Does Willingness-To-Pay for Rate Conditions Change over the Booking Horizon? A novel time-dependent conjoint analysis approach

Bjorn Arenoe, Arenoe Marketing Intelligence, Jean-Pierre van der Rest, Leiden University

Abstract

This paper proposes a novel Choice-Based Conjoint (CBC) model to predict guests' preferences towards hotel room rate conditions as a function of time. Through the model the notion is explored whether willingness-to-pay for cancellation (without penalty) changes over the booking horizon. The choice model includes time as an additional 'attribute'. This attribute, however, does not present a feature of the choice propositions, but instead is associated with the choice context. An empirical study was carried out to test the proposed model using three common booking conditions (i.e., free cancellation, free date change, pay on departure). The results show strongly significant and positive time-dependent mean components for cancellation and date change booking conditions. Despite substantial model complexity and a limited sample size, all significant effects had expected directions (i.e., no parameter reversals) providing evidence of the robustness of the model. This indicates that the ability to cancel or change the date of a booking is preferred more when the booking horizon is longer. In other words, willingness-to-pay for rate conditions is higher when the advanced purchase period is further away from the intended date of arrival. This finding has major practical implications for revenue optimization.

Key Words: *Conjoint Analysis, Pricing, Revenue Management, Cancellation, Psychological Distance, Construal Level Theory*

Track: *Three (organisations in the hospitality and tourism industry)*

Focus of Paper: *Theoretical/academic (empirical)*

Kind of submission: *Original Paper*

Introduction

The capacity constrained hotel industry has three strategic levers to maximize the revenue of rooms: the allocation of capacity, control of the length of stay, and optimization of the mix of prices and associated terms and booking conditions (Kimes & Renaghan, 2011). These levers enable hotels to avoid opportunity costs by stimulating demand from price-sensitive guests who are prepared to book early to help fil capacity. As rooms are service products that are produced and consumed simultaneously, any booking of rooms essentially is a form of advance selling (Ng and Lee, 2008). Given this time dimension of selling rooms in advance both hotels and guests face uncertainty. Hotels have opportunity costs whereas guests may be confronted with a higher priced or fully booked hotel (Ng, 2007). To reduce such uncertainty, some guests decide to book their room in advance (Shugan & Xie, 2004). Hotels employ forecasting and overbooking algorithms (Png, 1989), and set rate conditions such as the (in)ability to modify or cancel a booking in advance.

Setting rate conditions, such as on cancellation, is a widely used practice in hotel room rate pricing where various different conditioned rates are generally offered in addition to an unconditioned rate. A complicating factor for the application of rate conditions is that booking horizons vary over time. That is, some guests book a room near the day of arrival whereas others plan their trip way in advance. Even though these booking horizons vary, in practice the difference between unconditioned and conditioned room rates is commonly fixed over time. In other words, the surcharge that guests need to pay in order to book an unconditioned room rate (e.g., a room without cancellation penalty) is independent of the booking horizon. Examining the differentiation of cancellation policies in the U.S. hotel industry, Chen and Xie (2013: 70) confirm that ‘only static policies are observed across different search time points’. They recommend investigations into a dynamic pricing approach to cancellation policies ‘in which the deadline and the price are changed based on the search time and the check-in dates’ (Chen & Xie, 2013: 70). Yet, so far cancellation policies have only been studied from a static point of view (e.g, Masiero, Heo & Pan, 2015).

Trope and Liberman (2010) argue that people are capable of thinking about the future, but that their mind-set depends on psychological distance. From their construal level theory, it can be assumed that guests who consider an unconditioned versus a conditioned room rate, will be influenced by a low-level construal for psychologically near bookings and a high-level construal for distant bookings. In other words, temporal distance influences how guests will construe a hotel booking. So will the probability of a cancellation be mentally construed in terms of concrete, detailed and contextualized attributes when a booking is psychologically near in time, whereas the same cancellation probability at a more distant future will be construed in a more abstract and decontextualized way (exacting the overall gist from the information that is used to assess the probability of cancellation). While no clear picture has emerged on the relationship between temporal distance and willingness-to-pay, for example because it depends on (i.e., is moderated by) how the choice is framed (Agrawal, Trope & Liberman, 2006) or presented (e.g., Lee, Fujita, Deng & Unnava, 2015), in an comprehensive online multiproduct experiment Isaak, Wilken and Dost (2015) show that more temporal distance leads to higher willingness-to-pay. Their research is in line with Ledgerwood, Wakslak and Wanga (2010) who found a positive moderating effect of temporal distance on the relationship between information type and willingness-to-pay. In the context of setting rate conditions, construal level theory thereby provides indications that the longer the booking horizon (i.e., the time interval between the date of the booking and the date of the stay), the bigger the acceptable surcharge for the option to cancel will be.

