Tourism Management 45 (2014) 234–243

Contents lists available at ScienceDirect

Tourism Management

journal homepage: www.elsevier.com/locate/tourman

Opening the online marketplace: An examination of hotel pricing and travel agency on-line distribution of rooms

Liuyi Ling, Xiaolong Guo*, Chenchen Yang

School of Management, University of Science and Technology of China, 96 Jinzhai Road, Hefei, Anhui 230026, PR China

HIGHLIGHTS

- Study the pricing game with OTAs when hotels open online marketing channel.
- Propose a game model to describe the channel competition between hotels and OTAs.
- Find the optimal pricing policy for hotels to maximize the profit.
- Give suggestions for hotels how to choose appropriate online partners.

ARTICLE INFO

Article history:
Received 2 August 2013
Accepted 4 May 2014

Keywords:
Hotel pricing management
Tourism supply chain management
Online marketplace
Online travel agencies

ABSTRACT

This paper studies the optimal pricing strategy of a hotel that establishes an online distribution channel through cooperation with an online travel agency (OTA). The OTA promotes the hotel and sells hotel rooms through its website and receives commission from the hotel for rooms sold. Through a sequence game model, this paper derives the optimal decision on the unit commission of the hotel and the optimal response of the OTA to that commission. The paper notes management implications, including (1) occupancy rate of a hotel before opening online marketing is an important metric for securing cooperation with an OTA; that is, a hotel with lower occupancy rates is more inclined to cooperate with an OTA to achieve an improvement in profits; and (2) a hotel is inclined to establish an online channel through an OTA with many online customers and/or few listed hotels.

© 2014 Elsevier Ltd. All rights reserved.

1. Introduction

Owing to the rapid development of information technology, more and more travelers reserve travel services online, such as flight tickets, hotel rooms and car rentals. According to Wu, Law, and Jiang (2013), one-third of the outbound travelers in Hong Kong searched for hotel information online, and approximately 50 percent of them made room reservations through the websites from which they obtained the information. Furthermore, from a survey of 249 leisure travelers, Toh, DeKay, and Raven (2011) found that 80 percent of the travelers searched for hotel information using web tools, with more than half making their bookings through hotels' host websites or third-party websites (i.e., online travel agencies, OTAs). The findings of studies on customer behavior suggest that the online channel plays a crucial role in the tourism and hospitality industry. As further evidence, approximately 6.5 percent of web inquiries are related to travel (Jansen, Ciamacca, & Spink, 2008), and more than 50 percent of the sales of major brand hotels was attributed to online marketing channels in 2010 (Pan, Zhang, & Law, 2013).

Many of the online bookings for hotel rooms are made through OTAs (Pan et al., 2013). Due to their small market scale and low popularity (Bastakis, Buhalis, & Butler, 2004; Ling, Guo, & Liang, 2011), some hotels usually pay a commission fee for cooperation with an OTA (such as Expedia, hotels.com, and Kuoni) that provides a large number of visitors. As demonstrated by Pan et al. (2013), hotels usually obtain more attention and clicks when ranked near the top of a search result list displayed on an OTA webpage. However, hotels have to pay a reasonable commission fee to an OTA to secure such desirable positions. Hence, hotels are faced with a tradeoff between obtaining a desirable position and paying a high commission fee. It is very important for hotels to obtain an optimal position in a search result list at an appropriate commission fee when establishing an online marketing channel through OTAs. Although numerous scientific researchers have demonstrated the

* Corresponding author. Tel.: +86 18655167702.
E-mail addresses: lyling@ustc.edu.cn (L. Ling), gxl@mail.ustc.edu.cn (X. Guo), yangcc@mail.ustc.edu.cn (C. Yang).

http://dx.doi.org/10.1016/j.tourman.2014.05.003
0261-5177/© 2014 Elsevier Ltd. All rights reserved.

importance of online marketing channels by studying customer behaviors in online searching and booking, little literature in the hospitality and tourism fields has studied the pricing problem of cooperation between hotels and OTAs.

To fill this gap and provide some suggestions for hotel managers on establishing their online marketplace through cooperation with OTAs, this paper proposes a game model to describe decision interactions in a tourism supply chain consisting of a hotel and an OTA. The hotel and OTA play a principal-agent game in which the hotel, as the principal player, determines the unit commission for the OTA's sales and the OTA, as the agent, distributes the hotel's information and sells rooms online. Some studies have shown that many travelers search for hotel information through OTAs first and then make reservations through a hotel's call center or host website (Toh, DeKay, et al., 2011; Wu et al., 2013). To induce travelers to make reservations through their website, OTAs undertake extra effort, such as providing discounts on travel packages (Toh, DeKay, et al., 2011), coupons or cash-back (Guo, Zheng, Ling, & Yang, 2014). Consequently, the OTA in our model ranks the hotel and determines its effort level for attracting travelers according to the commission fee paid by the hotel.

Based on an analysis of the game equilibrium reached in the centralized scenario in which the hotel and the OTA play as an integrated system and that reached in the decentralized scenario in which the two make decisions autonomously, we provide suggestions on how hotel managers can cooperate with OTAs. The rest of the paper is organized as follows. Section 2 reviews the related literature. Section 3 describes the problem of cooperation between an OTA and a hotel, and Section 4 models the cooperation. Section 5 presents the first-best and second-best solutions for cooperation in both the centralized and decentralized scenarios. Section 6 presents the results of numerical analyses. Section 7 concludes this paper by summarizing some of the managerial implications obtained and presenting future research issues.

2. Literature review

This section reviews two distinct of literature about online marketing: behavioral research focusing on consumer behavior to demonstrate the importance of online marketing and decision studies focusing on the strategic management between hotels and third parties.

2.1. Empirical literature about consumer behavior online

At the beginning of online marketing era, the growth of online travel booking was mainly attributed to three aspects: price transparency, the perception of lower prices (O'Connor, 2003; Sahay, 2007), and the economies of bundling (Toh, Dekay, et al., 2011). Today, more and more travelers search for travel information and make reservations online as a result of the convenience of e-commerce (Guo, Ling, Dong, & Liang, 2013).

Because online marketing has become an important part of the tourism and hospitality industry, numerous academic researchers have studied the behavior of online travelers to understand their requirements and desires. Kim, Wei, and Ruys (2003) used an artificial neural network to determine the variable that most significantly influences senior travelers' decisions and make market segmentations according to their findings. Using chi-square tests, Kim and Kim (2004) identified the most significant factors that affect online hotel consumer's intentions to purchase, including age, education level, personal preference, and time of Internet use. Grønflaten (2009) used the same method to select relevant variables and built a logistic regression model to forecast traveler's choices based on information sources and purchasing channels. Moreover, Law and Hsu (2006) tested the important attributes that differentiate online purchasers from non-purchasers through *t*-tests. Similar research can be found in the existing literature (e.g., De La Viña & Ford, 2001; Morosan & Jeong, 2008; Wong & Law, 2005).

Among studies concerning consumer behavior, researchers have found that some online travelers obtain hotel information from third-party websites or OTAs but make reservations through the hotel's host website (Garrow, Ferguson, Keskinocak, & Swann, 2006) or even switch to other booking channels, primarily by phone (Toh, Dekay, et al., 2011; Wu et al., 2013). In this regard, Toh, Raven, and DeKay (2011) studied how hotels can attract consumers to their own websites and call centers to save on considerable commission fees. Toh, DeKay, et al. (2011) indicated the percentage of online searchers who make a purchase online. Ting, Wang, Bau, and Chiang (2013) and Pan et al. (2013) studied which characteristics of websites and hotels are attractive to travelers.

