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Last-minute hotel-booking and frequency of dynamic price adjustments of hotel rooms in a cosmopolitan tourism city

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ABSTRACT

Although the Internet has contributed to lowering the cost of adjusting hotel room rates on Internet-enabled distribution channels and promoted last-minute hotel booking, research on the frequency of dynamic price adjustments of hotel rooms remains scarce. Using panel data techniques involving count data models, this study examined online pricing data of hotels in a cosmopolitan tourism city to identify supply-side factors and location attributes that can be used in conjunction with the established demand-based pricing strategy to explain the frequency of adjusting room rates. After controlling for spatial locations and demand, results indicated that the frequency of room rate change is also related to seller density, hotel size, star rating, and consumer heterogeneity reflected in different booking days. Practically, the findings have revealed subtle differences in the implementation of demand-based dynamic pricing that can be used by practitioners and consumers for strategic decision-making.

1. Introduction

Following the adoption of revenue management practices in the hotel industry and technological advancement in Internet-enabled distribution systems (IDS), demand-based dynamic pricing has become a popular practice in the hotel industry. Under this pricing strategy, hotels adjust their room rates over time and in line with the demand and supply situation (Guizzardi, Pons, & Ranieri, 2017, 2019). Prior research regarding demand-based dynamic pricing has indicated that a growing number of capacity-constrained firms including hotels have adopted this pricing strategy because it is a win–win policy for both the service suppliers and consumers (Abrate, Fraquelli, & Viglia, 2012; Guo, Ling, Yang, Li, & Liang, 2013; Şen, 2013). With the growth in IDS, an increasing number of hotels are continuing to adopt this pricing strategy because adjusting prices online is much easier and costs less than offline (Kauffman & Lee, 2007; Ropero, 2011). Responding to this, a growing number of hotel customers are also booking rooms through online channels as these channels offer them convenience and ability to compare prices and amenities (Saito, Takahashi, Koide, & Ichifuji, 2019). As the share of online bookings of hotels increases, the number of last-minute bookings is also rising due to the development of mobile technologies and new apps (Huang, 2016). According to Travel Agent Central (2017), while many last-minute reservations are made are from desktop and laptop, a whopping 72% of mobile hotel bookings on an OTA site or through an OTA app were made within 48-h prior to check-in.

In response to the growing application of dynamic pricing strategy by hotels and last-minute booking behaviour by customers, research in this area is required to fully comprehend the dynamic pricing behaviour of hotels within the last-minute booking window, particularly the frequency at which prices are dynamically adjusted. For both consumers and practitioners, this understanding can prove very useful in contributing to their ability to make strategic decisions. So far, attempts to address this need in the hospitality literature have been insightful in their respective goals; however, they have been limited to price variability without examining the determinants of the frequency of price adjustment (Abrate et al., 2012; Ropero, 2011). More recently, Jang, Chen, and Miao (2019) examined last-minute booking behavior to determine the impact of time on decision making and recommended that further research is need in this area. Other researchers have indicated that last-minute hotel sales represent a substantial market segment and should no longer be overlooked (Yang & Leung, 2018). To respond to these suggestions, this study seeks to achieve two main objectives, namely, to examine online pricing data of hotels in the last-minute booking window (0–7 days before check-in) and thus describe the frequency (or periodicity) at which room rates for particular night stays are changed, and to provide additional explanations supported by econometric analysis for the possible heterogeneity in the frequency of

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price adjustment. The study is limited to the last-minute booking window because of its prevalence. According to a Global Travel Insight Report cited by Jang et al. (2019), more than 60% of hotel bookings in the US were within 0–7 days before arrival, thus, making it an important window to study.

2. Literature review

The frequency of price adjustment in offline markets has been investigated under several theories (Cecchetti, 1986; Horváth, 2011). These theories suggest that the frequency of price adjustments is associated with market structure (Barron, Taylor, & Umbeck, 2004; Powers & Powers, 2001), information asymmetry (Ball & Romer, 1990; Stiglitz, 1999), demand-based factor (Borenstein, Cameron, & Gilbert, 1997; Sims, 2003), price adjustment costs (Zbaracki, Ritson, Levy, Dutta, & Bergen, 2004) and contract agreements (Bergen, Dutta, Levy, Ritson, & Zbaracki, 2003; Zbaracki et al., 2004). Relating the extant theories of price adjustments in the offline market to the digital economy, Kauffman and Lee (2007) argue that the frequency of price change in the digital economy could still be influenced by market structure, demand-based factors and cost-of-price-adjustment. In an apparent support of this viewpoint, Chakrabarti and Scholnick (2007) and Bergen, Kauffman, & Lee (2005) demonstrated heterogeneity in the frequency of price change among Internet retailers. Using the theory of managerial cost (Zbaracki et al., 2004), it can also be argued that firms in the digital economy may not change prices promptly, especially if the decisions of several individuals in a hierarchical organization are required to process and effect a price change.