The aim of this paper is, therefore, to answer to the call of Chen and Xie (2013) and to explore a dynamic pricing approach for cancellation policies by developing a novel time-dependent discrete choice model that examines consumer preferences and sensitivities for rate conditions over time (i.e., over the booking horizon). By modelling consumers’ preferences towards rate conditions as a function of time, the notion is explored whether the preference for rate conditions, as well as willingness-to-pay, changes over time. This is of particular interest to hotel revenue maximization in practice as Chen et al. (2011) and Smith et al. (2015) have found that the amount of the cancellation fee does not change a guest’s booking decision.

Method

Adaptations to conjoint analysis

The model proposed in this paper is based on choice-based conjoint (CBC) analysis which is a widely accepted method in the marketing research community to determine willingness-to-pay (Green, Krieger, & Wind, 2001). As a research methodology conjoint analysis, however, is inherently cross-sectional. That is, because choice experiments are administered at a single point in time, the time dynamics of a research problem are not necessarily handled ‘naturally’ within a conjoint model.

It is, therefore, proposed to consider time as an additional ‘attribute’ in the conjoint model. This attribute, however, is not a feature of the choice proposition (i.e., the room offering) itself, as it would be in a typical conjoint model, but instead is associated with the choice context. In particular, instead of asking guests a conjoint question according to its usual time-free format, e.g., “which of the following rooms would you choose?” the question will be framed within the context of a distinct timeframe, e.g., “imagine that you want to book a room for an overnight stay T days from now, which of the following rooms would you choose?" where T represents the experimentally varied booking horizon.

Model development

The model used most often in standard CBC applications is the Multi-Nomial Logit (MNL) model:

$$P_{iq} = \exp(V_{iq}) \Big/ \sum_{j=1}^{J} \exp(V_{jq}) , \tag{1}$$

where P_{iq} is the probability that a guest q chooses an alternative i from a set of alternatives where i ϵ {1..J}, and V_{iq} the deterministic part of the expected utility that a guest q associates with alternative i.

The MNL model follows directly from the basic axioms of rational choice plus the assumption that the random error term of the expected utility is distributed Extreme-Value Type 1 (McFadden, 1974; Louviere, Hensher & Swait, 2000). For most practical applications, the deterministic part of the expected utility for a certain product alternative (V_{iq}) is defined as an additive, main effects-only function of the product attributes, that is:

$$V_{iq} = \sum_{k=1}^{K} \beta_k X_{ikq} , \tag{2}$$

where in addition β_k is the marginal utility (i.e. part-worth) associated with attribute level k from a set of K attribute levels, and X_{ikq} the presence (X=1) or absence (X=0) of attribute level k in alternative i for guest q.

In this 'standard' formulation of utility formation, the total preference for a product alternative is assumed to be a weighted sum of the attractiveness of its constituting *static* features (i.e., attribute levels). However, in order to capture any *time-dependent* elements of the preference formation process, some additional assumptions are made on the relationship between time and utility. It is proposed here to model the effect that the length of the booking horizon has on the utility of a booking option by a series of interaction terms. More precisely, it is proposed to model the deterministic part of utility as:

$$V_{iq} = \sum_{k} (\beta_k + \chi_k f(T_q)) X_{ikq} , \tag{3}$$

where in addition β_k is the *constant* (or static) utility parameter associated with attribute level k, χ_k is the *time-dependent* utility parameter associated with attribute k, and $f(T_q)$ some function of the length of the booking horizon associated with the choice task for guest q.

Two functional forms for $f(T_q)$ were considered. Model 1 assumes a linear relationship between T and V, where $f(T_q) = T_q/10$. The division by 10 is for computational convenience as it minimizes extreme exponentiated values during estimation. Model 2 assumes a logarithmic relationship between T and V such that $f(T_q) = \ln(T_q)$. This latter definition corresponds to the notion that longer booking horizons may lead to a decreasing sensitivity to time.