2.2. Decision-making studies on managing the cooperation between hotels and OTAs

Clearly, channel conflict exists between OTAs' booking systems and hotels' hosted channels, including hotels' host websites, call centers, or reception desks. Some researchers have studied the cooperation problem between hotels and third parties. Medina-Munoz and García-Falcon (2000) identified the decisive factors that lead to successful cooperation between hotels and third-party companies. Abbott and Lewry (1999) and Tso and Law (2005) indicated that travel agencies and other third-party companies enjoy low room rates (i.e., room price) from their cooperating hotels. Hence, pricing is not only a key strategic lever deployed by hotels to manage revenue (Kimes & Chase, 1998) but also an important tool for building and enhancing cooperation. A few researchers have provided suggestions on pricing for online hotel distribution channels. Ling et al. (2011) studied the optimal pricing strategy for the cooperative third-party websites of hotels through a wholesale pricing model. However, the authors' assumption that the room rates of a hotel listed on different websites can be different is not currently common practice. In a supplemental study, Guo, Ling, Dong, et al. (2013) discussed the cooperation contract between hotels and OTAs through a network framework in which the room rates of a hotel in all channels are identical. Additionally, Guo and He (2012) and Dong, Ling, and Guo (2013) studied the pricing issue in which a hotel room is considered part of a packaged deal, which is also a common phenomenon in online marketplaces.

However, no study has addressed the problem of a new hotel that wants to open its online marketing channel by cooperating with OTAs. In this situation, the hotel has little information and experience regarding online marketplaces and knows little about how to obtain an appropriate position on an OTA's webpage by providing a reasonable commission fee. To enrich the scientific literature and provide some suggestions to hotels on how to pursue online marketing, this paper studies the optimal pricing strategy of hotels through the analysis of a simple supply chain composed of a single new entering hotel and an OTA.

3. Cooperation description

Considering the considerable market share of online travel in the tourism and hospitality industry, a hotel with capacity C cooperates with an OTA to open its online marketing channel. Without affecting the findings of this paper, suppose that all of the C rooms are identical and one room accommodates one customer (Guo, Ling, Dong, et al., 2013; Ling et al., 2011). Before opening the online channel, the hotel sells its accommodations at a standard room rate p, and the daily number of customers (we call them traditional customers compared with online travelers who learned about this hotel from the OTA) is x, which is distributed continuously with probability density function $f(x)$, cumulative distribution function $F(x)$, and mean value of $\mu < C$. The daily fixed cost of the hotel is F, and the daily variable cost of each occupied room is υ. Furthermore, we set $\upsilon = 0$, which has no effect on the outcome of our model because the variable cost can be included in the room rate.

Under the cooperation, the hotel sells its rooms through the OTA's website and its own channels at the same room rate p. As presented in the previous sections, the hotel determines the unit commission fee by maximizing its profit, and the OTA determines the ranking position of the hotel's information and the level of effort expended in attracting travelers, which has a very large impact on how many online travelers make bookings through its website.

The OTA provides marketing service for n hotels at an identical service level and has N potential customers for all hotels of this type. Knowing unit commission p_0, i.e., the payment from the hotel for each sold room, the OTA decides the hotel's position on its webpage. The hotel obtains more bookings when it is near the top of the webpage because most customers read hotel information from the top of a webpage to the bottom (Pan et al., 2013). However, the OTA allocates each ranking position on its webpage to one hotel and would like to place hotels a paying high unit commission near the top. When the hotel is ranked at position i, the OTA incurs an opportunity loss $\varphi(i)$, which is a convex decreasing function with $\varphi'(i) < 0$, $\varphi''(i) > 0$, and $\varphi(n) = 0$ (thus, an opportunity loss does not arise from placing the hotel at the bottom) because it must place some hotels at lower positions. Hence, the OTA determines the hotel's position on its ranking list according to the profit function constituting its potential revenue and opportunity loss.

The OTA obtains a commission from the hotel only when bookings for the hotel are made through its website. However, previous research (e.g., Toh, DeKay, et al., 2011; Wu et al., 2013) has shown that some online travelers obtain hotel information from OTAs but make reservations through the hotel's host website or other traditional channels. In this case, the OTA cannot obtain any commission.

To maximize its profits, the OTA makes some effort to induce customers to make reservations through its website. For example, the largest global online travel agency, Expedia (http://www.expedia.com), provides its customers with travel packages, such as "flight + hotel", "hotel + car", and "flight + hotel + car", at a good price. Furthermore, it also offers customers booking a hotel through its webpage a discount on travel or shopping near the hotel. Similarly, as the two leading online travel agencies in mainland China, Ctrip (http://www.ctrip.com) and eLong (http://www.elong.com) usually provide cash-back options to encourage their customers to make reservations through their distribution systems rather than those of hotels (Guo et al., 2014). Due to the OTA's effort, a proportion α of its online customers make reservations through its website. Meanwhile, the OTA incurs an effort cost $g(\alpha)$, which is a convex increasing function with $g'(\alpha) > 0$, $g''(\alpha) > 0$, and $g(0) = 0$.

Without fundamentally changing the insights afforded by our model, we assume that the OTA's opportunity loss and effort cost follow the quadratic functional forms $\varphi(i) = K_i(n-i)^2$ and $g(\alpha) = K_\alpha \alpha^2$, respectively, which are widely used in the cost management literature (e.g., see, Chen, 2005; Huang & Li, 2001; Kim, Cohen, & Netessine, 2007; Little, 1979). Here, K_i and K_α are the coefficients of opportunity loss and effort cost, respectively.

The OTA opportunity loss relies heavily on the marginal income that comes from the unit commission fee provided by its cooperative hotels. We assume $K_i = \overline{p}_0/n$, where $\overline{p}_0$ is the average marginal income of the OTA, i.e., $\overline{p}_0 = \sum_{i=1}^{n} p_{0i}/n$, where p_{0i} is the unit commission from hotel i. However, in practice, every hotel does not know the unit commissions provided by other hotels and has to estimate the average value of the unit commissions when making a decision. Here, we assume the unit commission P_{0i} from hotel i follows a uniform distribution over $[0, p]$, $i = 1, \ldots, n$. Hence, the hotels take $\overline{p}_0 = 0.5p$ as the expected marginal income of the OTA. Consequently, the OTA's opportunity loss is $\varphi(i) = p(n-i)^2/(2n)$.

Unlike the opportunity loss, the effort cost of the OTA is independent of the hotels. It is denoted as $g(\alpha) = k\alpha^2/2$, where $k/2$ is the cost that the OTA incurs to induce all of its potential customers to make their bookings through the OTA.

In practice, the number of potential customers of an OTA is stochastic and denoted as $\tilde{N} = N + \varepsilon$, where N is the mean number of potential customers and ε is a finite variance. In the model used in our paper, $\tilde{N}$ is the number of potential customers who would like to book rooms in the cooperating hotels, has a very high mean value, and is far greater than ε; hence, the variance can be ignored. Consequently, in the following discussions, we assume the number of potential customers is a constant N.

4. Modeling hotel and OTA profits

Under the cooperation with the OTA, the hotel has three types of customers: (1) customers who acquire hotel information from some sources other than the OTA and book rooms through the hotel's own channel; (2) customers who obtain hotel information from the OTA and book rooms through the hotel's own channel; (3) customers who learn about the hotel and book rooms through the OTA. For convenience of description, we denote the first type of customers as t-tourists, the second as o-tourists, and the third as d-tourists.