Considering that it is difficult to obtain cost-of-price-adjustment data (Blinder, Canetti, Lebow, & Rudd, 1998), empirical studies have used indirect proxies to capture firm-to-firm differences that may influence price adjustments. For example, in a study of price adjustments in grocery stores, Powers and Powers (2001) adopted the Okun's (1981) theory to explain why larger grocers less-frequently adjust their prices. In another study, Buckle and Carlson (2000) argued for a relationship between firm size and frequency of price change. According to the authors, larger firms are bound to change prices more often than smaller firms do because menu costs decline systematically as firm size increases. As a further theoretical backing for the possible relationships between hotel characteristics and frequency of price adjustment, the theory of quality signaling is also invoked. This theory has been used in luxury product markets to explain the reluctance of firms to adjust their prices (Blinder et al., 1998). In a leading explanation of the reasons why firms may exhibit heterogeneity in changing prices, Rotemberg and Saloner (1987) developed the market power justification which suggests that the frequency of price change by a firm is related to competition.

Drawing from the above-mentioned theories on price adjustment, this study conceptualizes the frequency of room rate change to be determined by market structure factors (demand/occupancy and seller density), hotel characteristics (chain affiliation, star rating, size and class) and location attributes (district, distance to airport and train station). Accordingly, the following two hypotheses are derived and tested.

H1. *Localized competition (measured by seller density) is positively associated with the frequency of room rate change such that the more competitive a local market is, the more frequent the hotels in that market vary their room rates.*

H2. *Hotel star rating (as a quality indicator) is negatively associated with the frequency of room rate such that high star-rated hotels vary their room rate less frequently as quality signaling consistency (rigidity) compared to low star-rated hotels.*

As a justification of the selection of the variables in the hypotheses, seller density has been used in the hospitality literature to measure localized competition due to data limitation on the use of other competition indices like the Herfindahl–Hirschman Index or concentration ratios (Balaguer & Pernías, 2013; Mohammed, Denizci-Guillet, & Law, 2019). For this reason, this study also adopted the seller density as a measure of localized competition. Following the tradition of using star rating to represent or signal quality (Abrate, Capriello, & Fraquelli, 2011), this study used the star rating to differentiate the hotels. As a proxy for differentiation, this variable was complemented by adding other variables such as chain affiliation, size, class and location to capture hotel-to-hotel differences that may be important for price adjustment. These variables have also been used extensively in similar empirical studies to represent differentiation among hotels (Abrate et al., 2011, 2012; Andersson, 2010; Balaguer & Pernías, 2013; Baum & Haveman, 1997; Becerra, Santaló, & Silva, 2013; Chen & Rothschild, 2010; Israeli, 2002; Lee & Jang, 2011; Ropero, 2011; Thrane, 2007; Urtasun & Gutiérrez, 2006).

3. Research methodology

3.1. Model specification and estimation

The frequency of room rate change is analysed using count data models. These models are applied when the dependent variable is a discrete variable generated from the counting process (Cameron & Trivedi, 2013; Winkelmann, 2003). Among the various count data models, the Poisson and the negative binomial models are the most commonly applied in empirical research (Hilbe, 2011). In terms of application, these two models differ in their assumptions of the conditional mean and variance of the dependent variable. In the Poisson model, the conditional mean and variance of the distribution are assumed to be equal (i.e., equidispersion assumption), whereas in the negative binomial model, this assumption is relaxed (Greene, 2008). In other words, the negative binomial is designed to handle overdispersion in the data, which arises when the variance is greater than the conditional mean. In practice, numerous empirical studies tend to use the negative binomial because the dependent variable is unlikely to be equally dispersed. However, this case was not apparent in this study. Thus, both models were applied to check the robustness of the results. As a foundational building block, the Poisson regression model for a panel data can be expressed as follows.

$$Prob(Y = y_{it} \mid X_{it}) = \frac{\exp(\lambda_{it})\lambda_{it}^{y_{it}}}{\Gamma(1 + y_{it})} \tag{1}$$

where,

$$\lambda_{it} = \exp(\alpha_{it} + X_{it}'\beta) \tag{2}$$

$$E(y_{it} \mid X_{it}) = \lambda_{it} \tag{3}$$

$$Var(y_{it} \mid X_{it}) = \lambda_{it} \tag{4}$$

X_{it} is the vector of covariates and β is the set of parameters to be estimated.