Heterogeneity

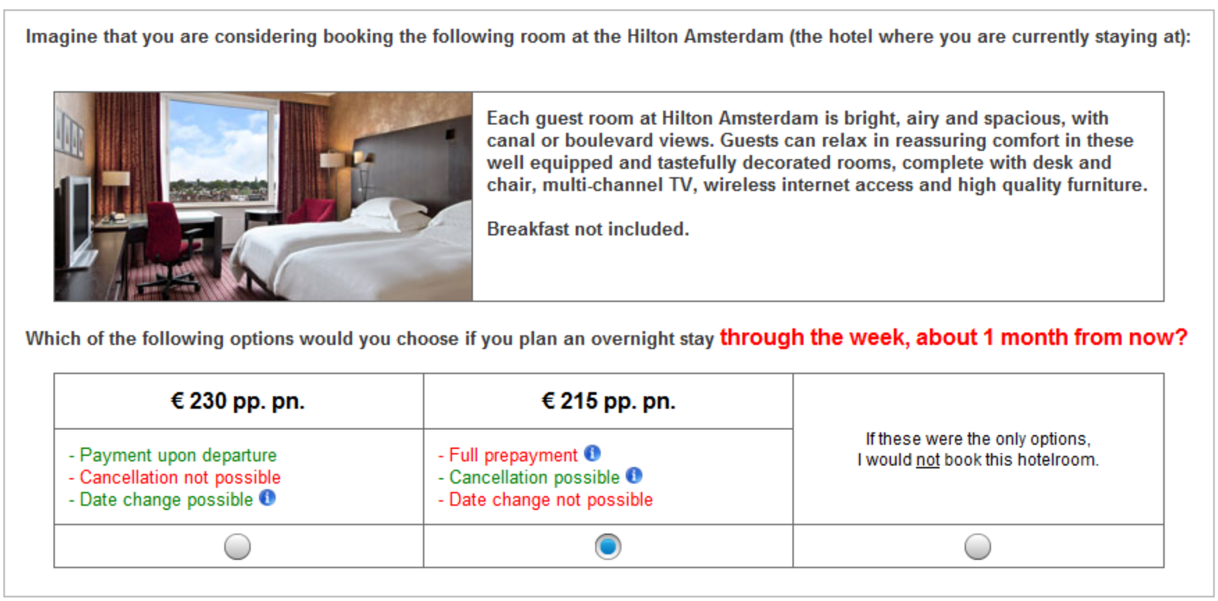
Although conveniently simple, the basic MNL model suffers from some major drawbacks, most importantly the questionable assumptions of 'Independence from Irrelevant Alternatives' (IIA) and homogeneity of tastes. IIA is the property that the presence or absence of an alternative in a choice set does not affect the ratio of the probabilities associated with the other alternatives in that choice set (Louviere, Hensher & Swait, 2000). Although this assumption greatly simplifies many aspects of model estimation, it is at the same time very restrictive. For example, it is questionable whether a high-priced, luxurious hotel will draw market share proportionally from another high-priced, luxurious hotel versus a cheap, low-standard hostel; an effect that would be predicted by the standard MNL model. In reality of course, one would expect similar propositions to compete more closely with one another than with propositions that are less similar. Also, the MNL assumption that all consumers share the same average taste weights ($\beta_{kq} = \beta_k$ for all q=1..Q and k=1..K) is both questionable and limiting. It has been repeatedly found that the basic MNL leads to biased parameter estimates and choice share forecasts if the actual taste weights are very heterogenic (Louviere, Hensher & Swait, 2000).

One way of dealing with these challenges is to use a Mixed Logit model, also known as a Random Coefficients Multi-Nomial Logit (RCMNL) model. In RCMNL, the $\beta_{1..K}$ are assumed to have some latent probability distribution over the guests, most typically K independent normal distributions with means $\beta_{1..K}$ and standard deviations $S_{1..K}$.

Design

An empirical study to test the proposed model was undertaken in collaboration with a leading global hotel chain. A total of 260 Computer-Aided Personal Interviews (CAPI) were carried out in the lobbies of three of the chain's properties in the Netherlands. The interviews were conducted by front office personnel on i-Pads and took about 10 minutes for the actual hotel guests to complete. Sawtooth Software SSI Web 8, a market-leading software package for designing, fielding and analyzing conjoint analysis studies, was used as the interviewing platform. A screenshot of one of the stimuli is illustrated by Figure 1. Both English and Dutch questionnaires were available to the respondents.

Figure 1. Screenshot of a typical choice task used in the study.



A number of observations should be made about the setup of these choice tasks. First of all, both the name of the properties in the first sentence and the hotels' standard room description were conditioned on the actual hotel property where the respondent was staying (established through a previous survey question). This was done to make the questionnaire as relevant as possible for each individual respondent. Secondly, one could observe the variable number of days prior to arrival stated in red (i.e., the length of the booking horizon: T) which varied over the choice tasks. The levels used for T where: 2 days, 7 days, 14 days, 30 days and 60 days. As can be seen, the guests were primed to consider an overnight stay *throughout the week*. This was done because the majority of the hotels' clientele were business guests and consequently the fieldwork was always conducted on working days. Thirdly, it can be seen that every choice task contained two booking alternatives with varying rate conditions and prices. Thus, the conjoint analysis design contained four attributes: three binary (on/off) attributes for the rate conditions (i.e., free cancellation, free date change, and pay on departure) and one price attribute varying on five levels (€185, €200, €215, €230, €245) representing typical standard room rates. By clicking on the blue 'i' buttons, the guest was able to activate pop-ups containing detailed information on the rate conditions. Finally, every choice task included a 'no-choice' option to establish a threshold utility for choice suspension ($V_{\text{no-choice}} = \beta_{\text{no-choice}}$).

