quadrant: Liaoning, Hubei, Hebei, Guangxi, Sichuan, Fujian, Inner Mongolia, Jilin and Xinjiang. These regions are clearly behind other regions in terms of hotel technical efficiency. This group accounts for much of the poorer performance of the Chinese hotel industry over time. DMOs in these regions need to examine the underlying problems associated with the low efficiency and find a way to surpass their better performing counterparts.

5.2. Antecedents of regional hotel efficiency

Slightly more than half of the studied DMUs, especially the regions within the zones of low efficiency, do not have satisfactory performance. Identifying the possible sources of inefficiency would be beneficial. Thus, the study further analyzes technical efficiency scores using a dynamic Tobit regression model (with the GLM heteroskedasticity-robust variance matrix estimators) to identify potential antecedents of technical efficiency for the Chinese hotel industry. Since the technical efficiency of a region's hotel sector would range between zero and one (a region with an efficiency value of one (1) is located on the frontier and is considered to be the most efficient DMU in the pool, while a region with a lower score implies less efficiency), the dynamic Tobit model is an appropriate method for estimating the relationship between the designated explanatory variables and a truncated dependent variable. In contrast, traditional ordinary least square (OLS) regression models do not satisfy the assumptions of normally distributed residuals when researchers restrict the dependent variable in relatively small ranges through censoring or truncation.

Table 4
Technical efficiency/stability matrix.

	Low efficiency	High efficiency
High stability	*Zone D* Liaoning, Hubei, Hebei, Guangxi, Sichuan, Fujian, nner Mongolia, Jilin, Xinjiang	*Zone A* Shanghai, Guangdong, Zhejiang, Jiangsu, Henan, Guizhou, Chongqing, Hunan, Anhui
Low stability	*Zone C* Tibet, Shannxi, Yunnan, Gansu, Hainan, Shongdong, Tianjin, Heilongjiang	*Zone B* Beijing, Shanxi, Jiangxi, Qinghai, Ningxia

The impacts of macro contextual variables on the hotel sectors' level of technical efficiency matter a great deal. Notably, industrial organization (IO) economics identify industry attractiveness as the primary foundation for superior profitability (Grant, 1991), which implies that hotel operation is concerned primarily with seeking favorable market environments and a moderate level of competition. In particular, the resource-based theory of traditional IO economics emphasizes that resources are the cornerstone of a firm's profitability (Conner, 1991), while the structure–conduct–performance (SCP) paradigm emphasizes that structural characteristics of an industry have a sizable influence on the performance of firms within an industry (McWilliams & Smart, 1993). Accordingly, subjecting the performance of hotels to tourism resource and attractiveness, market competition and regional trade openness would be advantageous. In addition, empirical studies indicate that employees' education and earning levels influence a firm's performance (Holzer, 1990; Ismail & Sulaiman, 2007). Therefore, the independent variables of the proposed model are the historical average technical efficiency score (HTE), richness of tourism resource (RTR), international tourism attractiveness (ITA), education (EDU), payment levels of employees (EARN), market competition (NH), regional trade openness (TO), and a time (2003) dummy variable (DUMMY). The study undertakes this examination by estimating the following dynamic Tobit regression model:

$$TE = \alpha + \beta_0(HTE) + \beta_1(RTR) + \beta_2(ITA) + \beta_3(EDU) + \beta_4(EARN) + \beta_5(NH) + \beta_6(TO) + \beta_7(DUMMY) + \varepsilon$$