The alternative specification of negative binomial is expressed similarly as the Poisson, but with an introduction of a latent heterogeneity in the conditional mean of the Poisson model (Greene, 2008), which can be expressed follows.

$$E(y_{it} \mid X_{it}, \varepsilon_{it}) = \exp(\alpha_{it} + X_{it}'\beta + \varepsilon_{it}) = \lambda_{it} h_{it} \tag{5}$$

where, $h_{it} = \exp(\varepsilon_{it})$ is assumed to have one parameter gamma distribution, G $(\theta, 0)$ with mean 1 and variance $\frac{1}{\theta} = k$ and a marginal negative binomial distribution:

$$Prob(Y = y_{it} \mid X_{it}) = \frac{\Gamma(\theta + y_{it}) r_{it}^{\theta}(1 - r_{it})^{y_{it}}}{\Gamma(1 + y_{it})\Gamma(\theta)} \tag{6}$$

$$y_{it} = 0,\ 1,\ ...,\ \theta > 0,\ r_{it} = \theta/(\theta + \lambda_{it}) \tag{7}$$

Table 1
List of variables and definitions.

Variable	Definition	Operationalization	Source	Reference
Dependent variable				
Frequency of price change	The number of times the best available rate changes within the seven days preceding a target date for check-in (i.e. frequency of price change)	Discrete count of any price change (increase or decrease)	Kayak.com	Baylis and Perloff (2002); Powers and Powers (2001)
Independent variables				
Occupancy	The proportion of the available rooms in a month sold by hotels	Percentages	STR	
Seller density	The number of hotels within 500m radius of a focal hotel	Count of hotels	Computed	Balaguer and Pernías (2013); Lewis (2008)
Chain	Independent or chain-affiliated	Dummy variable	STR	Balaguer and Pernías (2013); Hung, Shang, and Wang (2010)
Star rating	The official star category of the hotel	Dummy variables	Kayak.com	Becerra et al. (2013); Abrate et al. (2011)
Size	The number of rooms in a hotel	Categorized into three groups and operationalized by dummies	HKTB/STR	Becerra et al. (2013); Hung et al. (2010)
Class	The classification of a hotel according Luxury, Upper Upscale, Upscale, Upper Midscale	Dummies	STR	Canina, Enz, and Harrison (2005)
District	The official administrative district assigned to a hotel by the Hong Kong Tourism Board	Dummy variables	HKTB	Balaguer and Pernías (2013)
Distance to attractions	The sum of the distance between a hotel and the top ten tourist attraction	Mean Harversine distance in Kilometres (km)	Google maps	Becerra et al. (2013)
Distance to airport	The distance between a hotel and the Hong Kong International airport	Harversine distance in Kilometres (km)	Google maps	Balaguer and Pernías (2013)
Distance to MTR	The distance to nearest Mass Transit Railway station	Harversine distance in Kilometres (km)	Google maps	Balaguer and Pernías (2013)

Notes: the coordinates were measured in degrees, HKTB = Hong Kong Tourism Board, STR = Smith Travel Research. The top tourist attractions (according to HKTB) are the Avenue of Stars, the Peak, Ocean Park Hong Kong, Hong Kong Disney, Ladies' Market, Temple Street Night Market, Hong Kong Convention and Exhibition Centre (and Golden Bauhinia Square), Tsim Sha Tsui Promenade, Sik Yuen Wong Tai Sin Temple; and the Clock Tower.

$$Var(y_{it} \mid X_{it}) = \lambda_{it} + k\lambda_{it}^2 \tag{8}$$

$$h_{it} = \exp(X_{it}'\beta) \tag{9}$$

The dependent and independent variables used in both the Poisson and negative binomial models are defined in Table 1 with the corresponding references.

3.2. Data

Table 1 provides a detailed description of the variables and sources of the data required for this study and the corresponding sources from which these data were gathered. As shown in Table 1, multiple sources were used for the data collection.