Every guest received a total of ten choice tasks in which the attribute levels were varied according to a random stimulus design generated by SSI Web, thus effectively creating a unique choice design for every individual guest.[a] The ten choice tasks for every guest were then grouped into five sets of two choice tasks each. Each of these sets was associated with one of the five booking horizon levels in *descending* order (so: 60, 30, 14, 7 and 2 days respectively). This was done because a purely random ordering of the booking horizons across the choice tasks was perceived by the research analysts as to result in too much of a 'chaotic' experience for the respondent, potentially resulting in inconsistent choices. A descending order of the booking horizons (instead of ascending) was felt to be the most coherent with the feeling of a 'natural flow of time' (i.e., from a high-level (abstract) to a low-level (concrete) construal). Every subset of choice tasks was preceded by a text screen in order to prime the respondent for a particular booking horizon.

Since the likelihood function of the RCMNL model did not have a closed-form expression, the model estimation proceeded numerically through simulation. The statistical software package BioGeme (Bierlaire, 2003) was used for this purpose with the application of 150 Halton draws per guest in order to achieve stable results within acceptable runtimes (Train, 1999).

Results

Table 1 presents the estimated parameters and significance tests for a benchmark model (RCMNL), the proposed model with a linear specification for the booking horizon (Model 1: $f(T_q)=T_q/10$) and the proposed model with a logarithmic specification for the booking horizon (Model 2: $f(T_q)=\ln(T_q)$). The benchmark model is a standard RCMNL model with constant means and standard deviations for the price coefficient, the three binary coefficients for the rate conditions (free cancellation, free date change, pay on departure) and the no-choice constant. As can be seen from the bottom part of the table this model has a significantly higher explanation than a Null model (LL Ratio = 1287.6, $p < .01$, adj. $\text{Rho}^2 = .222$). All estimated means are strongly significant ($p < .01$) and have expected signs and relative magnitudes[b], indicating that all the attributes shown in the choice task have had an effect on the aggregate choice behavior of the respondents. However, only one of the five estimated standard deviations (for price) is significant ($p < .01$), indicating that consumers seem to be fairly homogenous in their sensitivity towards the rate conditions.

---

[a] The experimental design strategy as employed by the SSI Web platform is random in the sense that for every individual respondent, a unique fractional factorial stimulus design is constructed that is nearly orthogonal (the attribute levels for the profiles are chosen independently from one another), has approximate level balance (each level of an attribute is shown approximately an equal number of times within tasks) and minimal level overlap (each attribute level is shown as few times as possible in every choice task), thus offering great flexibility in post-hoc modelling of both the main effects as well as (possibly complex) interactions (the explicit goal of this paper), typically at the expense of no more than a 5%-10% loss in design efficiency compared to strictly orthogonal 'fixed' designs.

[b] In particular, the price coefficient is negative indicating a negative relationship between price and choice probability; the coefficients of the rate conditions are positive indicating a positive effect on choice probability of free cancellation, free date change and pay on departure. Furthermore, the coefficient for cancellation is higher than that for date change which is plausible due to the higher risk (higher expected monetary loss) associated with a full cancellation versus merely changing the date of a booking.

Table 1. Estimated parameters and significance tests for the benchmark and proposed models.

Estimation results (n=260 - 10 tasks per respondent)					
Moment	***Type***	***Attribute***	***RCMNL***	***Model 1 (lin T)***	***Model 2 (log T)***
Mean	Constant	Price	-8.05 **	-7.27 **	-11.30 **
Mean	Constant	Cancellation	1.66 **	0.94 **	1.04 **
Mean	Constant	Date change	0.99 **	0.44 **	0.37
Mean	Constant	Pay on departure	0.61 **	0.44 **	0.65 *
Mean	Constant	None	-25.00 **	-26.30 **	-34.20 **
Mean	Time-dependent	Price		-0.44 *	0.16
Mean	Time-dependent	Cancellation		0.71 **	0.57 *
Mean	Time-dependent	Date change		0.39 **	0.34 *
Mean	Time-dependent	Pay on departure		0.14	0.08
Std. Dev.	Constant	Price	5.45 **	4.21 **	6.25 **
Std. Dev.	Constant	Cancellation	0.60	0.09	0.99
Std. Dev.	Constant	Date change	0.69	0.06	0.14
Std. Dev.	Constant	Pay on departure	1.56	0.32	0.78
Std. Dev.	Constant	None	2.08	10.10 **	0.79
Std. Dev.	Time-dependent	Price		0.61 **	1.78 *
Std. Dev.	Time-dependent	Cancellation		0.80 **	0.65
Std. Dev.	Time-dependent	Date change		0.02	0.68
Std. Dev.	Time-dependent	Pay on departure		1.06 **	0.09
		LL at zero	-2856.39	-2856.39	-2856.39
		LL at convergence	-2212.61	-2178.97	-2182.75
		LL Ratio Null	1287.6 **	1354.8 **	1347.3 **
		LL Ratio RCMNL		67.3 **	59.7 **
		Rho2	0.225	0.237	0.236
		Adj. Rho2	0.222	0.231	0.230
		No. of parameters	10	18	18

Note: ** = p<0.01; * = p<0.05

Model 1 and 2 both offer a significantly higher explanation than the Null model (Model 1: LL Ratio = 1354.8, $p < .01$, adj. $Rho^2 = .231$ & Model 2: LL Ratio = 1347.3, $p < .01$, adj. $Rho^2 = .230$). Moreover, both models offer a significantly higher explanation than the benchmark model (Model 1: LL Ratio = 67.3, $p < .01$ & Model 2: LL Ratio = 59.7, $p < .01$). These results also suggest that the linear specification for the booking horizon provides a better fit than the logarithmic specification. Therefore, model 1 is chosen as the preferred model and model 2 is from here on dropped from further consideration.