In estimating the above model, the study uses the average technical efficiency scores obtained from the DEWA model for a particular year (TE) and its previous year (HTE) depicted in Table 3. More specifically, to introduce dynamism, the study incorporates the historical average technical efficiency score (HTE) in the immediate past year into the Tobit model to capture possible inherent efficiency performance in a DMU. The result is a total of 155 observations (31 regions across five years for the dependent variable ranging from 2002 to 2006). The study measures the contextual factors in the dynamic Tobit regression model in the same year as the dependent variable (TE). The contextual factors include (1) the richness of the tourism resource (RTR) in a region, measured by the percentage of national A-grade tourist attractions within a particular region; (2) the international tourism attractiveness (ITA) in a region, indicated by the ratio of inbound arrivals received by a particular region to the total inbound arrivals to China; (3) education level of employees (EDU) in a region, the proportion of urban employees with senior high school education or higher; (4) average annual earnings of employees in a regional hotel sector (EARN); (5) the number of hotels (NH) in a region, an indicator of the intensity of market competition within a particular region; (6) the degree of trade openness (TO) for a specific region, measured by the ratio of trade (regional imports plus exports) over regional GDP; and (7) a time dummy variable. The time dummy variable takes the value of one (1) for all DMUs in year 2003 (year of the SARS outbreak) and the value of zero (0) otherwise.

The study uses education composition of urban employees in a specific region as a surrogate variable because data related to educational attainment were not available for the hotel sector at the regional level. Moreover, as raw data related to variables EARN and NH are relatively larger in size and more skewed than the other independent variables, the researchers transform these two variables using the natural logarithm function before they are incorporated into the dynamic Tobit regression model. The notes for Table 5 list the sources of data pertaining to the independent variables of the dynamic Tobit regression model.

The proposed dynamic Tobit model is inherently cross-sectional and its estimation would yield inconsistent estimators, particularly in the presence of heteroskedasticity in the error terms. The heteroskedasticity-consistent covariance matrix estimators, also known as robust covariance estimators, are a common tool used for variance estimation of parameter estimates. Kauermann and Carroll (2001) examine and derive the properties of such estimators. With its increasing use in the econometric literature as well as with the growing popularity of generalized estimating equations, such estimators are available in a variety of software packages equipped to estimate Tobit regression models. In this regard, this study employs the software package *Eviews* using the option GLM Robust Covariance to estimate the dynamic Tobit model together with its static counterpart.

Table 5 indicates that, for the dynamic Tobit, six of the eight proposed predictors are statistically significant at or better than the .07 level. Specifically, the coefficients of historical technical efficiency (HTE), international tourism attractiveness (ITA), education level of employees (EDU), and average annual earnings of employees (EARN) have a positive impact on technical efficiency (TE) for the hotel sector in a region, while the degree of trade openness (TO) and the time dummy have a negative impact on the dependent variable. For the static Tobit model routinely used in the tourism and hospitality literature where the lagged average efficiency variable HTE is absent, the coefficient of the DUMMY variable is statistically insignificant. This result would mean, contrary to Fig. 1, that the SARS event has had no impact on the aggregate efficiency of the Chinese hotel industry during the studied period (2001–2006). Furthermore, a Wald test statistic (Kutner, Nachtsheim, Neter, & Li, 2005) given by $(Z_{HTE})^2 = 128.82$, distributed as χ^2 with one degree of freedom, is significant at the .001 level. These findings imply that the proposed dynamic Tobit model fits the technical efficiency data much better than its static counterpart.

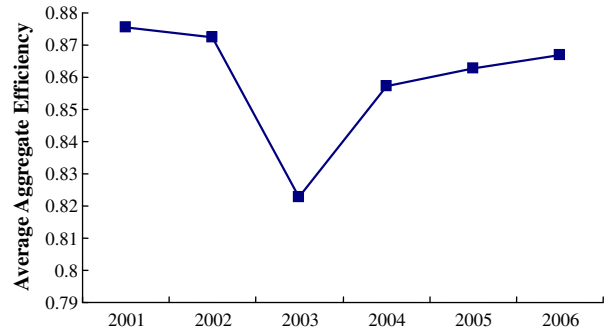

Fig. 1. Average aggregate efficiency of the Chinese hotel industry.