The sample for this study was drawn from establishments in Hong Kong that are officially registered with HKTB as hotels. In all, 186 hotels were selected based on the sample selection criteria: (a) hotels with advertised room rate on third-party channels accessible on kayak.com, and (b) hotels that have sufficient data for meaningful analysis. For all the sampled hotels, the unit of analysis was the best available rates (BAR) for a single night stay in a standard twin/double room. Similar to prior research (Abrate et al., 2012; Balaguer & Pernías, 2013; Becerra et al., 2013; Schamel, 2012) an automated web-scraping technique was used for the data collection in the present study. The duration of data collection was six consecutive months. Within this period, the target days for check-in were Tuesdays and Saturdays. Consistent with earlier studies (Abrate et al., 2012; Schamel, 2012), these days were purposively selected to represent business guests and leisure customers who typically book weekdays and weekends respectively. For each day, there were 26 target dates for the data collection. However, the actual data collection in respect of each target date started seven days in advance, the period within which prices are expected to change regularly. This procedure also followed similar practices by Balaguer and Pernías (2013) and Abrate et al. (2012), but for an extended period. Eventually, a balanced panel of 126 hotels involving 26 Saturdays and 26 Tuesdays (i.e., 3,276 observations each) was used for the analysis.

4. Results

4.1. Composition of sample

The composition of the sample according to age groups (years), size categories (number of rooms), star rating, mode of operation and class is presented in Table 2.

4.2. Descriptive results of the frequency of price change

Fig. 1a and b demonstrate the degree to which dynamic pricing was implemented among the sampled hotels in Hong Kong. In most of the cases (96.83%), the dynamic price adjustment was done at least once within the 7-day window (refer to Fig. 1a). The distribution also shows that the modal frequency of price change was five (5), indicating that out of the seven days, most hotels dynamically adjusted their room rates on five days. The average frequency of price change (in days) was estimated to be four, implying that for more than half of the days in a week, price could be expected to change approximately four times.

To highlight the implementation of dynamic pricing on a weekday (Tuesday) and weekend (Saturday), the data were further analysed separately for each of these days (see Fig. 1b). The striking difference between the dynamic pricing on Saturday and Tuesday is that, relative to Tuesday adjustments, most Saturday rates were adjusted more frequently. Conversely, most Tuesday rates were adjusted less frequently than Saturdays. These differences can be observed from Fig. 1b by comparing the height of the bar graphs to the left and right of the reference (broken) line. To the left of the reference line, the bars

Table 2
Composition of sample.

Variables	N = 126	%
Age(years)		
Less than 5 years	36	28.57
5–9 years	30	23.81
10–20 years	15	11.9
More than 20 years	45	35.71
Size (rooms)		
Small hotels (≤100)	23	18.25
Mid-sized hotels (101–300)	38	30.16
Large-sized hotels (> 300)	65	51.59
Star rating		
3-star	30	23.81
4-star	76	60.32
5-star	20	15.87
Operation		
Chain Management	59	46.83
Independent	67	53.17
Class		
Midscale	40	31.75
Upper Midscale	31	24.6
Upscale	24	19.05
Upper Upscale	11	8.73
Luxury	20	15.87

Notes: star rating is from kayak.com; size classification is based on McCann and Vroom (2010) study; class information is obtained from STR and it is a ranking of hotels based on Average Daily Rates (ADR). From the highest to the lowest ADR, the rankings are luxury, upper upscale, upscale, upper midscale, midscale and economy.

corresponding to Tuesdays are higher than those for Saturdays, whereas to the right of the reference line, the converse is the case.

Two interpretations can be offered to explain these subtle differences. On the one hand, the more frequent price changes on Saturdays can be interpreted to mean that because Saturday customers are predominantly leisure customers with higher price sensitivity, most hotels have to engage in frequent price adjustments to sell their rooms. This interpretation suggests that competition to sell rooms is probably keener on Saturdays than on Tuesdays; hence, prices have to vary more frequently to deal with the intense competition. On the other hand, the more infrequent price changes on Tuesday can be interpreted to mean that perhaps demand on weekday is more stable than on weekend because the buying decisions of business customers are more predictable.