In addition to all *constant* mean components being strongly significant predictors of choice ($p < .01$), model 1 also shows strongly significant and positive *time-dependent* mean components for cancellation and date change ($p < .01$). This indicates that the ability to cancel or change the date on a booking is indeed preferred *more* when the booking horizon is *longer*. Of the two rate conditions, free cancellation is more sensitive to the length of the booking horizon than free date change which seems logical as cancellation involves a higher potential risk to the guest than does a date change. Also, the sensitivity to pay on arrival does not appear be related to the length of the booking horizon at all, which again seems logical as the preference for a payment method does not have an obvious time-dependent risk associated with it.[c] An interaction effect between free cancellation and free date change was considered but did not result in a significant contribution within either Model 1 (Constant: $t = 1.35$, $p = .18$ & Time-dependent: $t = 1.04$, $p = .30$) or Model 2 (Constant: $t = .65$, $p = .52$ & Time-dependent: $t = 1.33$, $p = .18$).

[c] Note however that pay on arrival is still a highly significant factor influencing choice, albeit not time-dependent.

Interestingly, also the price attribute shows some sensitivity to time ($p < .05$). This unforeseen result might be indicative of the fact that guests may associate shorter booking horizons with capacity constraints, although this was not specifically stated in the choice tasks. Had we included a statement in the choice tasks such as "please assume that the hotel will never be full", we might have found that price was not dependent on the length of the booking horizon, although this remains speculation.

A closer inspection of the estimated standard deviations of the time-dependent effects, suggests that guests are quite heterogeneous in the degree to which their preference for price, cancellation, and pay on departure vary over time. For date change, time-varying preferences are more consistent across guests. The fact that pay on departure has an insignificant time-dependent mean but significant time-dependent standard deviation, indicates that although there is some variation in time-dependent preferences over booking agents, these average out at near zero across the sample.

Discussion

This paper answered to the call of Chen and Xie (2013) by exploring a dynamic pricing approach for rate conditions. It examined consumer preferences and sensitivities for rate conditions over the booking horizon by developing a novel time-dependent discrete choice model. Congruent with Isaak, Wilken and Dost (2015) the model shows that willingness-to-pay for the possibility to cancel or modify a hotel booking increases over the booking horizon.

The finding of time-dependent choice behavior has significant implications for hotel revenue management practice. The parameter estimates from the conjoint model can be used to empirically derive willingness-to-pay figures for the rate conditions at any specific time on the booking horizon. A common approach in conjoint analysis would be to calculate willingness-to-pay from any set of conjoint utilities that include a scalar monetary attribute (most typically room price) by simply dividing the utility of the rate condition by the negative of the scalar price utility (i.e., the marginal utility of a one-Euro price increase). That is:

$$WTP = -\frac{\beta_{rate\,\mathrm{condition}}}{\beta_{\mathrm{price}}} \tag{4}$$

However, as pointed out by Orme (2001) as well as Ofek and Srinivasan (2002), this notion of willingness-to-pay is naïve, as the formulation does not take the dependency on other product features or competitor products into account. Also, as pointed out by Scarpa, Thiene and Train (2008) the formulation in (4) may lead to extreme values when calculated on an individual respondent basis, as small values for β_{price} in the denominator may result in extremely large willingness-to-pay values for rate conditions which may render aggregation useless.

Ofek and Srinivasan (2002) suggest the 'Market Value of an Attribute Improvement' (MVAI) as an alternative measure for the willingness-to-pay and this is can be used to estimate willingness-to-pay for rate conditions in practice. MVAI may be interpreted as the price surcharge that a hotel can charge for a rate condition that creates equal choice probabilities between (1) a room with that rate condition plus the price surcharge; and (2) a room without that rate condition and no price surcharge. In other words: MVAI is the valuation, in monetary units, of the rate condition by the market as a whole. Note that MVAI does not in general define the optimal price point for the hotel in terms of optimal revenue or profit. It might well be that a price that is higher or lower than MVAI actually yields more revenue or profit than a price set at MVAI. MVAI should therefore merely be seen as an indication of the fair value of a rate condition as seen by the market as a whole (i.e., average guest). However, setting rate condition prices at MVAI might still be a reasonable strategy if the primary objective is to increase revenues by rate structuring without losing market share.[d]

[d] For a formal treatment of the full derivation and calculation of MVAI, please see Ofek and Srinivasan (2002).