N potential customers of the OTA access information about the n coessential hotels on the OTA webpage, and their selections heavily rely on the ranking list, i.e., the hotels' positions on the webpage: hotels near the top attract more customers. Although customers' decisions may be influenced by other factors, such as pictures, photos, and slide shows, such factors are not taken into account in this study because they are controlled by hotels and their influences may be ignored relative to the ranking. Denoting $\omega(i)$ as the probability that an online customer selects hotel i (i.e., the hotel ranked at position i), there must exist $\omega(i) > \omega(i+1)$ for every $i = 1, 2, \ldots, n-1$, where $\sum_{i=1}^{n} \omega(i) = 1$. To formulate this situation, we introduce $\omega(i) = 2(n+1-i)/(n(n+1))$, where i is the ranking number of a hotel and n is the number of the cooperative hotels. Consequently, $y = N\omega(i)$ online customers book hotel i, and $y_o = \alpha N\omega(i)$ of them make their reservations through the OTA. Here, we assume $y < C$, which is reasonable because there is no incentive for hotels to offer an extremely high unit commission to receive reservations that exceed their capacities.

Under the cooperation with the OTA, the hotel obtains more customers and its occupancy rate increases. However, it encounters a problem: when the total number of customers (including t-tourists, o-tourists, and d-tourists) exceeds its capacity, the hotel has to refuse some of the customers. This situation represents a management conflict between customer-relationship management and revenue management (Wang, 2012). To establish a long-term and well-operated cooperative relationship, the hotel provides d-tourists and o-tourists a priority to check in because it values relationship over immediate revenue (see also, e.g., Guo, Ling, Dong, et al., 2013; Ling et al., 2011). Because $y < C$, all d-tourists and o-tourists check in, and the refused customers are t-tourists.

That is, Max{x, $C-y$} t-tourists stay in the hotel. Thus, the expected number of t-tourists is

$$x_h = \int_0^{C-y} xf(x)\,dx + \int_{C-y}^{\infty} (C-y)f(x)\,dx = C - y - \int_0^{C-y} F(x)\,dx,$$

where $y = 2(n+1-i)N/(n(n+1))$.

Therefore, the profits of the hotel and OTA are formulated as follows, respectively:

$$\pi_h = p(y + x_h) - p_0\alpha y - F = pC - F - p\int_0^{C-2N(n+1-i)/(n(n+1))} F(x)\,dx - \frac{2p_0\alpha N(n+1-i)}{n(n+1)},$$

$$\begin{aligned}\pi_o &= \pi_0 + p_0\alpha y - \varphi(i) - g(\alpha)\\ &= \pi_0 + \frac{2p_0\alpha N(n+1-i)}{n(n+1)} - \frac{p(n-i)^2}{2n} - \frac{k\alpha^2}{2},\end{aligned}$$

where π_0 is the profit that the OTA obtains from the other $(n-1)$ hotels before cooperating with the studied hotel, which is a constant in this model.

5. Decision analysis

Neither the details of the hotel's ranking position on the OTA's webpage nor how the OTA sets its effort level is known to the hotel before the cooperation. However, the hotel could provide an appropriate incentive through the cooperation contract to induce the OTA to make the desired decisions. In the following discussion, we first present the benchmark model in which the hotel and OTA act as an integrated firm to maximize their global objective and then the decentralized model in which they make decisions autonomously and maximize their own objectives.

5.1. Benchmark: the integrated decisions

This subsection presents the cooperation problem in which the hotel and the OTA act as an integrated firm and make decisions by maximizing the total profit of the supply chain. Hence, the solution to the problem is first-best and taken as a benchmark. The problem is formulated as follows:

$$\begin{aligned}\max_{\{i,\alpha\}} \Pi &= \pi_h + \pi_o\\ &= \pi_0 + pC - F - p\int_0^{C-2N(n+1-i)/(n(n+1))} F(x)\,dx\\ &\quad - \frac{p(n-i)^2}{2n} - \frac{k\alpha^2}{2}.\end{aligned}$$

Obviously, when the integrated profit is maximized, α is zero. Furthermore, according to the first-order condition with respect to i, we are able to obtain the optimal ranking position of the hotel. The following proposition presents the first-best solution.

Proposition 1. *When the hotel and the OTA act as an integrated firm, the optimal solutions to the cooperation problem are:*

$$\begin{aligned}\alpha^{FB} &= 0,\\ i^{FB*} &= \arg_i\{F(C - 2N(n+1-i)/(n(n+1))) = (n-i)(n+1)/(2N)\}.\end{aligned} \tag{1}$$

In Equation (1), because $F(C-2N(n+1-i)/(n(n+1)))$ is an increasing function of i and $(n-i)(n+1)/(2N)$ decreases with i, the solution i^{FB^*} is unique. Because i^{FB^*} is not necessarily an integer, it is rounded up, rounded down, or rounded off to an integer i^{FB} that maximizes the total profit of the supply chain.

5.2. Private actions: the decentralized equilibrium

We now study the decentralized scenario, which is more common in practice. Based on the description presented in Sections 3 and 4, the sequence of events in the game between the hotel and the OTA is as follows. (i) The hotel provides the OTA with a cooperation proposal, which presents unit commission and is a take-it-or-leave-it contract; (ii) Accepting the proposal, the OTA determines the ranking position of the hotel and the commensurate level of effort required to attract online customers; (iii) On the target day, the hotel checks in customers; (iv) The OTA is paid by the hotel according to the contract terms.

According to the sequence of events, we analyze the optimal decisions of the OTA and hotel by backward induction. We first present the response of the OTA to the unit commission provided by the hotel and then analyze the hotel's optimal decision. Given unit commission, p_0, the OTA determines (i, α) by maximizing its expected profit as follows,

$$\max_{i,\alpha} \pi_o = \pi_0 + \frac{2p_0\alpha N(n+1-i)}{n(n+1)} - \frac{p(n-i)^2}{2n} - \frac{k\alpha^2}{2}.$$

The OTA's problem is not quasi-concave in i and α but unimodality can be achieved under mild parametric assumptions, which is reasonable in practice.

Proposition 2. *When $0 \le p_0 < (n+1)\sqrt{pkn}/(2N)$, the OTA has a unique optimal response as follows,*

$$i^* = n - \frac{4p_0^2N^2}{pkn(n+1)^2 - 4p_0^2N^2}, \tag{2}$$

$$\alpha^* = \frac{2p_0Np(n+1)}{pkn(n+1)^2 - 4p_0^2N^2}. \tag{3}$$

According to this proposition, the number of online travelers who choose this hotel can be determined according to $y = 2(n+1-i)N/(n(n+1))$ as follows,

$$y^* = \frac{2Npk(n+1)}{pkn(n+1)^2 - 4p_0^2N^2}.$$

Corollary 1. *When the condition in Proposition 2 holds, there are $\partial i^*/\partial p_0 < 0$ and $\partial\alpha^*/\partial p_0 > 0$.*

This corollary explains why there exists the optimal OTA response to the hotel's commission incentive. When the hotel provides a higher unit commission p_0, the OTA earns a greater margin profit from selling its rooms and would like to put the hotel's information in a more conspicuous place to attract online customers' attentions. At the same time, the OTA increases its effort level to encourage customers to make reservations through its booking system because it obtains no commission when booking is made through the hotel's host channels.