4.3. Estimation results

As explained in the methodology, two alternative models could be used to identify the determinants of the frequency of price change, namely, the Poisson and negative binomial models. The estimation results were obtained for both models as part of the robustness checks on the results but due to space limitation, only the results for the negative binomial are reported in Table 2. Considering that the objective of this study was not to determine the effect sizes of variables; the reported coefficients are not marginal effects. Also, all the coefficients were estimated with cluster robust standard errors. Aside from using different models to confirm that the results were robust, a key variable in the study representing the degree of localized competition (i.e., seller density) was used to conduct an additional robustness check. That is, in addition to the 500 m (i.e., 0.5 km) radius that was determined to correspond to the average number of competitors in the industry, the models were estimated with seller densities corresponding to 400 and 600 m radii. These radii (400 m, 500 m and 600 m) were selected to generate the average number of 4–8 competitors that is normally selected for competitive analysis in the hotel industry (Canina & Enz, 2006; Clark & Montgomery, 1999; Li & Netessine, 2012). As shown in Table 2, the qualitative results for the alternative definitions of seller density remained the same, further ensuring the robustness of the results.

From the results in Table 2 (and focusing on the grey column), the findings from the regression analysis can be summarized as follows. For both the Saturday and Tuesday results, the frequency of room rate change is influenced by the level of demand as measured by the average occupancy rate, the size of hotel as determined by the number of rooms, the quality rating of hotel as represented by the star rating, class of

Table 3
Results of negative binomial regression.

Variables	Saturday			Tuesday		
	400m	500m	600	400m	500m	600
Occupancy	0.0047*** (2.69)	0.0047*** (2.69)	0.0047*** (2.69)	0.0099*** (10.02)	0.0099*** (10.02)	0.0099*** (10.02)
Seller density	0.0146** (2.35)	0.0134*** (2.58)	0.0103** (2.36)	0.0140** (1.99)	0.0127** (2.16)	0.0105** (2.15)
Chain	−0.0113 (−0.03)	−0.0110 (−0.28)	−0.00902 (−0.23)	0.0137 (0.30)	0.0045 (0.09)	0.00547 (0.12)
4-star	0.0712 (1.52)	0.0654 (1.40)	0.0721 (1.54)	0.0342 (0.64)	0.0287 (0.54)	0.0349 (0.65)
5-star	−0.0756 (−0.95)	−0.0795 (−1.00)	−0.0618 (−0.78)	−0.192** (−2.11)	−0.195** (−2.16)	−0.179** (−1.98)
Medium-sized (101–300 rooms)	0.0823* (1.69)	0.0974* (1.75)	0.0823* (1.59)	0.0243 (0.39)	0.0386 (0.61)	0.0258 (0.41)
Large-sized (more than 300 rooms)	0.116** (2.01)	0.134** (2.27)	0.115** (2.00)	0.0950 (1.44)	0.111 (1.65)	0.0951 (1.45)
Midscale	−0.118 (−1.53)	−0.124 (−1.61)	−0.0999 (−1.31)	−0.166* (−1.87)	−0.170* (−1.92)	−0.149* (−1.71)
Upper midscale	−0.0169 (−0.22)	−0.0216 (−0.29)	−0.00495 (−0.07)	−0.0936 (−1.08)	−0.0972 (−1.12)	−0.0827 (−0.97)
Upper upscale	−0.00649 (−0.08)	−0.00555 (−0.07)	−0.0144 (−0.18)	−0.0902 (−0.96)	−0.0875 (−0.95)	−0.0704 (−0.77)
Upscale	−0.0320 (−0.42)	−0.0300 (−0.40)	−0.0128 (−0.17)	−0.0552 (−0.63)	−0.0523 (−0.60)	−0.0366 (−0.42)
Distance to Airport	0.00598 (0.70)	0.00635 (0.75)	0.00739 (0.86)	0.00757 (0.77)	0.00791 (0.81)	0.00904 (0.92)
Distance to nearest train station	0.0751* (1.75)	0.0745* (1.75)	0.0739* (1.85)	0.110** (2.23)	0.109** (2.23)	0.114** (2.33)
Mean distance to top attractions	−0.00645 (−0.50)	−0.00569 (−0.44)	−0.00503 (−0.39)	−0.00235 (−0.16)	−0.00168 (−0.12)	−0.0008 (−0.06)
District dummies (controlled)	Yes	Yes	Yes	Yes	Yes	Yes
Constant	16.89*** (49.50)	16.89*** (49.48)	16.65*** (48.45)	16.70 (0.14)	16.03 (0.09)	15.74 (0.19)
Log likelihood	−6495.131	−6494.595	−6495.099	−6632.438	−6632.105	−6632.122
Wald chi2	50.42***	51.86***	50.52***	136.59***	137.48***	137.45***
Lnalpha_constant	−3.790*** (−20.86)	−3.803*** (−20.85)	−3.791*** (−20.86)	−3.455*** (−20.53)	−3.462*** (−20.53)	−3.461*** (−20.53)
N	3276	3276	3276	3276	3276	3276

Notes: t-statistics in parenthesis; standard errors are robust; *p < 0.1; **p < 0.05; ***p < 0.01; 3-star is the comparison hotel for star rating; small hotel (less than 100 rooms) is the reference group for size; luxury hotel is reference group for class and Central & Western is the comparison group for district.

