Research Article

Do you really know who your customers are?: A study of US retail hotel demand

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ABSTRACT This study uses booking data from 28 US hotels to investigate the validity of two key assumptions in hotel revenue management: (1) customers who book later are willing to pay higher rates than customers who book earlier; and (2) demand is stronger during the week than on the weekend. Empirical results based on an analysis of booking curves, average paid rates and occupancy rates for group, restricted retail, unrestricted retail and negotiated demand segments challenge the validity of these assumptions. Based on these findings, new recommendations for segmenting transient demand and setting weekday versus weekend pricing are provided.

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INTRODUCTION

Within the airline industry, revenue management (RM) has a well-established track record of increasing profitability and has played an integral role in strategic and tactical decision-making. Over time, the utilisation of analytics has evolved from using simple descriptive analysis to manage inventory to solving complex optimisation problems that automatically set rate[1] (price) availability and other inventory controls. Based on the initial success of RM within the airline industry, it was not long before other industries began to adopt these practices. Currently, there are numerous industries using RM and many others considering using RM, including airlines, hotels, car rentals, casinos, restaurants, grocery chains, golf courses, cruise lines, apartment rentals, sports, performing arts, media and so on (for example, see Heching *et al*, 2002; Kimes and Schruben, 2002; Kimes *et al*, 2002; Kuyumcu, 2002; Lieberman and Dieck, 2002; Hawtin, 2003; Lippman, 2003; Vinod, 2004; Kimes, 2005; Garrow *et al*, 2006; Gu, 2006; Garrow and Ferguson, 2008). Although the growth in RM across industries is impressive, one may nonetheless question the wisdom of applying RM techniques originally developed for the airline industry to other industries without considering market characteristics.

The objective of this paper is to investigate whether fundamental assumptions related to customer demand patterns typically observed in the airline industry also hold for the US retail hotel sector. Empirical results, based on a study of 28 US hotels representing five different brands and booking histories for 420 arrival dates (60 weeks), suggest that hotel retail demand is different from airline demand. Specifically, this study challenges two classic assumptions used for the majority of hotel RM applications, namely (1) late booking customers are willing to pay higher rates than early booking customers; and (2) weekday demand is higher than weekend demand.

In our analysis, hotel demand is classified into four distinct segments according to macro-channel as well as restrictions typically associated with the demand classes. *Group demand* refers to bookings that are associated with an allocated block of rooms, as would be the case for a conference or a corporate event. *Negotiated demand* refers to bookings that are associated with a corporate customer or large booking agency. Rates for this segment generally do not vary over time once they are negotiated and are available only to corporate employees or customers that book through an agency. The final two segments fall under the category of *retail demand*. Retail demand refers to all demand that is not group or negotiated. Retail customers book through channels that are available to the general public. In general, retail demand can be classified as *unrestricted* or *restricted*. In this study, unrestricted retail demand refers to bookings that have no advance purchase requirements and no cancellation fee.[2] Restricted retail demand refers to bookings that have associated restrictions, specifically advance purchase requirements, cancellation fees and/or customer qualifications (for example, requires American Association of Retired Persons (AARP) or American Automobile Association (AAA) membership). Unrestricted retail demand is generally considered to be more valuable, as these customers are assumed to be willing to pay more for liberal cancellation policies and the ability to book close to arrival. Figure 1 portrays the relationships among four customer segments that define *total demand*.

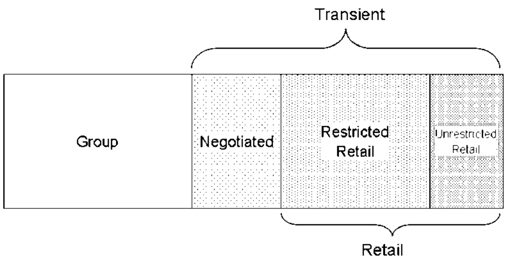

Figure 1: Breakdown of total hotel demand.

The expectation that late booking customers are willing to pay higher rates is shared across the airline, hotel and car rental industries (for example, see Belobaba, 1989 and Alstrup *et al*, 1986 for airline applications; Ben Ghalia and Wang, 2000; Baker and Collier, 2003 and Schwartz, 2000 for hotel applications and Carroll and Grimes, 1995 for car rental applications).

The second assumption examined in this study is that hotel demand is stronger on weekdays versus weekends, particularly for business-oriented properties that comprise the majority of hotels for large hospitality enterprises (and that also forms the basis for this analysis).[3] This assumption commonly appears in the hotel literature (Jeffrey and Barden, 2000; Choi and Kimes, 2002) and has been validated by several empirical studies. For example, Rushmore (2000) empirically observed that transient demand is weaker on weekends and Jeffrey *et al* (2002) found that business customer occupancy was higher on weekdays using 15 years of hotel data from England. Many hotels and industry experts believe this assumption to be true, as seen by the fact that some hotels promote weekend products to compensate for the perceived 'weak' or 'soft' weekend demand:

> J. W. Marriott Jr, CEO, Marriott International Inc. (as cited in Ruggles, 2008): 'The company (Marriott) continues to see weak weekend leisure demand and is beginning to see softer mid-week demand.'