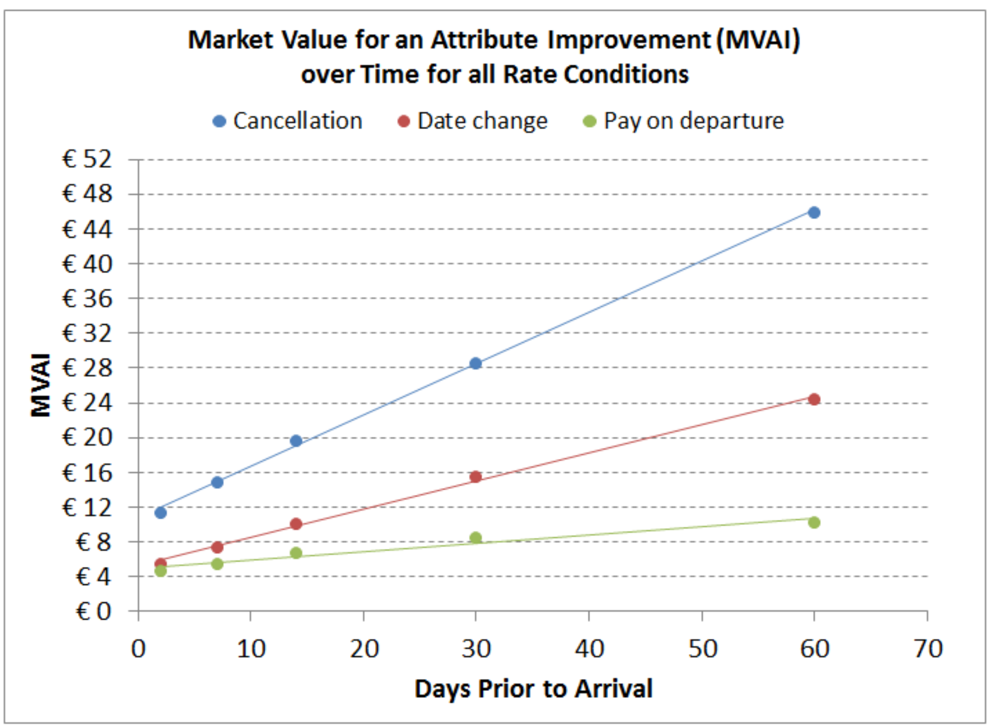
The calculation of MVAI in practice would require the revenue manager to provide a complete specification of the choice set, which in this illustration is a standard room with rate conditions (i.e., none of the booking flexibilities) at a room rate of 215 Euro (i.e., average for all properties) plus the 'no-choice' option. Table 2 contains the MVAI values for the three rate conditions at varying lengths of the booking horizon.

Table 2. MVAI values for the rate conditions at varying lengths of the booking horizon.

Booking horizon length (days to arrival)	Cancellation	Date change	Pay on departure
2	11.40	5.46	4.74
7	14.87	7.44	5.53
14	19.69	10.10	6.74
30	28.60	15.52	8.51
60	45.93	24.42	10.32

Table 2 shows that the MVAI for Cancellation, with its highly significant time-varying utility parameter, quite strongly depends on the length of the booking horizon. With only two days between booking and arrival, the average guest is willing to pay only 11.40 Euros for the ability to cancel, which gradually increases to 45.93 Euros at a 60-day booking horizon. Thus, the longer the booking horizon, the more consumers are willing-to-pay for the ability to cancel the booking (without penalty). The same general result applies to date change, although the effect is less pronounced. Both at 2 days (5.46 Euros) and at 60 days (24.42 Euros) the willingness-to-pay is approximately half that of cancellation. The premium for pay on departure is the least affected by the length of the booking horizon (from 4.74 Euros at 2 days to 10.32 Euros at 60 days), which is illustrative for the fact that the time-dependent utility parameter for this rate condition is not significantly different from zero. The results are graphically depicted in Figure 2.

Figure 2. Chart of the willingness-to-pay figures.