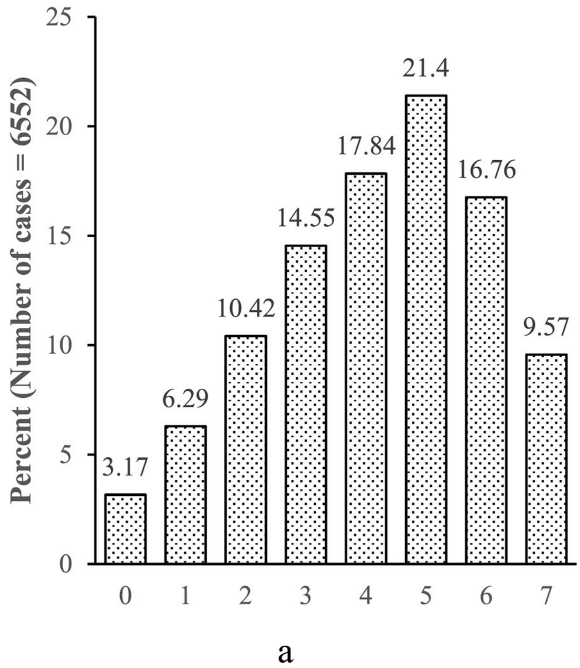

Fig. 1a. Frequency of price changes.

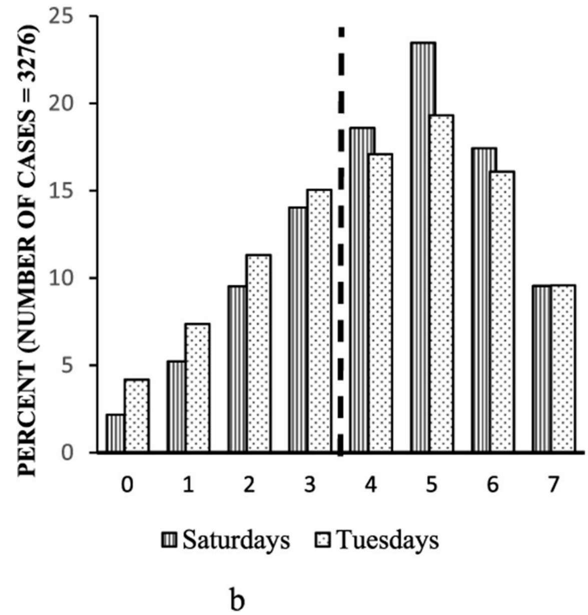

Fig. 1b. Frequency of price change by day.

hotel as segmented by ADRs, accessibility to transport facility as proxied by distance to the nearest train station and the degree of localized competition as captured by seller density within a localized market. As would be expected, the significant coefficients have different signs and, therefore, their respective interpretations are warranted.

Starting with the market structure variables, the effects of occupancy and seller density on the frequency of room rate change were statistically significant and consistent with a priori expectation. In both the Saturday and Tuesday regression outputs, occupancy had a significant positive effect on the frequency of room rate change, indicating that as demand increased relative to a fixed supply, the frequency at which room rate changes also increased. This finding confirmed that adjustments in room rate were indeed related to demand as supported by the established demand-based pricing. Moreover, the regression results of seller density indicated a positive effect on the frequency of room rate change, suggesting that as the number of localized competitors increased, the frequency of room rate change by the surrounded hotel also increased. This positive relationship between seller density and frequency of room rate change can be explained by the dependence of frequency of room rate change on the microstructure of the market because higher seller density is an indication of higher competition.