> Jonathan Langston, Managing Director, TRI Hospitality Consulting (as cited in Strauss, 2007): 'They (London, Paris, Amsterdam hotels) balance strong weekday demand from business with weekend tourist traffic.'

> *Hotels Magazine* (2007): 'Sage is partnering with established brands like Sheraton, Marriott, Best Western and Holiday Inn, with the goal of opening about 20 parks in the United States by 2008. It is focusing on suburban and semi-urban locations that have steady weekday business travel but soft weekend sales.'

It is important to note that these observations refer to total demand versus retail demand. Although the negotiated segment, mainly comprised of midweek business customers, can be strong during the weekdays, the price for this segment is typically fixed by a pre-determined contract. However, if the assumption of strong midweek demand is primarily based on the patterns from negotiated demand (or total demand) and not the pure retail, it could mislead important retail pricing decisions.

To investigate the validity of these assumptions, we undertook extensive statistical analysis using booking curves, average paid rates and occupancy rates. Although it is not possible to directly observe the validity of these two assumptions using only actual booking data, it is possible to observe whether the expected relationships among these assumptions and booking curves, prices and occupancy rates hold. As shown in Table 1, one would expect to observe the following relationships if the assumptions were valid.

Empirical results based on an analysis of the expected outcomes suggest that these assumptions may not be valid for US hotel retail customers. Consequently, new recommendations for how to apply RM to transient hotel customers and how to price weekday versus weekend rates are presented. To this extent, we hope that this study will serve as a broader warning of applying model assumptions developed for the airline industry to other industries without considering the market

Table 1: Anticipated relationships between demand assumptions and observable data

Assumption	*Expected outcome that can be observed*
1. Late booking customers are willing to pay higher rates than early booking customers	• Higher-valued, unrestricted booking classes book later than lower-valued, restricted booking classes • Average paid rates increase as the arrival date approaches
2. Weekday demand is higher than weekend demand	• Occupancy rates are higher during weekdays • Booking rates are higher during weekdays

context. An example of such case is the price discrimination experiment by Amazon.com (for example, see Talluri and van Ryzin, 2004, pp. 614–619 for details). In the airlines, charging different fares for the same economy seat is a widely accepted practice. However, contrary to the airline passengers who are used to paying different prices for the same type of seats on the same flight, Amazon customers regarded the price discrimination as unfair.

DATA

The data for this analysis are based on 60 weeks of booking data from March 2006 to April 2007. The data set represents 28 different hotels in the United States that span five different brands ranging from limited to premium full service. The hotels include five luxury, eight premium full-service, six full-service business, six limited service and three extended stay hotels. These hotels are located in city centre (12), suburban (10), airport (5) and highway (1) locations. Of these hotels, only one property is located in a purely leisure destination, the others are either heavily business oriented or mixed business-leisure properties. For each property, competitive unrestricted retail rates are available for two to seven competitors. Competitor rate data were obtained through a company that routinely collects shopping data through various channels including Global Distribution Systems and the Internet.

ARE LATE BOOKING CUSTOMERS WILLING TO PAY HIGHER RATES?

Different statistical analysis can be used to investigate the assumption that late booking customers are willing to pay higher rates than early booking customers. Specifically, if the assumption is true, one would expect that higher-valued, unrestricted classes book later than lower-valued, restricted classes and that the average rate paid by customers increases as the arrival date approaches.

Comparison of booking profiles

If higher-valued customers tend to book later than lower-valued customers, one would expect to see the distribution of unrestricted bookings more concentrated towards the day of arrival relative to the distribution of restricted bookings. However, this relationship is only weakly observed in the data. On average, restricted retail bookings occur 3 days earlier than unrestricted retail bookings (17 versus 20 days, respectively), as shown in Table 2(a). The median booking days from arrival are similar (5 versus 7 days). Also, although in general, the unrestricted bookings appear later in the booking horizon than the restricted bookings, 26.6 per cent of the arrival dates in our data set have restricted bookings that appear (on average) later than the unrestricted bookings.

Table 2(b) and (c) shows the same statistics for the 3 largest and 10 smallest hotels, respectively, where size is defined in terms of the number of bookings. The three largest hotels have 27.6 per cent of total retail bookings and the 10 smallest hotels have 10.2 per cent. For large hotels, the restricted retail booking dates are on average closer to arrival dates than unrestricted retail booking dates, contrary to the common belief.

In addition to comparing descriptive statistics for unrestricted and restricted retail segments, one can examine their booking profiles. Figure 2(a), which portrays the log of bookings for the restricted and unrestricted retail segments by days before arrival, indicates that statistically there is no discernable difference between the slopes of the booking profiles for restricted and unrestricted retail segments. The slopes of linear approximations for log unrestricted and log restricted bookings are displayed in Table 3. A two-sample *t*-test cannot reject the null hypothesis that the slopes are the same ($P=0.55$). For comparison, the log of bookings for negotiated and all retail bookings are shown in Figure 2(b).