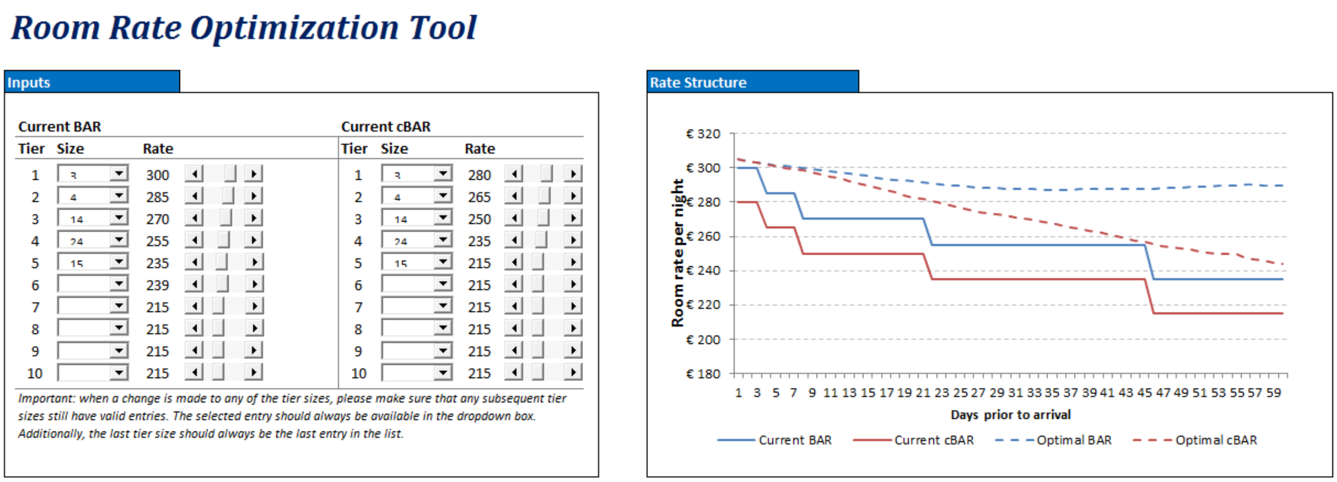


Practical Demonstration

The results in Table 1 can subsequently be used by the revenue manager in practice to explore the optimal conditioned and unconditioned room rate structure over the booking horizon. What is termed 'optimal' in this sense, is an important decision to be made by the management team and should be motivated by the business objective (e.g., revenue or profit maximization) as well as the constraints that need to be satisfied (e.g., the maximum acceptable loss in volume due to price increases).

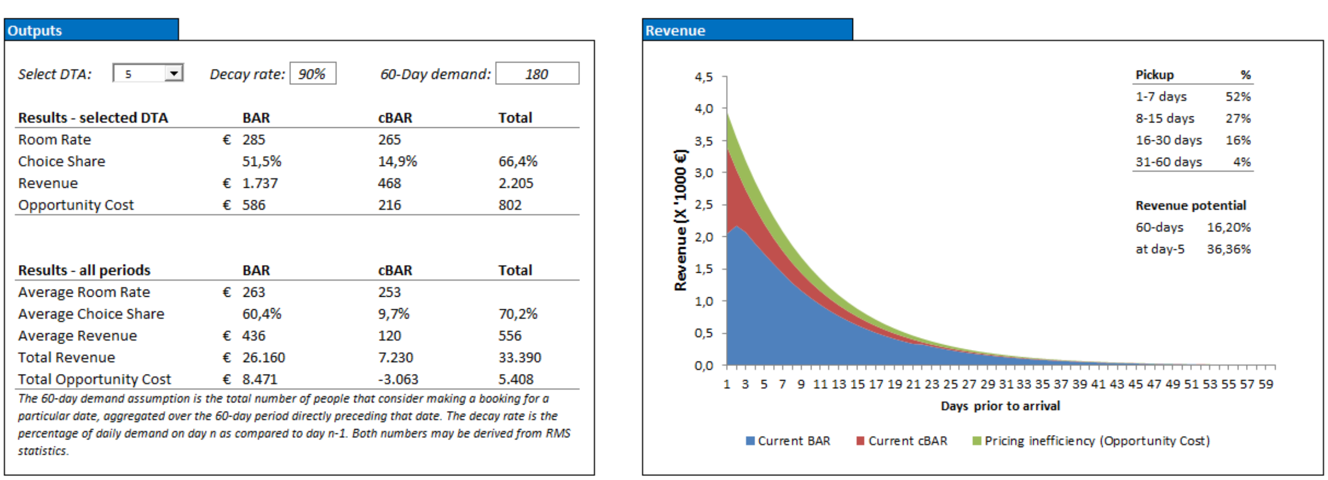
Based on the time-dependent conjoint model an optimization tool was developed for one of the hotels in the study. To simulate the results for analysis, Microsoft Excel was used with 10.000 'simulated' guests in order to obtain stable results. Price was coded as a single scalar for parsimony (i.e., 'linear attribute coding'). The tool indicated a potential increase of 16,20% in revenue when rate conditions were priced dynamically over the booking horizon as compared to the static/fixed €20 surcharge the hotel set for each unconditioned room rate (BAR) in relation to the standard conditioned best available room rate (cBAR). The hotel had 180 rooms.

Figure 3. Static versus Optimal Dynamic Conditional Pricing over the Booking Horizon.



As the rate structure in Figure 3 illustrates, the hotel's static conditional pricing policy was suboptimal at all 60 days of the booking horizon.

Figure 4. Revenue Implications of Static Conditional Pricing Policy over the Booking Horizon.



Simulating that for example 52% of all bookings were made within seven days to arrival (DTA), as Figure 4 shows, the tool predicted for day 5 of the booking horizon a potential revenue loss of €802. For the whole 60-day period the static policy amassed to a potential revenue loss of €5,408. The tool thus enabled the revenue manager to explore any pick-up scenario and rate structure. It therefore served as an supplementary tool to analyse what-if scenarios.

