

# Exploring the Determinants of Strategic Revenue Management with Idiosyncratic Room Rate Variations

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## Abstract

For considerable time, studies on revenue management have focused on the short-term, *tactical* aspects of demand forecasting, implementation and outcomes. Recent studies suggest, however, for hotels the consequences of *strategic* pricing in the long-run. Meanwhile, due to the difficulty in distinguishing between *tactical* and *strategic* room rate changes of hotels, only a limited number of studies examining performance implications have been published. In order to fill the research gap, this study utilizes Kim et al.'s (2016) spatial panel econometric method to estimate idiosyncratic prices using panel data from the Houston lodging market and analyses the hotel-specific determinants of *strategic* revenue management. Results suggest that age, brand affiliation, competition and location of hotels significantly affect the hotels' *strategic* revenue management in the long run.

**Keywords:** strategic revenue management, idiosyncratic room rates, spatial panel econometrics, weighted least squares (WLS)

## 1 Introduction

In contemporary hotel management, a general consensus is reached between the academia and industry that competitive revenue management is a prerequisite of success. Effective revenue management policies and implementation have been credited with generation of additional revenues (Koushik, Higbie, & Eister, 2012), as well as improving occupancy rates during low points of the business cycle (Ortega, 2016). Major players in the industry have extensively invested on pertinent systems and human resources development (Pekgun et al., 2013). Consonant with the high interest of the practitioners, considerable research efforts are explicated by the rich research stream that has revolved on the topic (Queenan, Ferguson, & Stratman, 2011).

Lately, efforts on this topic have attempted to draw the distinction between two different dimensions of revenue management: *tactical* and *strategic*. Although conventional research views revenue management as a pricing tool to respond to expected demand changes and pertaining market conditions in the near future (Weatherford & Kimes, 2003), recent studies point out that such practice is short-term in nature and that greater consideration should be given to long-term price positioning due to its prolonged effect on hotel performance (Noone, Canina, & Enz, 2013). In this regard, Abrate and Viglia (2016) consider both dimensions of revenue management and posit many of the price-determining factors such as hotel

characteristics, seasonality, and competition are *tactical* in nature and that pertaining price changes do not explain the long-term *strategic* decisions of hotels.

Whereas the importance of *strategic* revenue management is cited, related empirical works have been rather sparse. Specifically, despite the agreement on long-term effects of *strategic* pricing, little is known about its determinants, or hotel-specific factors that influence long-run pricing decisions. An important reason is the difficulty in attributing price changes to each dimension, as both dimensions simultaneously influence room rates. In order to resolve the issue, Noone et al. (2013) used “relative price position” of the hotel to evaluate the hotel’s strategic stance, while Abrate and Viglia (2016) utilized both the hotel’s catalogue and actual prices to partial-out the *strategic* and *tactical* components.

In spite of their meaningful contributions, however, the above methods may not be easily replicated in future studies, as calculation of relative price position requires definition of the competitor set a priori, and catalogue prices may not be available for many hotels. In this light, Kim et al.’s (2016) study is noteworthy in that it utilizes the spatial econometric model to decompose room rates into two components: *systematic* and *idiosyncratic*. According to Kim et al. (2016), room rates are in part *systematic*, which imply the joint outcomes of hotels under price competition, product differentiation and market conditions at every time period, and therefore, price changes through these effects are not representative of the *idiosyncratic*, strategic price positioning of hotels. In this line of reasoning, we posit that *systematic* portion of room rates include the *tactical* variations in room rates induced by competition, differentiation and market conditions, while the *idiosyncratic* variations are wholly attributed to the hotel’s *strategic* relative price positioning.

Therefore, the objective of this study is as follows. Although the literature on hotel revenue management distinguishes *strategic* revenue management from its *tactical* counterpart, only a handful of studies have been available to date. Moreover, these studies (Kim et al., 2016; Abrate & Viglia, 2016; Noone et al. 2013) focus on the long-run effects of *strategic* revenue management, while little is known about the individual characteristics of the hotel that lead to differences in pricing decisions. To fill this gap, the current study utilizes panel data from the Houston lodging market and the spatial econometric model to 1) decompose room rates into *systematic* and *idiosyncratic* parts and 2) examine the effect of hotel-specific factors on *idiosyncratic* room rate variations.

## **2 Methodology**

Quarterly data of the Houston lodging market statistics between 2005 Q1 to 2016 Q1 (45 quarters) was obtained from Source Strategies, Inc database, which includes all hotel properties that report \$18,000 or more in quarterly revenues. Using the Smith Travel Research US Chain Scale Index, the sampled hotels were categorized into six segments: luxury, upper upscale, upscale, upper-midscale, midscale, and economy. Independent hotels not included in the Chain Scale Index were assigned to the independent category. As a result, a total of 309 hotels were sampled, and the total number of observations was 13,287. Following Lee’s (2015) approach, data on the location attributes of each hotel was also gathered: the distances to the nearest airport,

Amtrak station, beach, and interstate highway exit, as well as the number of tourist attractions and competitors within each hotel's 10-mile radius.