Finally, booking profiles can be examined in terms of their cumulative frequencies. If the assumption that higher-valued customers tend to book later than lower-valued customers is true, one would observe that the cumulative distribution of unrestricted demand lies below the cumulative restricted retail distribution. This is observed in Figure 3, as the cumulative distribution associated with the unrestricted retail bookings is slightly below the restricted booking cumulative distribution. This is

Table 2: Summary statistics of booking days for unrestricted and restricted retail segments

Demand	*Median*	*Mean*	*SD*
(a) *Statistics for overall bookings*			
Unrestricted retail	5	17.0	32.5
Restricted retail	7	20.0	34.4
(b) *Statistics for the three largest hotels*			
Unrestricted retail	9	24.9	41.4
Restricted retail	7	20.7	36.2
(c) *Statistics for the 10 smallest hotels*			
Unrestricted retail	3	12.8	28.1
Restricted retail	6	16.1	28.9

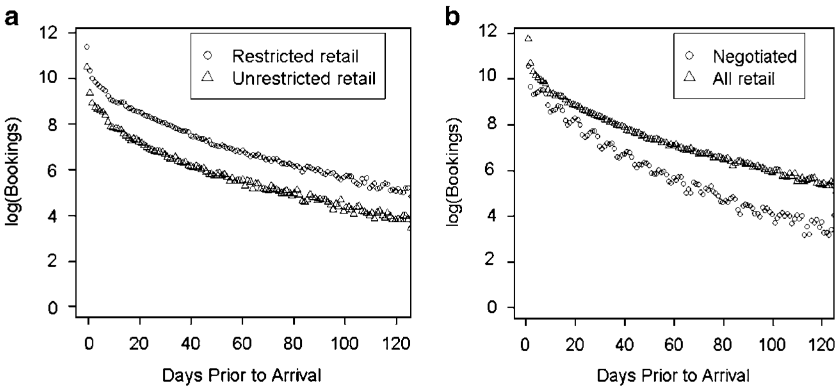

Figure 2: Log of arrivals for restricted and unrestricted retail segments. (**a**) Log of unrestricted and restricted retail bookings. (**b**) Log of negotiated and all retail bookings.

Table 3: Slope of linear approximation for log(unrestricted bookings) and log(restricted bookings)

Demand	*No. of observations*	*Slope*	*SE*	*P-value*	R^2
Unrestricted retail	348	−0.0194	0.00039	$\ll 0.001$	0.88
Restricted retail	365	−0.0191	0.00032	$\ll 0.001$	0.68
Negotiated	328	−0.0237	0.00052	$\ll 0.001$	0.87

statistically confirmed via the Kolmogorov–Smirnov test (bootstrap version),[4] which rejects the null hypothesis that the unrestricted retail booking curve does not lie above the restricted booking curve ($P = 0.076$).

To summarise, the statistical analysis provides only weak evidence that the distribution of unrestricted bookings is more concentrated towards the day of arrival relative to the distribution of restricted bookings. Moreover, for large hotels, we observe the opposite; restricted retail products are booked later than unrestricted retail products on average. Hence, from a practical perspective, the assumption that higher-valued customers book closer to arrival date may not be entirely appropriate for hotel RM applications.

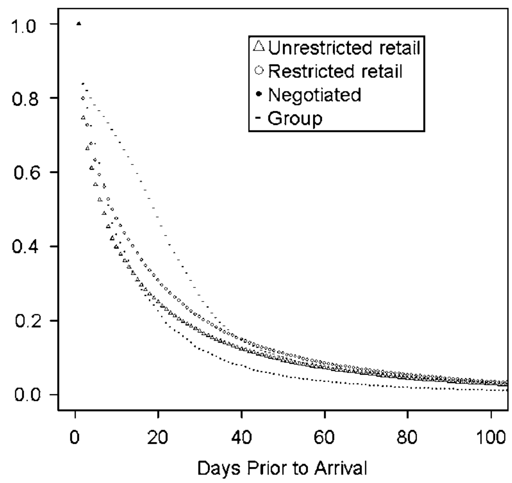

Figure 3: Cumulative frequency distributions by demand segment and days before arrival.

Comparison of average paid rates

The assumption that higher-valued customers tend to book later than lower-valued customers can also be investigated by comparing average paid rates. Figure 4 shows the evolution of average paid prices in the booking cycle for traditional hotel demand segments. Consistent with expectation, Figure 4 illustrates that the unrestricted retail rates are, on average, 35.6 per cent higher than all retail rates. However, the average rates paid (defined using arrival date as the unit of analysis) for hotel rooms *declines as the day of check-in approaches, for both retail and negotiated demand segments*. This result is also observed for competitor hotels. Table 4 summarises linear regression models that report the slopes of the average daily rate profiles. Note that the decline in average daily rates is steepest for the unrestricted retail segment (that is, a decline of \$0.59 per day).[5] This is somewhat counterintuitive given that unrestricted retail products are generally designed for customers who book closer to arrival date (and in theory are willing to pay more for the flexibility of booking later and the ability to change plans without cancellation fees).