Discussing a few observations related to the findings of the dynamic Tobit depicted in Table 5 is advantageous. First, the coefficient of the time dummy variable is negative and highly significant, which means that the technical efficiency dropped dramatically in 2003, consistent with Fig. 1. Second, international tourism attractiveness (ITA), indicated by the proportion of inbound arrivals, shows a positive influence (p-value = .07) on regional hotel sectors' technical efficiency. That is, as a region receives more inbound arrivals, its hotel sector tends to operate at higher technical efficiency. Inbound arrivals may indicate longer duration of travel and higher travel budget than that of domestic tourists. As a result, more inbound arrivals are likely to contribute to the hotels' operation through a longer stay and higher expenditure for better accommodation quality and other related services. The finding implicitly reveals the important role of the inbound traveler market segment to the hotel industry.

Third, the results also reveal that the higher the education level of employees in a region, the more efficient its hotel sector (p-value = .01). This finding is consistent with the assertion that education would contribute to efficiency. However, a paucity of empirical studies that use formal education as a proxy for working skill observes dissimilar results. For example, when studying technical efficiency in Malay manufacturing firms, Ismail and Sulaiman (2007) suggest that education is negatively correlated with technical efficiency in the food and beverage industry, while the education effect is not statistically significant in other industries (e.g., metal and fabricated metal products, paper products, etc.). According to a recent study of the hotel general manager profile in China, unlike their counterparts in the international market, only a small number of Chinese hotel general managers have university degrees in hospitality, while having more than nine years of hotel managerial experience on average (Li, Tse, & Xie, 2007). Reducing the gap in efficiency differential by hiring employees with a better educational background and relatively longer working experience seems to be an effective human resource strategy in the Chinese hotel sector.

Fourth, hotel sectors in a region of higher average annual earnings for hotel employees (EARN) are more likely to be technically efficient (p-value = .05). The wage efficiency theory suggests that wages affect worker efficiency. Companies that pay higher wages are found to

Table 5
Estimation of the dynamic and static Tobit regression models.

	Dynamic Tobit			Static Tobit		
	Coefficient	Z-statistic	P-value	Coefficient	Z-statistic	p-value
Constant	−.26	−1.02	.31	.04	.13	.90
HTE	.72	11.35	<.001			
RTR	.09	.24	.81	−.43	−.82	.41
ITA	.30	1.81	.07	.57	2.48	.01
EDU	.25	2.58	.01	.32	2.38	.02
Ln(EARN)	.05	1.94	.05	.09	2.31	.03
Ln(NH)	−.01	.61	.54	−.01	−.49	.62
TO	−.07	−1.88	.06	−.08	−1.63	.10
DUMMY	−.05	−3.36	.001	−.03	−1.48	.14
Adjusted R^2		.53			.13	
Log likelihood		166.36			118.82	
Number of observations		155			155	

HTE historical average technical efficiency score (2001–2005), obtained from DEWA analysis;
RTR the percentage of national A grade tourist attractions within a particular region (2002–2006), based on http://www.cnta.gov.cn/szfc/Ajjq.asp accessed on April 3, 2009;
ITA the ratio of inbound arrivals received by a particular region to the total inbound arrivals to China (2002–2006), from various issues of *The Yearbook of China Tourism Statistics*;
EDU educational attainment composition of urban employment (2002–2006), obtained from various issues of *China Labor Statistical Yearbook*;
EARN average annual earnings of employees in the China hotel industry (2002–2006), obtained from various issues of *China Labor Statistical Yearbook;*
NH the number of hotels (2002–2006), obtained from various issues of *The Yearbook of China Tourism Statistics*;
TO trade openness (2002–2006), calculating by regional GDP, regional imports and exports obtained from various issues of *China National Bureau of Statistics* (2003–2007);
DUMMY a time dummy variable which takes the value of 1 in year 2003 and the value of zero otherwise.

offset more than half of their higher wage costs through improved productivity and lower hiring and turnover costs (Holzer, 1990). The finding of a positive influence of hotel employees' wage is consistent with Holzer (1990) study.