The following spatial lag model (SLM), in matrix notation, is first estimated to partial-out systematic variations from the room rates:

$$\text{ADR} = \gamma \mathbf{W}\text{ADR} + D_{\text{LUXURY}}\alpha_1 + D_{\text{UPPERUP}}\alpha_2 + D_{\text{UPSCALE}}\alpha_3 + D_{\text{UPPERMID}}\alpha_4 + D_{\text{MIDSCALE}}\alpha_5 + D_{\text{ECONOMY}}\alpha_6 + \mu_t + \varepsilon \quad (1)$$

where ADR is the vector of average daily room rates and  $\mathbf{W}$  is the NT-by-NT spatial weighting matrix that formalizes the network structure among hotels. Elements  $w_{ij}$  are defined as the squared inverse of the distance between hotels  $i$  and  $j$ , which takes a nonzero value for two neighbouring hotels. To ensure that each hotel has at least one neighbour, the threshold distance was set at 3.73 miles, which was the minimum distance to ensure that all hotels had at least one neighbour (competitor) to ensure feasible spatial econometric estimation. Before pre-multiplying,  $\mathbf{W}$  is row-standardized so that each row sums to unity. Hence  $\mathbf{W}\text{ADR}$  can be interpreted as the distance-weighted average of neighbour prices, and significant  $\gamma$  implies variation in hotels' ADR from price competition. Segment dummies account for average prices of the segment, and time effects vector  $\mu_t$  controls for systematic market effects that may be correlated with time, such as economic conditions, seasonality and trend.

As a result,  $\varepsilon$  can be understood as the *idiosyncratic*, or hotel-specific, price variation unexplained by the systematic factors, but rather attributed to the management decisions of respective hotels. After estimation of (1),  $\hat{\varepsilon}$  can be approximated as:

$$\hat{\varepsilon} = \text{ADR} - \hat{\gamma}\mathbf{W}\text{ADR} - D_{\text{LUXURY}}\hat{\alpha}_1 - D_{\text{UPPERUP}}\hat{\alpha}_2 - D_{\text{UPSCALE}}\hat{\alpha}_3 - D_{\text{UPPERMID}}\hat{\alpha}_4 - D_{\text{MIDSCALE}}\hat{\alpha}_5 - D_{\text{ECONOMY}}\hat{\alpha}_6 - \hat{\mu}_t \quad (2)$$

where parameters with hats refer to the empirically estimated coefficients. Two variables, means ( $\mu_\varepsilon$ ) and standard deviations ( $\sigma_\varepsilon$ ), are calculated from  $\hat{\varepsilon}$  to examine the *strategic* components of revenue management regarding relative position and consistency (Noone et al., 2013).

As a final step, the two *strategic* revenue management variables,  $\mu_\varepsilon$  and  $\sigma_\varepsilon$ , are regressed on the set of observable, hotel-specific characteristics:

$$\mu_\varepsilon = \beta_0 + \text{AGE}\beta_1 + \text{BRAND}\beta_2 + \text{AIRPORT}\beta_3 + \text{AMTRAK}\beta_4 + \text{BEACH}\beta_5 + \text{INTERSTATE}\beta_6 + \text{ATTNUM}\beta_7 + \text{COMPETITORS}\beta_8 + v \quad (3)$$

$$\sigma_\varepsilon = \beta_0 + \text{AGE}\beta_1 + \text{BRAND}\beta_2 + \text{AIRPORT}\beta_3 + \text{AMTRAK}\beta_4 + \text{BEACH}\beta_5 + \text{INTERSTATE}\beta_6 + \text{ATTNUM}\beta_7 + \text{COMPETITORS}\beta_8 + v \quad (4)$$

where AGE is the hotel's number of years in operations, BRAND the binary variable taking a value of unity for brand hotels, AIRPORT, AMTRAK, BEACH and INTERSTATE the hotels' distances in miles to each location, and ATTNUM and COMPETITOR the number of tourist attractions and hotels within 10-mile radii. Descriptive statistics of the variables used in this study are shown in Table 1. The mean of  $\mu_\varepsilon$  is zero as expected, as all idiosyncratic price movements are calculated as deviations from the theoretical average. However, the variance among the idiosyncratic price movements is considerably large. It is seen that during the period a

hotel priced \$17.03 higher than a similar competitor, while another priced \$10.10 lower.