One note of caution applies to the above result. Specifically, the result in Figure 4 may be

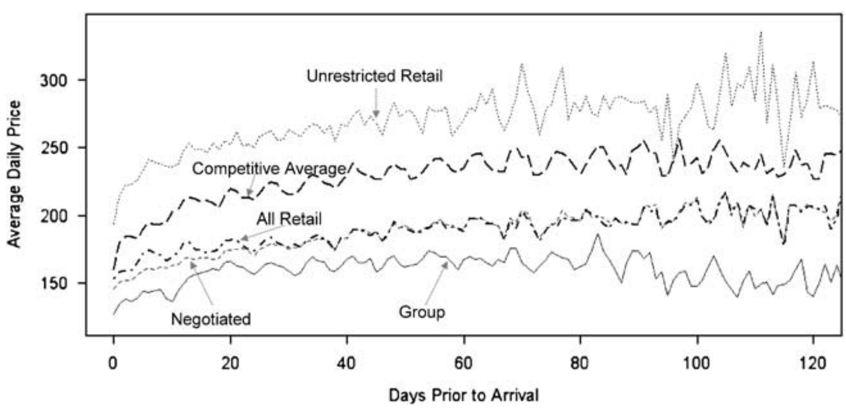

Figure 4: Average daily prices by days before arrival.

Table 4: Regression results for average daily price as a function of days prior

Demand	*No. of observations*	*Slope*	*SE*	*P-value*
Unrestricted retail	95 515	0.589	0.01300	$\ll$0.001
All retail	314 666	0.269	0.00526	$\ll$0.001
Group	134 509	0.109	0.00658	$\ll$0.001
Transient	405 219	0.347	0.00450	$\ll$0.001
Competitor average	501 182	0.373	0.00383	$\ll$0.001

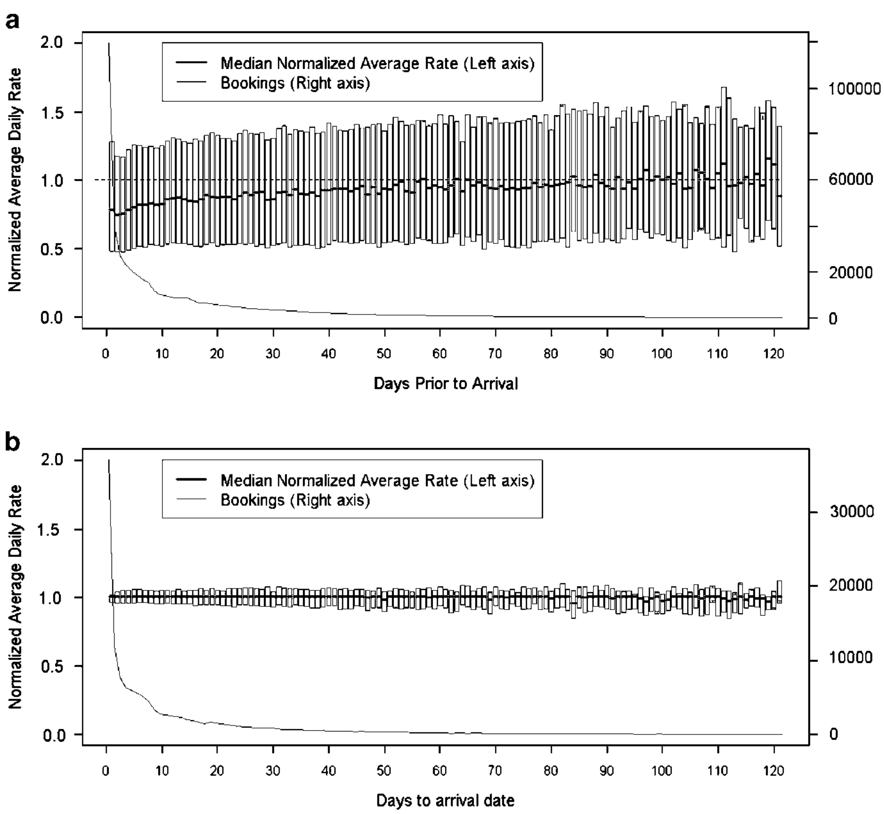

Figure 5: Restricted and unrestricted retail bookings and normalised rates by days before arrival. (**a**) Restricted retail bookings and average normalised daily rate. (**b**) Unrestricted retail bookings and average normalised daily rate.

influenced by ‘soft’ demand days in which a large number of bookings at deeply discounted rates occur close to the arrival date and/or in which a few bookings at very high rates occur far from the arrival date. In order to control for this potential effect, average booked rates were normalised to the average rate for each arrival date. Figure 5(a) and (b) portrays the normalised curves for restricted and unrestricted retail bookings, respectively. Figure 5 contains a box plot of average daily rates by days before arrival and the total bookings curve. The top and bottom edges of a box for a given number of days before arrival represent 25th and 75th percentiles of the normalised average daily rates.

Table 5: Regression results for normalised average rate as a function of days prior

Demand	*No. of observations*	*Slope*	*SE*	*P-value*
Unrestricted retail	93 096	−0.00010	0.0000253	≪0.001
Restricted retail	245 296	0.00190	0.0000558	≪0.001

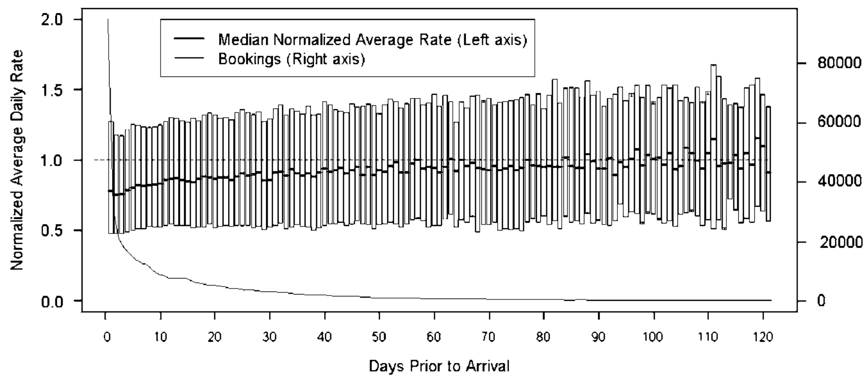

Figure 6: Restricted retail bookings and normalised rates by days before arrival (high restricted rate sales within 7 days to check-in excluded).