Finally, the relationship between trade openness and efficiency (p-value = .06) presents a controversial issue. On one hand, theoretical support for a positive relationship can be found among the proponents of endogenous growth theories (Lucas, 1988). The assumption is that high trade openness (i.e., represented by high share of imports and exports to GDP) favors the adoption of new technology and the use of a region's resources to produce aggregate output, and leads to more efficient production (Christopoulos, 2007; Edwards, 1998). On the other hand, Rodriguez and Rodrik (2000) are skeptical of this theoretical proposition and claim that the empirical evidence to date does not provide enough convincing evidence. This relationship requires further examination.

6. Conclusion and implications

The current study presents findings from a dynamic evaluation of technical efficiency in the Chinese hotel industry during the period of 2001–2006. The findings allow the investigation of the antecedents of technical efficiency at the sub-national level. As such, the present study makes two major contributions. First, the study employs a data envelopment window analysis (DEWA) in conjunction with a dynamic Tobit regression model (unlike previous tourism and hospitality studies that exclusively use a static Tobit model) to examine the impacts of macro contextual factors on hotel sectors' technical efficiency over time.

While previous research addresses the impacts of micro contextual factors (e.g., hotel size) on hotels' relative efficiency levels, this study extends the scope of efficiency antecedents to macro socio-economic factors at the sub-national level. Second, the present study introduces a novel two-dimensional efficiency-based matrix to assess the competitive advantage of different regions of the Chinese hotel sector. Strategic market implications for hoteliers, government decision-makers, and destination management organizations (DMOs) are presented. As a result, the findings enhance the understanding of hotel efficiency evaluation in a dynamic setting. The study reveals an overall low efficiency measure during the SARS outbreak in 2003 as shown in Fig. 1, and the dynamic Tobit regression findings in Table 5 confirm this result.

Overall, the result of an average aggregate technical efficiency score of .85 indicates that the Chinese hotel industry is approaching a technically efficient operation. The research detects a statistically significant and negative correlation between average efficiency scores and their standard deviations, suggesting that DMUs with relatively low average efficiency are most likely to have high dispersion. Based on the level of technical efficiency observed over time, the study classifies hotel sectors in the 31 regions into four categories. Regarding the two-dimensional efficiency-based matrix in Table 4, government decision-makers and hoteliers can gain insight into the benchmarked best practice (i.e., those DMUs in the zone of high efficiency and high stability) in the Chinese hotel industry. Nevertheless, researchers should interpret the empirical findings with caution as the DEWA outcome could be different when other inputs and outputs are employed in the analysis.

The second part of the study explores macro contextual factors driving technical efficiency. The positive effects of historical technical efficiency (HTE), international tourism attractiveness (ITA), education level of employees (EDU), and payment level of employees (EARN) on technical efficiency are in conformity with the standard economic view that market share and human incentives are keys to economic development and greater technical efficiency. However, whether a positive effect of trade openness in terms of technology diffusion and resources allocation may be offset to the full extent by a negative effect of overcapacity of hotels in China's highly competitive hospitality industry requires further examination in future research.

In addition to the contextual factors examined in the present study, many other factors that may influence the technical efficiency of the Chinese hotel industry exist. Possibly influential factors include the agglomeration effects of industrial clusters (Barros & Dieke, 2008), and scale and scope economies (Chung & Kalnins, 2001) among others, which future studies are expected to investigate. Given the underlying differences between China and western countries, conducting a cross-national study, comparing the efficiency of the hotel sector industry between China and a sizable western country like the United States would be of value. Furthermore, researchers may conduct further study in a broader global setting (e.g., using hotel industry data from both developed and developing nations) to shed light on the operational efficiency of the global hotel industry. Effective practice of benchmarking would be an aid to better decision making as part of the overall global investment process.