In terms of hotel characteristics variables, the results indicate that except chain affiliation, frequency of room rate change was statistically related to star rating, size and class of hotel with some notable differences depending on the booking day. In the case of star rating, the significant effect was with respect to the 5-star dummy and negative for Tuesdays but not Saturdays. That is, compared with 3-star hotels, 5-star hotels have a lower frequency of price change on Tuesday bookings. Considering the coefficient of size, the results suggested that size of hotel significantly influences the frequency of room rate change on Saturdays but not on Tuesdays. Of the four location-related attributes included in the regression model (i.e., the administrative district in which hotels are located, hotel distance to international airport, distance to the nearest train station and average distance to top tourist attractions), only distance to the train station is significant. In both regression outputs (Saturdays and Tuesdays), the coefficient of distance to the nearest train station is positive and significant, indicating that hotels located farther from the train station changed their prices more frequently. Other location-related variables were not significant because of the small size of Hong Kong, in which hotels by their very location do not necessarily have to incur extra cost for inaccessibility by virtue of the efficient transport system that Hong Kong is known for (Li, Fang, Huang, & Goh, 2015).

5. Discussion

The findings have indicated that within seven days prior to checking in a hotel, room rates are dynamically adjusted according to the demand situation. In addition, the frequency of price adjustment was found to be related to hotel characteristics, such as star rating, size and class, as well location proximity to a train station. Compared with previous studies in the hotel industry that investigated dynamic pricing (Abrate et al., 2012; Ropero, 2011), the frequency of room rate change in the present study appeared to be more frequent and widespread (i.e., 96.83% of the observation showed price adjustment). In the study conducted by Ropero (2011), 20.4% of the 572 hotels and tourists' apartments observed in the Spanish hotel market were found to have varied their rates during the 12-week period that was studied. Moreover, for nearly 1,000 hotels in eight European capital cities that were monitored for 90 days, Abrate et al. (2012) reported that 46% and 71% of the hotels changed their prices during the last week for check-in during Tuesdays and Saturdays, respectively.

Although the finding on the percentages of hotels implementing dynamic pricing as reported in the studies of Ropero (2011) and Abrate et al. (2012) may be regarded as dated, the comparison can usefully be interpreted as a mark of an increasing adoption and practice of dynamic pricing in recent years. However, the findings do not suggest that all of the hotels implement dynamic pricing in a similar fashion. Several hotels adjust their rates less frequently, whereas others adjust them more frequently depending on their characteristics. In the larger context of revenue management, the significant influence of occupancy rate on the frequency of room rate change signifies that the practice of dynamic pricing in the Hong Kong hotel market is in accordance with the theory of RM.

The finding on seller density also confirms the market structure explanation of the reasons why firms may exhibit heterogeneity in changing their prices (Hannan & Berger, 1991; Rotemberg & Saloner, 1987). At the broader level, the finding also fit into the structure conduct performance theory of Bain (1951) in which the structure of a market predictably determines the conduct of its firms (in this case the frequency of price adjustments). Consistent with this prediction and the market structure hypothesis, the positive causal effect of seller density on frequency of room rate change indicates that as the degree of localized competition increases, the frequency of room rate change increases, implying that hotels in a relatively denser locations tended to vary their room rate more frequently than those in sparsely populated location owing to the heightened rivalry to sell among them.

Although this study did not observe the cost of price adjustment directly, the relationship between the frequency of room rate change and the size of hotel appears to offer some partial evidence to suggest that managerial cost of price adjustment could still be important in explaining the heterogeneity of room rate change in an Internet distribution channel. According to the results, the frequency of room rate change is positively influenced by the size of hotel, which supports the argument by Buckle and Carlson (2000) that large firms are bound to change price more often than smaller firms because menu cost tended to decrease systematically with increase in firm size. In a study of dynamic pricing policies of hotel establishments in an online travel agency, Ropero (2011) also averred that price adjustment costs for larger establishments were lower.

Furthermore, the negative effect of star rating on the frequency of room rate change seemed to confirm the theory of quality signalling that suggest that in an environment where quality of service is not observable, highest-quality offering firms might be reluctant to lower their price for fear of being incorrectly interpreted as lowering quality (Blinder et al., 1998). Relating this finding to the empirical work of Abrate et al. (2012), some consistency can be noted. Abrate et al.'s (2012) study revealed that hotels belonging to the high-star category (four and five) maintained more stable prices, particularly when the general price pattern was declining. In light of this consistency, it can be suggested that perhaps high-star-rated hotels attempted to transmit a certain image of price stability to its customers.