The normalised and non-normalised average daily rate curves paint a slightly different picture. Table 5 summarises the results of linear regression models associated with the slope of the normalised average daily rate profiles. Consistent with the non-normalised data, the restricted retail rates tend to decrease as the arrival date approaches; however, in contrast to the non-normalised data, the unrestricted retail rate slightly increases as the arrival date approaches. Nonetheless, from a practical perspective, the estimated increase in the normalised unrestricted retail rate, although statistically significant, will have little to no financial implications (the increase is only 0.2 per cent of the average daily rate per day).

Figures 4 and 5 do not consider how product availability changes throughout the booking horizon, which may influence the observed average rate patterns. The normalised and actual average rates paid can decrease when hotels over protect inventory, resulting in discount products available only close to check-in dates. If the prices of these discounted products are very low for some arrival dates, we may observe that aggregated average rates paid (as shown in Figure 5) decrease as the check-in date approaches, even when the prices on other arrival dates do not. To ensure this is not happening, we excluded arrival dates that had unusually high restricted bookings[6] within 7 days of check-in and plotted the normalised average rates again.

Figure 6 shows a decrease in the normalised average rates paid. This decrease is similar to that observed in Figure 5. In addition, regression results for the two data sets are almost identical (0.0018 versus 0.0019 slope coefficients). Thus, we can conclude that in our data, normalised average rates paid are not being influenced by discount product availability.

To summarise, the analysis of booking curves for unrestricted and restricted classes as well as the average daily rates paid by customers provide only weak evidence in support of the assumption that late booking customers are willing to pay higher rates than early booking customers. The results reported in this section were obtained with data containing all length of stay products; however, these findings are consistent for each length of stay products as well (the analysis in this section was also repeated separately for different length of stay products).

IS WEEKDAY RETAIL DEMAND HIGHER THAN WEEKEND DEMAND?

Statistical analysis can also be used to investigate the assumption that weekday (Sunday through Thursday) demand is higher than weekend (Friday and Saturday) demand. Specifically, if the assumption were true, one would expect that occupancy rates and booking rates are higher during the weekdays, as the belief that retail demand is strongest midweek will lead to a general pricing strategy of charging higher rates during the week and lower rates during the weekend. The strategy is based upon the rationale that if occupancies are lower on the weekend, then prices should be lowered to stimulate more demand. Figure 7 clearly demonstrates the presence of such a pricing strategy both at the properties used in this study set as well as those of their competitors.

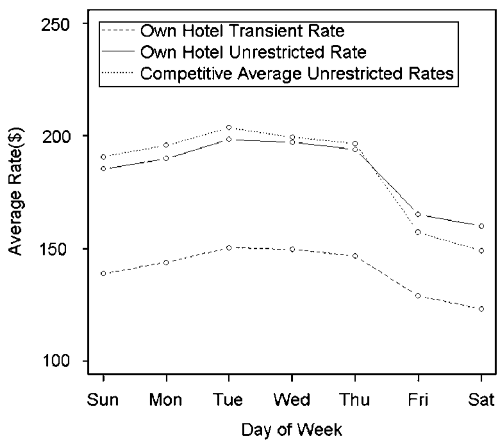

Figure 7: Transient, unrestricted retail and unrestricted competitor rates by day of week.

Comparison of occupancy rates and demand

Latent (or unconstrained) demand is difficult to measure. However, constrained demand is often strongly correlated with unconstrained demand when capacity is not tight and can be measured. Occupancy is simply the constrained demand divided by the capacity. An analysis of occupancy rates for total demand reveals a pattern that is consistent with current industry intuition, namely, that hotels tend to be busier during the weekdays versus weekends (see Figure 8(a)). Specifically, the weekday occupancy rates are consistently higher than weekend occupancy with the exception of Sunday. Richer insights can be gained by examining occupancy rates by demand segments (see Figure 8(b)) which reveal,

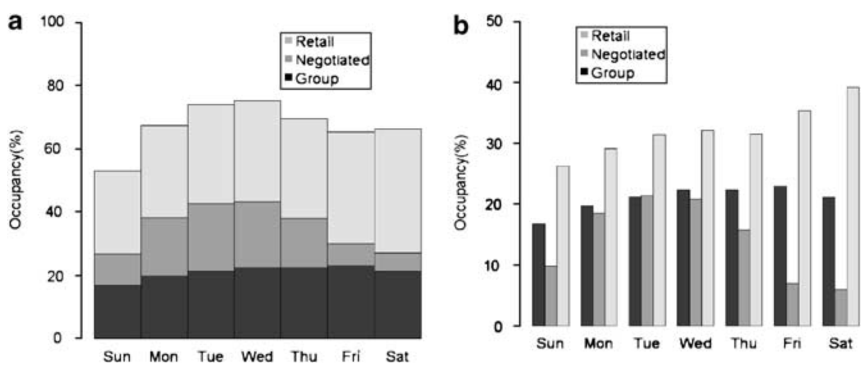

Figure 8: Average occupancy by day of week and demand segment.