Appendix A. Measuring relative efficiency by data envelopment analysis

The DEA-CCR model, named after the imaginative work of Charnes et al. (1978), is instrumental in a phenomenal expansion of DEA models. Notable extensions include the DEA-BCC model, named after the seminal work of Banker et al. (1984). Charnes et al. (1994) and Wöber (2002) provide further information on DEA models and their applications.

The analyst is often concerned with the nature of returns to scale that would best reflect the operations of DMUs. Constant return to scale (CRS) implies a proportionate rise in outputs when inputs are increased. That is, the scale of operations does not influence the efficiency of the unit. On the other hand, variable return to scale (VRS) implies a disproportionate rise or fall in outputs when inputs are increased. That is, as a unit grows in size, its efficiency would either fall or rise. Also, in running DEA, the analyst has the model options of input minimization or output maximization. Input minimization examines the extent to which analysts can reduce inputs while maintaining the output level. Alternatively, output maximization investigates the extent to which analysts can raise outputs given the current input level.

The original CCR model assumes that the DMUs are operating under constant returns to scale while the BCC model relaxes the CRS constraint and assumes variable returns to scale. Given that reducing the sunk cost is next to impossible (e.g., high initial investment) in the hotel industry (at least in the short run), an output-oriented model that identifies the relative technical efficiency with a focus on maximizing output of the analyzed DMUs is appropriate to evaluate the technical efficiency of the China hotel industry. Furthermore, Cullinane, Song, and Wang (2004) endorse using the output-oriented model for planning and examining strategic objectives. Similar to Keh, Chu, and Xu (2006) work, the assumption is VRS in view of the large dispersion in the number of employees, hotel rooms and fixed assets among the studied 31 hotel sectors. The output-oriented BCC model employed in the paper measures the technical efficiency as the ratio of weighted outputs to weighted inputs, devoid of scale efficiency effects by solving the linear programming problem (A2) depicted below. Ahn, Charnes, and Cooper (1988) prove theoretically that the results in the form of efficiency or inefficiency are robust, even though they apply different models.

The study defines the relative efficiency, RE, as the ratio of output over input (i.e., RE = output/input). To move to multiple inputs and outputs and their treatment, the study defines relative efficiency of a

DMU as the ratio of weighted sum of outputs to weighted sum of inputs. The technical efficiency (h_o) score is as follows:

$$h_o = \frac{\sum_{r=1}^{s} u_r y_{ro}}{\sum_{i=1}^{m} v_i x_{io}} \tag{A1}$$

where

s	number of outputs;
u_r	weight of output r;
y_{ro}	amount of output r produced by the DMU;
m	number of inputs;
v_i	weight of inputs i; and
x_{io}	amount of input i used by the DMU.

Model (A1) translates into the following: unit r_0 is said to be efficient ($h_0 = 1$) if no other unit or combination of units can produce more than unit r_0 on at least one output without producing less in some other output or requiring more of at least one input.

Banker et al. (1984) relax the CRS constraint and address variable returns to scale. They introduce a new controllable variable (C_o) to separate scale efficiency from technical efficiency. The related linear programming problem takes on the form Model (A2) depicted below.

$$max\ h_o = \sum_{r=1}^{s} u_r y_{ro} - c_o, \tag{A2}$$

subject to

$$\sum_{i=1}^{m} v_i x_{io} = 1,$$

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} - c_o \leq 0,$$

$$u_r, v_i \geq \varepsilon.$$

Unit o is efficient if the technical efficiency (TE) h_o score is equal to unity, while TE<1 indicates technical inefficiency. Empirically, a sensible approach to select between the CRS (i.e., CCR model) and VRS (i.e., BCC model) is to run both models and then compare the efficiency scores. If analysts assess the majority of DMUs as having different efficiency scores under both models, then they should employ the BCC model (i.e., the model under the VRS assumption) (Avkiran, 1999). In the current study, an empirical comparison of the efficiency scores generated by both models warrants the selection of the BCC model.

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