Knowing that the OTA will respond to its commission by choosing the ranking position i and effort level α according to Equations (2) and (3), the hotel determines p_0 by maximizing its profit as follows,

$$\max_{p_0}\ \pi_h = pC - F - p\int_0^{C-2N(n+1-i)/(n(n+1))} F(x)\,\mathrm{d}x - \frac{2p_0\alpha N(n+1-i)}{n(n+1)}.$$

By substituting the OTA's responses i^* *and* α^* into the hotel's objective function, we can obtain the first-order condition as follows,

$$F\left(C-\frac{2Npk(n+1)}{pkn(n+1)^2-4p_0^2N^2}\right)=\frac{(n+1)\left(pkn(n+1)^2+4p_0^2N^2\right)}{2N\left(pkn(n+1)^2-4p_0^2N^2\right)}. \tag{4}$$

Because $0 \le p_0 < (n+1)\sqrt{pkn}/(2N)$, the left side of Equation (4) is a decreasing function of p_0, whereas the right is an increasing function. Hence, there exists an optimal solution to Equation (4) that maximizes the expected profit of the hotel. We denote this solution with the superscript SB (which indicates the second-best solution). However, the explicit analytical form of p_0^{SB} cannot be derived from Equation (4). Hence, to gain additional insights with circumventing this difficulty, we provide a numerical illustration in the following section.

6. Numerical studies

In this section, we present a numerical example of the proposed problem, where the number of t-tourists follows a Normal distribution. We illustrate our findings through the example and show that how our model can be applied in practice to the strategic and operative decision making of hotels and OTAs. We present the base example in Section 6.1 and the sensitivity analysis of the model parameters in Section 6.2.

6.1. Base example

A hotel establishes an online distribution channel through cooperation with an OTA. The hotel's capacity C is 250, its daily fixed cost F is 15,000, and the demand from its t-tourists follows a Normal distribution with $\mu = 100$ and $\sigma = 50$. The OTA provides an online distribution service for $n = 50$ hotels, has $N = 5000$ potential customers, and incurs effort cost $k/2 = 4000$ in inducing all potential customers to make their reservations through the OTA. Under the cooperation, the hotel sells its rooms at an identical price $p = 100$ to customers regardless of whether rooms are sold through the OTA or its hosted reservation channels. Without affecting the findings, we assume that the OTA's profit from the other $(n-1)$ hotels before cooperating with the studied hotel is zero, i.e., $\pi_0 = 0$. Hence, the *OTA profit* presented here is the additional profit earned from providing an online service to the studied hotel.

Based on the parameters set above, we try to determine the optimal commission that the hotel provides to the OTA and the corresponding ranking position as well as the OTA's effort level by a simulation implemented in Wolfram Mathematica® 8.0.1.0. The solutions of our model are shown in Table 1, where i^* is the theoretical solution of the optimal ranking position and i is its integral value.

As shown in Table 1, the total profit of the supply chain under the decentralized scenario is less than that under the integrated one. In the decentralized situation, to induce customers to make reservations through its website, the OTA incurs an additional cost, i.e., effort cost, which leads to revenue gain for the OTA but revenue loss for the supply chain. However, the OTA can gain rich profits by cooperating with hotels.

6.2. Sensitivity analysis

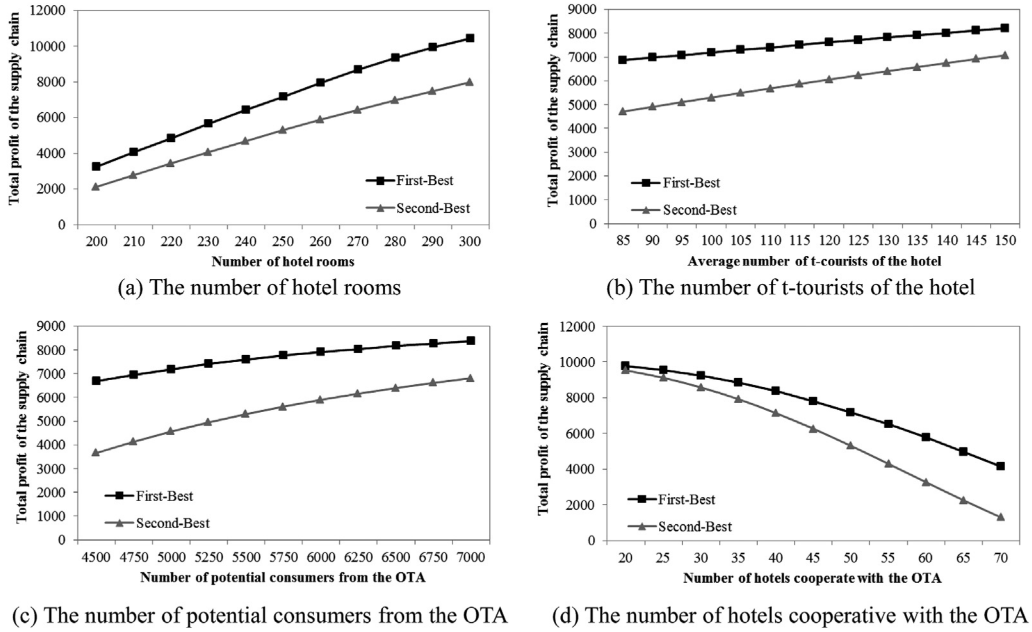
This subsection analyzes the effects of the parameters (characteristics of the hotel and the OTA) on the decision variables and the profits. Based on the parameters set above, Figs. 1 and 2 show the effects on the total profit of the supply chain and the optimal ranking positions in the centralized and decentralized scenarios, respectively; Figs. 3 and 4, respectively, show the effects on the optimal commission provided by the hotel to the OTA and the OTA's optimal responses, the ranking position of the hotel's information, and its effort level in the decentralized scenario; and lastly, Fig. 5 shows the effects of their characteristics on the profits of the hotel and OTA in the decentralized scenario.

As shown in Fig. 1, the total profit is less in the decentralized scenario than in the integrated scenario, owing to the double marginalization effect and competition between the OTA's reservation channel and the hotel's. In particular, the total profit of the supply chain increases with the numbers of hotel rooms, t-tourists, and potential customers. The total profit decreases with the number of hotels cooperating with the OTA because the OTA incurs higher opportunity loss when cooperating with more hotels.

Fig. 2 shows the effects of the parameters on the optimal ranking position in the decentralized and integrated scenarios. The ranking of the hotel is higher (ranked number is smaller) in the integrated scenario than in the decentralized scenario. The ranked number decreases (that is, the hotel is closer to the top of the ranking list) with the number of hotel rooms and increases with the number of potential customers from the OTA and the number of t-tourists of the hotel. However, the effects of the number of hotels cooperating with the OTA under the two scenarios do not show the same trend. In the integrated scenario, the ranked number of the hotel gets smaller along with the increase in the number of cooperative hotels because the integrated firm makes more profit this way. In the decentralized scenario, the ranked number of the hotel fluctuates between 10 and 12 when the OTA cooperates with fewer than 60 hotels; otherwise, it increases with the number of cooperative hotels because the OTA has to make a tradeoff between the marginal profit earned from the hotel and the corresponding considerable opportunity loss incurred.

Table 1
Optimal solutions and profits in different situations.