Table 6: *t*-test from ANOVA model of weekend retail, transient and total rooms

Demand	*Coefficient*	*t-statistics*	*P-value*	*Interpretation*
Retail rooms sold	1.161	33.3	$\ll 0.001$	Stronger retail demand on weekends
Transient rooms sold	−0.304	−6.36	$\ll 0.001$	Stronger transient demand on weekdays
Total rooms sold	−0.122	−1.46	0.145	Cannot determine which is stronger

Table 7: Summary of analysis, findings and implications

Assumption	*Expected outcome*	*Observed outcome*	*Implication*
1. Late booking customers are willing to pay higher rates.	Higher-valued customers book later than lower-valued customers.	Higher-valued retail customers book at the same pace or only slightly later than lower-valued retail customers.	Raises serious doubts regarding the assumption that late booking customers are willing to pay higher rates. If they are willing to pay higher rates, there is no evidence that they are being charged higher rates.
	Average rates paid increase as the booking date approaches the arrival date.	Average rates for restricted retail demand decrease as day of arrival approaches. Average rates for unrestricted retail demand are flat or slightly increasing.	
2. Weekdays have higher demand than weekends.	Occupancy is higher during the week than on the weekend.	Total hotel occupancy is not significantly greater during the week than on the weekend. Although transient demand is stronger during the week, retail demand is in fact highest on the weekend.	Based on occupancy, weekday demand is not much stronger than weekend demand. Moreover, the key retail segment experiences peak demand on the weekend. At the same time, retail rates are significantly lower on the weekend. One must ask the question – is it really necessary to lower rates so much on the weekend?
	Weekday rates are higher than weekend rates.	Own property and the competitive set consistently price lower on the weekend.	

counter to current business intuition, that the retail demand is actually stronger on the weekends (Friday and Saturday) than on weekdays. This observation is confirmed via an analysis of variance (ANOVA) model of retail, transient and total rooms sold (Table 6). The coefficients capture how much the weekend retail and total rooms sold differ from the weekday. In the case of retail occupancy, the estimate for the weekend coefficient is positive and statistically significant, indicating that, on average, the weekend retail demand is larger than the weekday retail demand.

One may question whether the availability of rooms is influencing the demand patterns in Figure 8. For instance, if the hotel is sold out on most weekdays with high negotiated demand, the graph would look like Figure 8(b), but this would not necessarily mean that the retail demand is weaker on weekdays compared to weekends. However, we find that the occupancy is less than 95 per cent for 95 per cent of the time (both weekdays and weekends), hence the capacity is rarely influencing (unrestricted) retail demand patterns.

Table 6 describes the statistical tests for the observations from Figure 8. When the traditional definition of 'transient demand' that combines retail and negotiated is used, model results show that the transient occupancy for weekends is lower than the weekday occupancy. However, if we focus only on the retail segment, we see that retail demand is in fact strongest on the weekends (P-value $\ll 0.001$), which reconfirms the finding from Figure 8. The retail demand pattern is opposite to the pattern observed for the combined transient demand pattern (defined as the combination of negotiated and retail demand) – the latter of which forms the foundation for a common industry perception of weaker weekend demand compared to weekday demand. In the case of total occupancy, the average weekday occupancy is not statistically different from the weekend occupancy.

This is a particularly interesting finding, as most current hotel RM systems seek to optimise the transient segment. Negotiated rates are generally fixed, thus the price cannot be adjusted up or down. Moreover, most corporate negotiated rates have a last room availability (LRA) clause, that is, hotels are obliged to offer rooms to products with LRA as long as there is a vacancy and thus cannot control the availability of these products in the RM system. The hotels used for this study have 71.7 per cent of the negotiated rooms sold under the LRA accounts. Even when transient demand is strongest during the week, which is the case on average for this study, a strategy that seeks to set length of stay controls or optimise rates based on a transient forecast would lead to suboptimal decisions. We submit that it is the retail segment in isolation that should be the focus of 'individual demand' RM, that is, dynamic pricing (rate optimisation) and inventory control actions.

It is also important to note that because retail demand is really strongest during the weekend and softest during the week, one may raise questions about the appropriateness of having lower retail rates on the weekends. Further study is required before one can conclude that having lower rates on the weekend is an incorrect (or correct) strategy. There are many factors that are likely to impact customers' willingness to pay for higher retail rates on the weekend, including price elasticity and competitive rates.

DISCUSSION

Using data from 28 different hotels, this paper investigates two assumptions common in the application of hotel pricing and RM: (1) customers who book later are willing to pay higher rates than customers who book earlier; and (2) demand is stronger during the week than on the weekend. Empirical analysis indicates that rates, particularly retail rates, do not increase as the day of arrival approaches. Assumption two, although seemingly true in the aggregate, does not apply to the retail demand segment, yet the retail demand segment is the only segment impacted by traditional RM and dynamic pricing strategies. These findings challenge the current pricing and RM practices of most hotel companies. Table 7 provides a summary of the analysis, findings and implications from this study.