The results also indicate that size of hotel significantly influenced the frequency of room rate change on Saturdays but not on Tuesdays. Specifically, the coefficients of medium- and large-sized hotels are both positive, indicating that in comparison to small-sized hotels, these hotels have a higher frequency of room rate change. This finding contradicts Powers and Powers' (2001) study, in which the authors found evidence to support the position that large groceries changed price less frequently. The finding of this present study is inconsistent with the findings of Powers and Powers (2001) because different from other industries, such as the grocery, where customers frown upon price adjustment, the practice of revenue management pricing is more acceptable to hotel customers (Choi & Mattila, 2004; Kimes, 2002).

The variables for the class of hotel did not show significant differences. The only significant difference was between midscale and luxury hotels. The statistically significant negative coefficient of midscale hotels dummy variable indicated that in comparison with luxury hotels, the frequency of room rate change by midscale hotel was lower. This finding appeared to be at variance with a priori expectation as suggested by Abrate et al. (2012) that high-quality high-price hotels were expected to maintain price stability. Nonetheless, the competitive pressures to vary price by midscale hotels could be lessened by the absence of economy hotels in the sample.

5.1. Implications

The findings of this study have theoretical and practical implications. Theoretically, the findings provide insights on how the frequency of dynamic price adjustment of hotel rooms can be explained using demand and supply factors. The study integrates price adjustment theories relating to market structure with quality signaling theory to provide a framework that conceptualizes frequency of room rate change as a function of market structure factors (demand/occupancy and seller density), hotel characteristics (chain affiliation, star rating, size and class) and location attributes (district, distance to airport and train station) and proceeds to test two hypotheses using last-minute booking data. Practically, hotel practitioners and customers can use the findings to guide their decision making.

For hotel practitioners in Hong Kong, the finding that the frequency of temporal adjustment in room rate is independent of the district in which hotels are located implies that they can continue to practice last-minute dynamic pricing without regard to the location of their hotels. Rather, what they need to consider are the number of hotels in their localized market and the overall market demand. Another implication for hotel practitioners in Hong Kong market is that as room rates change frequently due to dynamic pricing, customers may not be able to identify hotels that sell at the lowest or highest price based on past experience. In other words, the indirect consequence of the price adjustment by all hotels is that the rankings of hotels continually move up and down within the price distribution. Therefore, hotel practitioners can continue to implement dynamic pricing strategy in accordance with demand conditions without fear of possible customer antagonization that may simply be triggered by dynamic pricing.

For customers, the identified relationships between the frequency of room rate change and hotel characteristics such as size and star rating can be used to determine the relative propinquity of having to pay higher or lower when booking a hotel belonging to a particular star category or size group. In particular, for customers who might wish to minimize the risk of having to pay higher for a room, this information can serve as a useful guide to their strategic decision making. Importantly, the findings also reveal the differences in how frequent room rate changes on either a Saturday or Tuesday. This information can benefit leisure customers who tend to stay on weekend and business guests alike who usually make reservations for a weekday.

6. Conclusion and suggestions for future research

Different from previous online pricing studies, this research has examined extended online data to identify the factors that can be used in conjunction with the established demand-based pricing strategy to explain the room rate adjustment of hotels. The results offered indicated that in addition to linking the frequency of room rate change to changes in demand, hotel-to-hotel differences such as star rating, number of rooms and segments were significant in determining the frequency of hotel room rate changes. By finding empirical evidence to support the influence of location attributes and hotel characteristics on the frequency of price change, the contributions of this study are manifold. Most importantly, the study has offered a comprehensive framework drawn primarily from the industrial organisation literature and augmented with relevant hotel-industry-specific literature to identify the factors that can be combined with demand-based pricing policy to explain the heterogeneous pricing behaviour of hotels. Precisely, the advanced framework states that the frequency of price change is explained by market structure variables (including demand and seller density), hotel characteristics (including chain affiliation, star rating, number of rooms and class), and location attributes (including distance to the nearest train station).

The study has also offered empirical evidence to add to the dearth of existing literature on pricing studies in the hotel industry, particularly the frequency of price change. Notably, the findings have contributed empirical evidence to identify location-related attributes specific to the hotel industry that influence the frequency of room rate change. In the large context of price adjustment theories, this study has added a new finding that product attributes can also influence the frequency of price adjustment. In conclusion, although the findings of this study have significantly contributed to knowledge that can improve RM practice, the study has nevertheless, some limitations which provide opportunities or avenues for further research. These opportunities for further research are primarily related to the scope of the study and data collection. Thus, future research can address this shortfall by expanding the scope of this study to cover different countries, different room types, and all the seven days in a week.

Conflicts of interest-

No conflict of interest.

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