Type of situations	p_0	$i(i^*)$	α	π_o	π_h	Π
First-best	–	4 (3.605)	0	–	–	7195.3
Second-best	31.87	10 (9.963)	0.6403	40.04	5260.7	5300.7



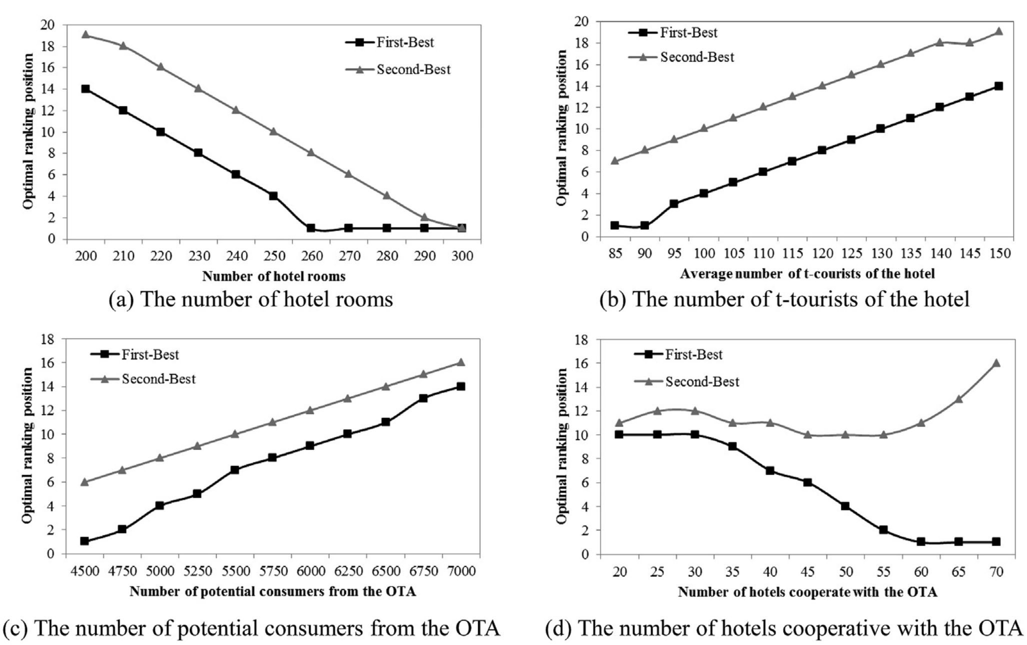
(a) The number of hotel rooms (b) The number of t-tourists of the hotel

(c) The number of potential consumers from the OTA (d) The number of hotels cooperative with the OTA

Fig. 1. The effects on total profit of the supply chain under different situations.

In the decentralized scenario, the effects on the optimal unit commission provided by the hotel to the OTA are shown in Fig. 3. The commission increases with the number of hotel rooms or the number of hotels cooperating with the OTA, whereas it decreases with the number of t-tourists or the number of potential customers of the OTA. That is, when the hotel has more rooms for sale, the hotel increases its unit commission to encourage the OTA to offer a better ranking that is conducive to sale. When the OTA provides an online distribution service to more hotels, the hotel has to provide a higher commission to obtain the same position on the webpage because the OTA incurs a higher opportunity loss of providing the position. Similarly, when the number of customers (either t-tourists or potential customers of the OTA) increases, the hotel's unit commission decreases because the OTA operates at a low effort level.

The optimal responses of the OTA in the decentralized scenario are presented in Fig. 4. As indicated in this figure, the OTA would like to make more effort for hotels that are closer to the top of the webpage, from whom the OTA obtains a higher marginal profit. Furthermore, when the number of cooperative hotels increases, the level of effort for the hotel does not decrease, whereas the ranking of the hotel becomes worse. Because in this situation, the hotel pays a high unit commission to the OTA, which leads to high marginal profit for the OTA (see Fig. 3).



(a) The number of hotel rooms (b) The number of t-tourists of the hotel

(c) The number of potential consumers from the OTA (d) The number of hotels cooperative with the OTA

Fig. 2. The effects on optimal ranking position under different situations.

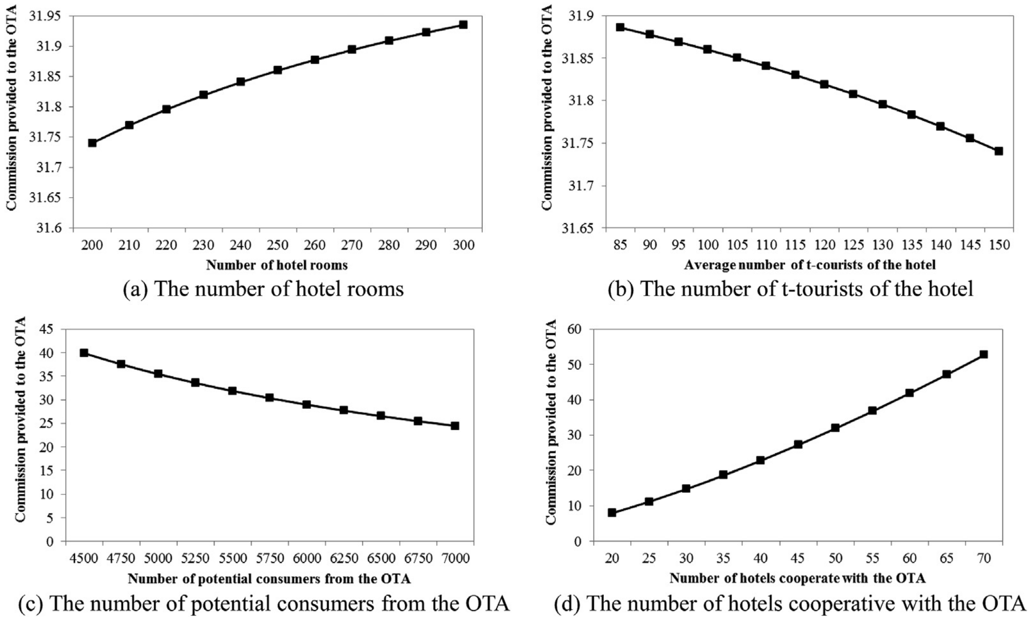


Fig. 3. The effects on the optimal commission in the decentralized scenario.

Fig. 5 presents the effects on the profits of the cooperation participants. As shown in Part (a), the profits of the hotel and OTA increase with the number of hotel rooms. Parts (b) and (c) show that the hotel profit increases with the number of t-tourists of the hotel or the number of potential customers of the OTA, whereas the OTA profit decreases, because the hotel decreases its unit commission when it has a large number of customers (see Fig. 3). As shown in Part (d), the hotel's profit decreases with the number of cooperative hotels, whereas the OTA's profit increases first and then decreases. The hotel has to pay a higher unit commission to secure the same position on the webpage when the OTA cooperates with more hotels. Nevertheless, when the number of cooperative hotels exceeds a certain threshold value (60 in our example), the hotel decreases its unit commission due to its deteriorating ranking position.

From the findings of the numerical analyses, hotels cooperate with OTAs with a large number of potential customers (large volume of visits of online travelers) and few cooperative hotels at an identical service level, and OTAs cooperate with hotels with a large capacity and low occupancy rate.