One possible explanation for why hotel rates do not increase as the arrival date approaches – as observed in the airline industry – could be due to the different capacity constraints between the two industries. In general, airlines are more capacity constrained than hotels. The International Air Transport Association (2008) reports a North America average utilisation (load factor) of 80.9 per cent in 2006, where US hotels had an average occupancy rate of 63.4 per cent in the same year (Smith Travel

Research, 2007). According to classic microeconomic theory, a positive shift of supply in a competitive market with other factors equal will result in lower equilibrium prices (for example, see Varian, 1992).

Differentiation is another key factor that must be considered when translating traditional airline RM to the hotel industry. It is hard to differentiate one airline seat from another for a specific itinerary. Both leave from the same (or one of a few) origin airports and arrive at the same (or one of a few) destination airports. Hotels, on the other hand, are strongly differentiated by their location. Only one hotel can be closest to a traveller's intended destination. Finally, hotels have a tremendous advantage over airlines in their ability to differentiate the customer experience through amenities and quality of service. Hotels seemingly have many opportunities to differentiate by both price and product attributes.

The combination of lower utilisation rates and greater product differentiation suggests that hotels should apply approaches different from those learned from traditional RM (as practised by the airline industry). Simply matching competitor rates to avoid losing market share is not necessarily a profit optimal strategy for hotels. On days when inventory is near capacity, traditional RM tactics deliver tremendous value, but these should be augmented by incorporating price response of demand and competition effects. On days when demand is soft and occupancy is projected to be low, price- and competition-based strategies are likely to be more effective.

In this study, only slight differences in the booking patterns between high- and low-valued customers were observed. The fact that high- and low-valued customers tend to book at the same time raises serious questions about the appropriateness of applying traditional RM methods that seek to protect rooms for late booking, high-valued customers. For example, Cooper *et al* (2006) show that applying the assumption 'high valued demand books later' can lead to a downward spiral of rates in situations where demand is low. When hotel demand is high, this is less of a concern. However, most in the hospitality industry saw their rates dramatically decrease during the recession after September 11, 2001. Leading hotel companies should revisit the assumptions inherent in their RM and pricing strategies as we enter into the next travel recession.

The general pricing strategy observed for properties in this study was to offer lower rates on the weekend. This strategy is common – if not dominant – in the hotel industry, yet the retail segment is strongest on the weekend, suggesting that retail customers might be willing to accept higher rates. Retail customers booking over the weekend are likely to be leisure customers who only have leisure time on the weekend. Would they still travel and book a hotel room if the rates were slightly higher than the current rates? In some cases, probably they would. An understanding of the retail customer's response to own and competitive rates would be required to determine if retail rates could be increased over the weekend.

Hotels must re-evaluate their pricing strategies and RM programmes. Central to this re-evaluation is to move from the traditional group-transient segmentation to further differentiate true retail demand from negotiated demand. Negotiated demand can only be priced at the time of contract negotiation. Once set, these rates are not (typically) changed during the contract period. It is mainly the retail segment that is subject to the full array of both inventory controls and pricing actions. While restricting the focus of existing RM models to the retail segment, hotels must develop new approaches to ensure that revenue is also maximised for the group and negotiated segments and, in turn, for the entire hotel.

Before optimising the rate structure, revenue mangers need to thoroughly explore the data and truly understand the retail response to price, competition and other non-price factors, particularly day of week. Modelling demand response to price with any degree of precision is not straightforward; however, developing such models will be a critical determinant of success for RM going forward. With a clear understanding of how demand will change under different market conditions and pricing structures, yield management and pricing models can be enhanced to incorporate the true nature of hotel demand. With this understanding, hotels will be able to use pricing as a powerful tool for maximising profit.

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NOTES

1 The terms 'price' and 'rate' are used interchangeably.
2 Rates that require cancellations before 5 pm on the day of check-in are defined as having no cancellation fee.
3 A potential counter-example would be a leisure-oriented resort hotel that has higher demand on the weekend. However, even in this case, many hotels believe they experience a midweek demand peak, as guests arrive on Friday to Sunday and stay for five or six nights.
4 The Kolmogorov–Smirnov (K–S) test is not exact when the underlying distribution is discrete. Since the days prior distribution in nature is discrete, the bootstrap version of the K–S test was used (Abadie, 2002).
5 Note that because 'days' decreases as one nears the check-in date, a *positive* coefficient associated with days from arrival implies that the average daily price *decreases*.
6 The criteria used to determine 'unusually high restricted bookings within seven days of check-in date' by each property is as follows: Percentage of restricted bookings within seven days to check-in $\geqslant$ {average + one standard deviation of percentage of restricted bookings within seven days to check-in}.

REFERENCES

Abadie, A. (2002) Bootstrap tests for distributional treatment effects in instrumental variable models. *Journal of the American Statistical Association* 97: 284–292.

Alstrup, J., Boas, S., Madsen, O.B.G. and Vidal, R.V. (1986) Booking policy for flights with two types of passengers. *European Journal of Operational Research* 27(3): 274–288.