Limitations

While all significant effects had expected directions (i.e., no parameter reversals) despite substantial model complexity and a limited sample size, both providing evidence of the robustness of the model, it should be noted that a convenience sample was used for this study which consisted mainly of guests who not necessarily were actual booking agents. Especially in a business-oriented hotel environment guests may be less price-sensitivity than (professional) booking agents as they are typically not involved in making the booking themselves and certainly not at their own expense. The three hotels under study are notably business oriented as is confirmed by the fact that 77.7% of all the respondents reported on their stay to be mainly for business purposes as opposed to leisure purposes. In order to test this notion, ideally questions should have been included in the questionnaire on whether respondents made the booking by themselves and at their own expense and split the results accordingly. The fact that these questions were not included in the questionnaire can be regarded as a major shortcoming of the research. Data were available on whether respondents described their visit as mainly for business (n=202) or mainly for leisure (n=58). As a general indication of whether price sensitivity would differ between guests who generally made a booking by themselves and at their own expense (leisure guests), and guests who generally did not (business guests), model 1 was separately estimated for both groups. The results indicate that the price sensitivity is indeed lower for business than for leisure guests, t (258) = 10.81, p < .01, but this may or may not be due to business guests not booking by themselves and at their own expense.

References

Bierlaire, M. (2003). BIOGEME: A free package for the estimation of discrete choice models, *Proceedings of the 3rd Swiss Transportation Research Conference*. Ascona, Switzerland.

Chen, C-C., Schwartz, Z., & Vargas, P. (2011). The search for the best deal: how hotel cancellation policies affect the search and booking decisions of deal seeking customers. *International Journal of Hospitality Management, 30*(1), 129-135.

Chen, C-C., & Xie, K.L. (2013). Differentiation of cancellation policies in the U.S. hotel industry. *International Journal of Hospitality Management, 34*, 66-72.

Green, P. E., Krieger, A. M., & Wind, Y. (2001). Thirty years of conjoint analysis: Reflections and prospects. *Interfaces, 31*(3), S56-S73.

Kimes, S.E., & Renaghan, L.M. (2011). The Role of Space in Revenue Management. *In:* Yeoman, I. and McMahon-Beattie, U. (Eds.), *Revenue Management. A Practical Pricing Perspective* (pp. 17-28). Palgrave Macmillan, New York.

Law, R., & Wong, R. (2010). Analysing Room Rates and Terms and Conditions for the Online Booking of Hotel Rooms. *Asia Pacific Journal of Tourism Research, 15*(1), 43-56.

Louviere, J.L., Hensher, D.A., & Swait, J.D. (2000). *Stated Choice Methods: analysis application*. Cambridge: Cambridge University Press.

Masiero, L., Heo, C.Y., & Pan, B. (2015). Determining guests' willingness to pay for hotel room attributes with a discrete choice model. *International Journal of Hospitality Management, 49*, 117-124.

McFadden, D. (1974). Conditional Logit Analysis of Qualitative Choice Behaviour. *In:* Zarembka, P. (Ed.). *Frontiers in Econometrics* (pp. 105-142). New York: Academic Press.

Ng, I.C.L. (2007). Advanced demand and a critical analysis of revenue management. *Service Industries Journal, 27*(5), 525-548.

Ng, I.C.L., & Lee, K.S. (2008). Competition in the Advanced Sale of Service Capacity. *International Journal of Revenue Management, 2*(4), 307-326.

Ofek, E., & Srinivasan, V. (2002). How Much Does the Market Value an Improvement in a Product Attribute?, *Marketing Science, 21*(4), 398-411.
Orme, B.K. (2001). Assessing the Monetary Value of Attribute Levels with Conjoint Analysis: Warnings and Suggestions, *Sawtooth Software Research Series*.
Png, I.P.L. (1989). Reservations: customer insurance in the marketing of capacity. *Marketing Science, 8*(3), 248-264.
Shugan, S., & Xie, J. (2004). Advance Selling for Services. *California Management Review, 46*(Spring), 37-54.
Train, K. (1999). Mixed Logit Models for Recreation Demand. *In*: Herriges, J. and Kling, C. (Eds.), *Valuing Recreation and the Environment* (pp. 121-140). Northampton, MA: Edward Elgar.
Trope, Y., & Liberman, N. (2010). Construal Level Theory of Psychological Distance. *Psychological Review, 117*(2), 440-463.
Scarpa, R., Thiene, M., & Train, K. (2008). Utility in Willingness to Pay Space: a tool to address confounding random scale effects in destination choice to the Alps. *American Journal of Agricultural Economics, 90*(4), 994-1010.
Smith, S.J., Parsa, H.G., Bujisic, M., & Rest, J.I. van der (2015). Hotel Cancellation Policies and Consumer Patronage: The Moderating Role of Social Fairness on Willingness-To-Purchase and Word-Of-Mouth. *Journal of Travel & Tourism Marketing, 32*(7), 886-906.