7. Extension for heterogenous hotels

In the foregoing analysis, we assumed that all of the cooperative hotels of the OTA are homogenous. To verify the validity of the model, this section extends our model to the heterogenous-

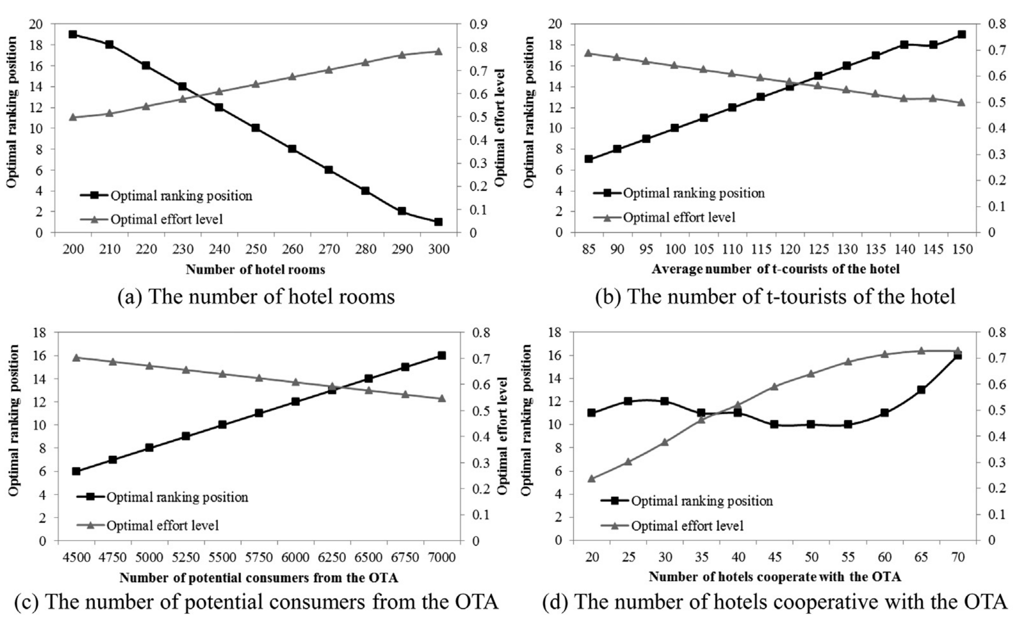
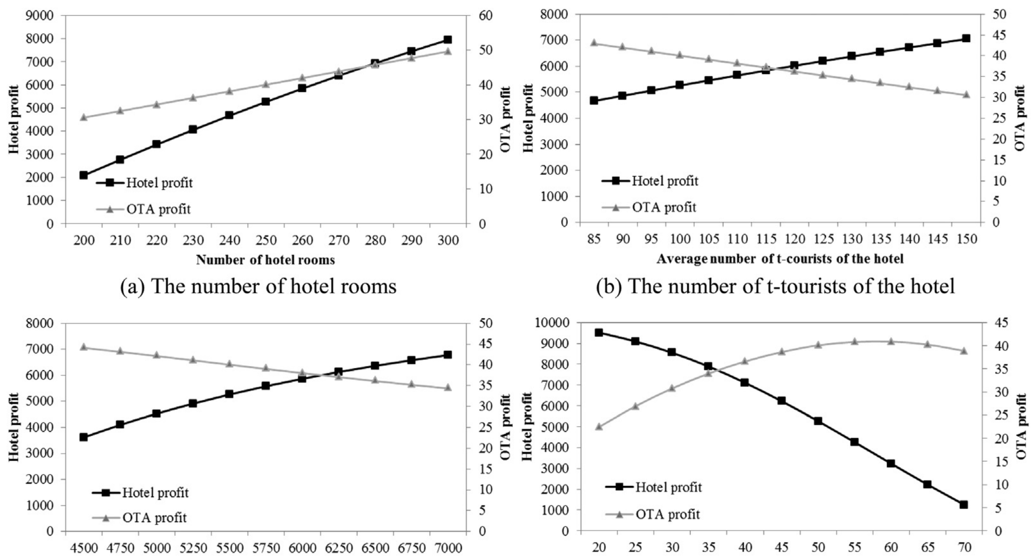


Fig. 4. The effects on the OTA responses in the decentralized scenario.



(a) The number of hotel rooms
(b) The number of t-tourists of the hotel
(c) The number of potential consumers from the OTA
(d) The number of hotels cooperative with the OTA

Fig. 5. The effects on the profits of hotel and OTA in the decentralized scenario.

hotel scenario in which the OTA provides marketing service for n hotels at m different service levels. The hotels' room rates depend on their service levels, i.e., a high level means a high room rate. For instance, economic rooms are provided at a low rate, comfortable ones at a moderate rate, and luxury ones at a high rate. Consequently, the potential customers of the OTA are faced with m levels of rooms and book one room at a certain level according to their preferences (Chawla, Malec, & Sivan, 2012). As indicated by Thanassoulis (2004), Chawla, Hartline, and Kleinberg (2007), and Chawla et al. (2012), potential customers can be classified into $(m+1)$ types according to their preferences for service level. Type l denotes the customers who prefer rooms at level l, $l = 1, 2, \ldots, m$, and type 0 denotes the customers who do not prefer a room at any level and do not book any room. Given the room rates of the hotels, the probability $L(l)$ of a customer falling into type l can be obtained based on the method reported by Chawla et al. (2007).

Hotel i denotes the hotel ranked at position i on the OTA webpage. The potential demand for hotel i is dependent on not only its service level l but also its ranking position i. Here, the probability that an online customer falling into type l chooses hotel i from the website is denoted as $\varpi(i)$ with $\varpi(i) > \varpi(i+1)$, and the total number of potential online customers of the OTA is denoted as $\mathbb{N}$.

As a result, the number of online customers for hotel i at level l is $y(l, i) = \varpi(i)L(l)\mathbb{N}$. In essence, $y(l, i)$ is similar to $y = N\omega(i)$, which is the number of online customers for hotel i in the homogenous hotel scenario. Hence, the heterogeneity of the hotels does not affect the validity of the results of our model. In the following, we present how to derive the expected demand for hotel i.

Suppose n_l hotels at level l provide room services at room rate p_l, $l = 1,2$. Based on the results of Thanassoulis (2004) and Chawla et al. (2012), the utility of room service at level l for each online potential customer is independently and uniformly distributed in the interval $[\underline{v}_l, \overline{v}_l]$, $l = 1,2$. Based on Fig. 6, $L(l)$ can be formulated as follows,

$$L(1) = \frac{R(1)}{R(0)+R(1)+R(2)} = \frac{(\overline{v}_1 - p_1)\left(\overline{v}_2 + p_2 - 2\underline{v}_2\right)}{2\left(\overline{v}_1 - \underline{v}_1\right)\left(\overline{v}_2 - \underline{v}_2\right)},$$

$$L(2) = \frac{R(2)}{R(0)+R(1)+R(2)} = \frac{(\overline{v}_2 - p_2)\left(\overline{v}_1 + p_1 - 2\underline{v}_1\right)}{2\left(\overline{v}_1 - \underline{v}_1\right)\left(\overline{v}_2 - \underline{v}_2\right)},$$

where $R(l)$ is the expected number of online customers preferring room service at level l, $l = 1, 2$, and $R(0)$ is that of online customers preferring no room service at any level.

With regard to the effect of ranking position on the OTA's webpage, the expected demand for hotel i is formulated as follows and as shown in Fig. 7.

$$y(l,i) = L(l)\varpi(i)\mathbb{N},$$

where $\varpi(i)\mathbb{N}$ is the expected number of potential online customers preferring hotel i.