Baker, T.K. and Collier, D.A. (2003) The benefits of optimizing prices to manage demand in hotel revenue management systems. *Production and Operations Management* 12(4): 502–518.

Belobaba, P.P. (1989) Application of a probabilistic decision model to airline seat inventory control. *Operations Research* 37(2): 183–196.

Ben Ghalia, M. and Wang, P.P. (2000) Intelligent system to support judgmental business forecasting: The case of estimating hotel room demand. *IEEE Transactions on Fuzzy Systems* 8(4): 380–397.

Carroll, W. J. and Grimes, R.C. (1995) Evolutionary change in product management: Experiences in the car rental industry. *Interfaces* 25(5): 84–104.

Choi, S. and Kimes, S. E. (2002) Electronic distribution channels' effect on hotel revenue management. *The Cornell Hotel and Restaurant Administration Quarterly* 43(3): 23–31.

Cooper, W. L., Homem-de-Mello, T. and Kleywegt, A. J. (2006) Models of the spiral-down effect in revenue management. *Operations Research* 54(5): 968–987.

Garrow, L., Ferguson, M., Keskinocak, P. and Swann, J. (2006) Expert opinions: Current pricing and revenue management practice across U.S. industries. *Journal of Revenue and Pricing Management* 5(3): 237–247.

Garrow, L.A. and Ferguson, M.A. (2008) Revenue management and the analytics explosion: Perspectives from industry experts. *Journal of Revenue and Pricing Management* 7(2): 219–229.

Gu, Z. (2006) Product differentiation: Key to Macau's gaming revenue growth. *Journal of Revenue and Pricing Management* 4(4): 382–388.

Hawtin, M. (2003) The practicalities and benefits of applying revenue management to grocery retailing, and the need for effective business rule management. *Journal of Revenue and Pricing Management* 2(1): 61–67.

Heching, A., Gallego, G. and van Ryzin, G.J. (2002) Mark-down pricing: An empirical analysis of policies and revenue potential at one apparel retailer. *Journal of Revenue and Pricing Management* 1(2): 139–160.

Hotels(Online edn.). (2007) Sage enters waterpark niche. 1 February, http://www.hotelsmag.com/article/CA6485006.html, accessed 22 December 2008.

International Air Transport Association. (2008) Monthly Traffic Analysis, January 2008. International Air Transport Association, http://www.iata.org/NR/rdonlyres/E868EDA2-B19F-4B02-9906-B6A4D0058752/0/MIS_Note_Jan08.pdf, accessed 13 January 2009.

Jeffrey, D. and Barden, R.R.D. (2000) Monitoring hotel performance using occupancy time-series analysis: The concept of occupancy performance space. *International Journal of Tourism Research* 2(6): 383–402.

Jeffrey, D., Barden, R.R.D., Buckley, P.J. and Hubbard, N.J. (2002) What makes for a successful hotel? Insights on hotel management following 15 years of hotel occupancy analysis in England. *Service Industries Journal* 22(2): 73–88.

Kimes, S.E. (2005) Restaurant revenue management: Could it work? *Journal of Revenue and Pricing Management* 4(1): 95–97.

Kimes, S.E. and Schruben, L.W. (2002) Golf course revenue management: A study of tee time intervals. *Journal of Revenue and Pricing Management* 1(2): 111–120.

Kimes, S.E., Wirtz, J. and Noone, B.M. (2002) How long should dinner take? Measuring expected meal duration for restaurant revenue management. *Journal of Revenue and Pricing Management* 1(3): 220–233.

Kuyumcu, A.H. (2002) Gaming twist in hotel revenue management. *Journal of Revenue and Pricing Management* 1(2): 161–167.

Lieberman, W.H. and Dieck, T. (2002) Expanding the revenue management frontier: Optimal air planning in the cruise industry. *Journal of Revenue and Pricing Management* 1(1): 7–24.

Lippman, B.W. (2003) Retail revenue management – Competitive strategy for grocery retailers. *Journal of Revenue and Pricing Management* 2(3): 229–233.

Ruggles, R. (2008) Hotels upgrade offerings to boost foodservice sales. *Nation's Restaurant News*, 30 June: 128–130.

Rushmore, S. (2000) Mid-rate extended-stay provides best return. *Hotels* 34(5): 42.

Schwartz, Z. (2000) Changes in hotel guest's willingness to pay as the date of stay draws closer. *Journal of Hospitality & Tourism Research* 24(2): 180–198.

Smith Travel Research. (2007) Smith Travel Research (STR) announced full year 2006 results for the U.S. lodging industry today. *Hospitality NET Industry News*, 26 January, http://www.hospitalitynet.org/news/4030077.html, accessed 13 January 2009.

Strauss, K. (2007) 2007's Hot spots for operations. *Hotels (Web extra)*, 1 March, http://www.hotelsmag.com/article/CA6485168.html, accessed 22 December 2008.

Talluri, K.T. and van Ryzin, G.J. (2004) *The Theory and Practice of Revenue Management*. New York: Springer.

Varian, H.R. (1992) *Microeconomic Analysis*, 3rd edn. New York: W.W. Norton.

Vinod, B. (2004) Unlocking the value of revenue management in the hotel industry. *Journal of Revenue and Pricing Management* 3(2): 178–190.