**Table 1.** Descriptive Statistics of Data

Variable	Mean	St. Dev	Max	Min	Variable	Mean	St. Dev	Max	Min
$\mu_e$	0.00	3.47	17.03	-10.10	AMTRAK	10.15	0.30	44.28	0.33
$\sigma_e$	19.69	5.31	38.43	11.01	BEACH	22.17	0.78	67.98	6.79
AGE	22.27	9.79	69.00	9.00	INTERSTATE	2.66	0.53	16.44	0.07
BRAND	0.77	0.42	1.00	0.00	ATTNUM	14.91	0.27	19.00	2.00
AIRPORT	11.16	6.03	54.09	0.32	COMPETITOR	21.87	0.69	58.00	2.00

### 3 Result

Due to concerns in heteroscedasticity, estimation of models (3) and (4) were done via Weighted Least Squares (WLS). Before inference, each variable was checked for endogeneity using the Wu-Hausman test, which yielded no significant statistic for all variables at  $p < 0.1$ . Results in Table 2 show that a number of hotel characteristics significantly influence *strategic* pricing. First, older hotels have on average higher idiosyncratic prices, but also have greater price variations. It is implied that experienced revenue managers adjust room rates flexibly accordingly to demand, and in turn, achieve higher revenues. Hotels that are branded and closer to train stations have higher mean and lower variance of idiosyncratic prices, suggesting that these are factors for consistent premiums in room rates. Meanwhile, proximity to interstate exits reduce mean and increase variance, suggesting inferiority of location but greater freedom in their pricing decisions. Lastly, number of competitors does not reduce the mean but only the variance of idiosyncratic prices, implying less freedom in pricing.

**Table 2.** Estimation Results for Weighted Least Squares (WLS) Regression

Variable	Coef	Std. Err	t-stat	p-value	Coef	Std. Err	t-stat	p-value
<b>Model 1: Dependent Variable <math>\mu_e</math></b>				<b>Model 2: Dependent Variable: <math>\sigma_e</math></b>				
(Intercept)	1.36	0.98	1.39	0.17	18.01	2.69	6.70	0.00
AGE	0.03**	0.01	3.22	0.00	0.05*	0.02	2.35	0.02
BRAND	0.48**	0.20	2.46	0.02	-2.37***	0.54	-4.41	0.00
AIRPORT	-0.00	0.03	-0.13	0.90	-0.04	0.09	-0.43	0.67
AMTRAK	-0.10**	0.04	-2.66	0.01	-0.27*	0.11	-2.56	0.01
BEACH	-0.02	0.05	-0.42	0.68	0.16	0.13	1.20	0.23
INTERSTATE	0.08*	0.04	2.13	0.03	0.32**	0.10	3.04	0.00
ATTNUM	-0.06	0.04	-1.60	0.11	0.18	0.11	1.66	0.10
COMPETITOR	-0.01	0.01	-0.91	0.36	-0.12***	0.02	-6.51	0.00

R<sup>2</sup>: 0.18, Adj. R<sup>2</sup>: 0.16, F-stat: 8.12\*\*\*  
Sig. codes denote: \*: p<0.5, \*\*: p<0.01, \*\*\*: p<0.001

R<sup>2</sup>: 0.37, Adj. R<sup>2</sup>: 0.35, F-stat: 21.13\*\*\*

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## 4 Conclusion

In line with the growing research interest on *strategic* dimension of revenue management, this study explored the effects of hotel-specific factors on idiosyncratic price variables. Results suggest that age, brand affiliation, number of competitors, as well as location significantly affect strategic revenue management decisions of hotels. Brand affiliation and proximity to train station yielded consistent pricing power over the sample period, while experienced hotels improved performance with flexible revenue management strategies. Proximity to interstate exits allowed greater degree of price variability, albeit the lower rates, whereas competition reduced such degree. Implications of the study are straightforward. Brand affiliation of hotels will allow a stable pricing power over time, while hiring experienced revenue managers in hotels will likely improve performance. Location and competition of the hotel must be taken into consideration when developing revenue management strategies, as they not only affect the room rates but also the long-run revenue management strategies.

This study is not free from limitations. The nature of spatial panel data requires use of caution when generalizing the results to other markets, as market geography, structure, and behaviour of the sellers may vary considerably. The panel data also includes recessionary period, which would have influenced the revenue managers' decisions. Nevertheless, as the first empirical investigation on the determinants of *strategic* revenue management, findings of the study significantly contribute to the literature. Future studies seem warranted on the effects of other tangible and intangible hotel characteristics, as well as on data from diverse geographies, market structures and time to further the understanding on revenue management theory and practice.

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