The service levels of the hotels influence the number of potential online customers as well as opportunity loss K_i incurred from ranking the studied hotel at position i on the webpage. However, service levels cannot exert significant effect on $\varphi(i)$ because $\varphi(i) = K_i(n-i)^2$. Hence, the findings of our model are still valid in the heterogenous hotel scenario.

8. Conclusions, limitations and future research

This paper studies the pricing game of a hotel with an OTA, where the hotel is opening its online marketplace and distributing accommodation information and sales through the OTA's marketing channel. The hotel provides unit commission to the OTA for each room sold, and the OTA determines the ranking position of the hotel's information on its webpage as well as the effort level at which it encourages online customers to book hotel rooms through its website. The two players make decisions autonomously to maximize their own profits. The first-best solution is set as a benchmark, which is obtained in the centralized scenario in which the players act as an integrated system, and the second-best one is obtained in the decentralized scenario in which the players maximize their own objectives.

Analyses revealed that the optimal unit commission increases with the number of hotel rooms or the number of hotels

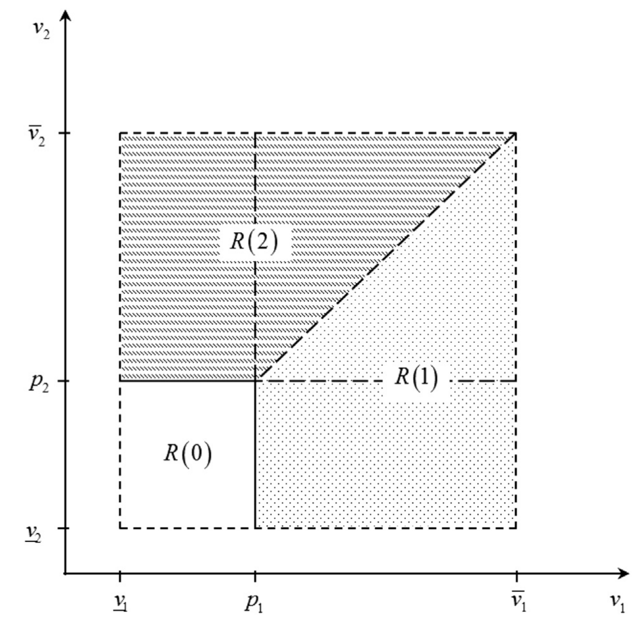


Fig. 6. Valuation sets of online potential customers for different room services.

cooperating with the OTA and decreases with the number of t-tourists or the number of potential customers of the OTA. The OTA arranges a better position on the webpage for the hotel when the hotel has more available rooms, whereas a worse one is set when the hotel has more t-tourists or the OTA has more potential customers. Interestingly, the OTA exerts greater effort when the hotel is ranked in a better position. That is, the effort level is correlated to the ranking position.

Furthermore, the profits of the players are influenced by many factors. An OTA with a high visitor volume is helpful in improving the hotel's revenue. However, an OTA with many cooperative hotels at an identical service level offers low profits to the hotel because the hotel has to pay the OTA a high unit commission for a desirable position on the webpage. Moreover, The OTA obtains a high unit commission from hotels with a low occupancy rate before opening

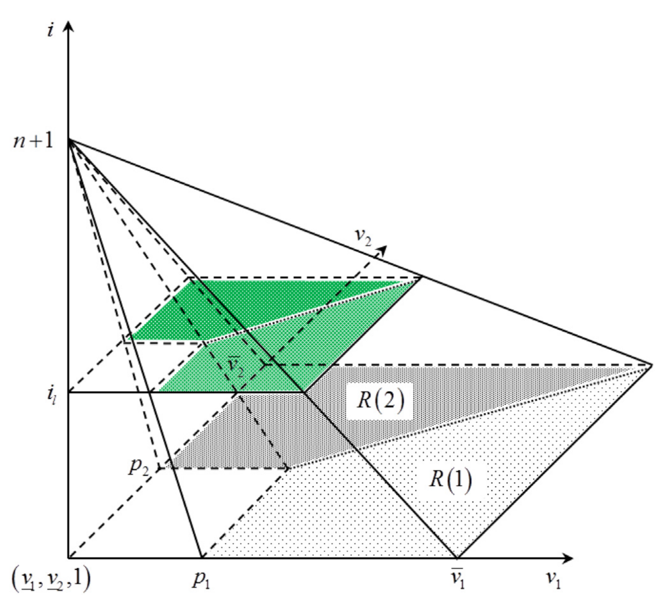


Fig. 7. Expected demand for hotels ranked at position *i*.

the online channel. This finding implies that such hotels have strong motivation to establish their online channel through an OTA. That is, the occupancy rate of hotels before online marketing is a very important metric for cooperating with OTAs. Hotels with a low occupancy rate are advised to cooperate with OTAs to improve their revenues, whereas those with a high occupancy rate do not appear to be encouraged to participate in such activities. These findings provide hotels with suggestions on how to choose partners to establish and extend their online market.

The model developed in this paper is subject to several assumptions that can be relaxed in future studies. First, we assume the demand for a hotel only depends on its position on the OTA's webpage. If the demand depends on both its position and attributes such as location and traffic convenience, then what should the pricing policy of the hotel be? This extension may require a complex additional assumption regarding the demand function, but it is worth studying from the perspective of hotel management. Second, this model can be extended to a network scenario with multiple OTAs cooperating with several hotels at different service levels. In this scenario, customers can choose a hotel room according to room rates, the service levels of the hotels, and the service levels of the OTAs. Third, our model and analysis mainly focus on the decentralized scenario in which hotels and OTAs make decisions autonomously and demonstrate that the profit of the supply chain is far from the benchmark. Hence, an effective coordination contract that leads to the first-best situation is worth working on, which is also a core topic in tourism supply chain management (Chen, 2012). Fourth, the hotel industry always faces a problem called *cancellations and no-shows*; hence, it is valuable to take overbooking strategies into account in cooperative scenarios to increase the hotel occupancy rate. Fifth, name-your-own price (NYOP) (Shapiro, 2011; Wang, Gal-Or, & Chatterjee, 2009) is another effective strategy for improving the utilization of travel products; hence, application of the NYOP strategy to the cooperation between hotels and OTAs should be expected in practice. Lastly, dynamic pricing (Guo, Ling, Yang, Li, & Liang, 2013) based on reservation lead time and room occupancy rate is implemented through OTA marketing channels.

Acknowledgments

This work was supported by the National Natural Science Foundation of China (Nos. 71271197; 71301156), the China Postdoctoral Science Foundation (No. 2013M541845), the Foundation for Innovative Research Groups of the National Natural Science Foundation of China (No. 71121061), the Foundation for International Cooperation and Exchange of the National Natural Science Foundation of China (No. 71110107024) and the Scientific Fund for Innovative Research Groups of USTC (No. WK2040160008). Xiaolong Guo would also like to thank the Foundation of the USTC Special Grant for Postgraduate Research, Innovation and Practice.

References

Abbott, P., & Lewry, S. (1999). *Front office: Procedures, social skills, yield and management*. Oxford: Butterworth Heinemann.

Bastakis, C., Buhalis, D., & Butler, R. (2004). The perception of small and medium sized tourism accommodation providers on the impacts of the tour operators' power in eastern Mediterranean. *Tourism Management, 25*(2), 151–170.

Chawla, S., Hartline, J. D., & Kleinberg, R. (2007). Algorithmic pricing via virtual valuations. In *Proceedings of the 8th ACM conference on electronic commerce* (pp. 243–251). ACM.

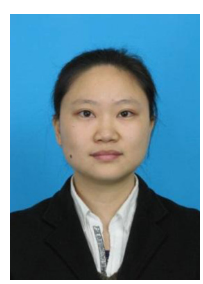
Chawla, S., Malec, D., & Sivan, B. (2012). The power of randomness in Bayesian optimal mechanism design. *Games and Economic Behavior*. http://dx.doi.org/10.1016/j.geb.2012.08.010.

Chen, F. (2005). Salesforce incentives, market information, and production/inventory planning. *Management Science, 51*(1), 60–75.

Chen, P. (2012). Efficient tourism website design for supply chain management. In X. Qu, & Y. Yang (Eds.), *Information and business intelligence* (pp. 660–665). Berlin Heidelberg: Springer-Verlag.
De La Viña, L., & Ford, J. (2001). Logistic regression analysis of cruise vacation market potential: demographic and trip attribute perception factors. *Journal of Travel Research, 39*(4), 406–410.
Dong, Y., Ling, L., & Guo, X. (2013). Travel package modeling: optimal bidding strategy of tour operator to cooperative hotels. *Asia Pacific Journal of Tourism Research.* http://dx.doi.org/10.1080/10941665.2013.866581.
Garrow, L., Ferguson, M., Keskinocak, P., & Swann, J. (2006). Expert opinions: current pricing and revenue management practice across us industries. *Journal of Revenue and Pricing Management, 5*(3), 237–247.
Grønflaten, Ø. (2009). Predicting travelers' choice of information sources and information channels. *Journal of Travel Research, 48*(2), 230–244.
Guo, X., & He, L. (2012). Tourism supply-chain coordination: the cooperation between tourism hotel and tour operator. *Tourism Economics, 18*(6), 1361–1376.
Guo, X., Ling, L., Dong, Y., & Liang, L. (2013). Cooperation contract in tourism supply chains: the optimal pricing strategy of hotels for cooperative third party strategic websites. *Annals of Tourism Research, 41*, 20–41.
Guo, X., Ling, L., Yang, C., Li, Z., & Liang, L. (2013). Optimal pricing strategy based on market segmentation for service products using online reservation systems: an application to hotel rooms. *International Journal of Hospitality Management, 35*, 274–281.
Guo, X., Zheng, X., Ling, L., & Yang, C. (2014). *Online marketing cooperation and competition between hotels and online travel agencies: From the perspective of cash back after stay.* Working paper. University of Science and Technology of China. http://dx.doi.org/10.2139/ssrn.2296447. available at SSRN.
Huang, Z., & Li, S. X. (2001). Co-op advertising models in manufacturer–retailer supply chains: a game theory approach. *European Journal of Operational Research, 135*(3), 527–544.
Jansen, B. J., Ciamacca, C. C., & Spink, A. (2008). An analysis of travel information searching on the web. *Information Technology & Tourism, 10*(2), 101–118.
Kim, J., Wei, S., & Ruys, H. (2003). Segmenting the market of West Australian senior tourists using an artificial neural network. *Tourism Management, 24*(1), 25–34.
Kim, S. H., Cohen, M. A., & Netessine, S. (2007). Performance contracting in after-sales service supply chains. *Management Science, 53*(12), 1843–1858.
Kim, W. G., & Kim, D. J. (2004). Factors affecting online hotel reservation intention between online and non-online customers. *International Journal of Hospitality Management, 23*(4), 381–395.
Kimes, S. E., & Chase, R. B. (1998). The strategic levers of yield management. *Journal of Service Research, 1*(2), 156–166.
Law, R., & Hsu, C. H. (2006). Importance of hotel website dimensions and attributes: perceptions of online browsers and online purchasers. *Journal of Hospitality & Tourism Research, 30*(3), 295–312.
Ling, L., Guo, X., & Liang, L. (2011). Optimal pricing strategy of a small or medium-sized hotel in cooperation with a web site. *Journal of China Tourism Research, 7*(1), 20–41.
Little, J. D. C. (1979). Feature article—aggregate advertising models: the state of the art. *Operations Research, 27*(4), 629–667.
Medina-Muñoz, D., & García-Falcón, J. M. (2000). Successful relationships between hotels and agencies. *Annals of Tourism Research, 27*(3), 737–762.
Morosan, C., & Jeong, M. (2008). Users' perceptions of two types of hotel reservation web sites. *International Journal of Hospitality Management, 27*(2), 284–292.
O'Connor, P. (2003). On-line pricing: an analysis of hotel–company practices. *The Cornell Hotel and Restaurant Administration Quarterly, 44*(1), 88–96.
Pan, B., Zhang, L., & Law, R. (2013). The complex matter of online hotel choice. *Cornell Hospitality Quarterly, 54*(1), 74–83.
Sahay, A. (2007). How to reap higher profits with dynamic pricing. *Sloan Management Review, 48*, 53–60.
Shapiro, D. (2011). Profitability of the name-your-own-price channel in the case of risk-averse buyers. *Marketing Science, 30*(2), 290–304.
Thanassoulis, J. (2004). Haggling over substitutes. *Journal of Economic Theory, 117*(2), 217–245.
Ting, P.-H., Wang, S.-T., Bau, D.-Y., & Chiang, M.-L. (2013). Website evaluation of the top 100 hotels using advanced content analysis and eMICA model. *Cornell Hospitality Quarterly, 54*(3), 284–293.
Toh, R. S., DeKay, C. F., & Raven, P. (2011). Travel planning searching for and booking hotels on the internet. *Cornell Hospitality Quarterly, 52*(4), 388–398.
Toh, R. S., Raven, P., & DeKay, F. (2011). Selling rooms: hotels vs. third-party websites. *Cornell Hospitality Quarterly, 52*(2), 181–189.
Tso, A., & Law, R. (2005). Analysing the online pricing practices of hotels in Hong Kong. *International Journal of Hospitality Management, 24*(2), 301–307.
Wang, T., Gal-Or, E., & Chatterjee, R. (2009). The name-your-own-price channel in the travel industry: an analytical exploration. *Management Science, 55*(6), 968–979.
Wang, X. L. (2012). Relationship or revenue: potential management conflicts between customer relationship management and hotel revenue management. *International Journal of Hospitality Management, 31*(3), 864–874.
Wong, J., & Law, R. (2005). Analysing the intention to purchase on hotel websites: a study of travellers to Hong Kong. *International Journal of Hospitality Management, 24*(3), 311–329.
Wu, E. H., Law, R., & Jiang, B. (2013). Predicting browsers and purchasers of hotel websites a weight-of-evidence grouping approach. *Cornell Hospitality Quarterly, 54*(1), 38–48.

Liuyi Ling holds his PhD from the University of Science and Technology of China and now is a senior lecturer of Management Science at School of Management, University of Science and Technology of China. His research interests include tourism supply chain management, tourism economics, pricing and revenue management, and tourism strategic management.

Xiaolong Guo received his PhD degree from University of Science and Technology of China and currently a postdoc researcher of the School of Management, University of Science and Technology of China. His research interests include logistics and supply chain management, service operations research and hospitality & tourism management.



Chenchen Yang received her doctoral degree of management science and engineering from the University of Science and Technology of China in 2012, and now is a Postdoctoral researcher of the School of Management, University of Science and Technology of China. Her research interests include decision science, DEA and performance evaluation.