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# Strategic consumer behavior in online hotel booking

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# Strategic consumer behavior in online hotel booking


**Abstract**

This study investigates strategic consumer behavior in online hotel booking. Free cancellation policies enable consumers to rebook the hotel room at a later time should the price drop prior to the date of stay. A discrete choice experiment is used to infer consumer preferences for free cancellation and non-refundable rates under different scenarios. The study also examines the moderating role of the risk attitude of consumers. Risk-seeking consumers show preference for a free cancellation rate that increases with the availability of an automatic rebooking service. Although a higher booking window increases the utility of the free cancellation rate, such impact decreases as risk propensity increases. The identification of four distinct consumer segments provides clear implications for industry practitioners.



**Keywords**

Strategic consumer, hotel rebook, online hotel booking, risk attitude, discrete choice modeling.

# 1. Introduction

When booking a hotel room online, consumers typically have the option to book either without free cancellation or with free cancellation at a premium price. While the free cancellation policy has always been perceived as an insurance toward the uncertainty of future change in travel plans, the policy has been recently associated with strategic consumer behavior due to the increasing popularity of dynamic hotel pricing. In this context, the selection of a free cancellation rate not only guarantees a refund in case of a change in travel plans but also gives the consumer the opportunity to cancel and rebook the hotel room at a lower rate should the price drop prior to the date of stay. Following this trend, new services are emerging online to support strategic consumer behavior. Tingo, for example, is an online travel agency provided by TripAdvisor, which originally offered consumers who booked with free cancellation the additional service of constant monitoring and automatic rebooking at a lower rate any time the price dropped. Other online platforms now provide similar services (e.g., Pruvo).

The present research aims to analyze strategic consumer behavior in online hotel booking. Strategic consumer behavior has received increased attention in management research. For instance, Cachon and Swinney (2011) investigate the intentional delay in purchasing an item at full price to buy it during a clearance sale. With the advancement of dynamic policies, strategic behavior becomes even more intriguing. In response to this phenomenon, certain theoretical models define the optimal behavior of strategic consumers with respect to dynamic pricing policies. Aviv and Pazgal (2008) study the behavior of forward-looking (strategic) consumers observing dynamic pricing policies. Levin, McGill, and Nediak (2009) present a dynamic pricing model for firms that sell perishable goods to multiple segments of strategic consumers who base their purchases according to dynamic prices. Nonetheless, these stylized models do not present an empirical validation to understand the strategic preferences of consumers when taking booking decisions in the service domain.

As part of the hotel-booking process, various elements affect consumers' preference for different available room rates (Schwartz, 2006). This study investigates the preference of consumers for refundable and non-refundable hotel room rates by focusing on four main elements, namely, price, probability of price drop, booking window, and availability of an automatic rebooking service. The analysis of consumer preferences unveiled in a discrete choice experiment integrates the expected utility theory (EUT) and non-EUT into the random utility maximization (RUM) model. The findings reveal that strategic consumers consider expectations about future price changes when they select the room rate. Specifically, the utility of the free cancellation rate is higher when the consumer expects a price drop and the premium for free cancellation is small, when the time between the booking date and check-in date is long, and when the seller offers an automatic rebooking service. As proposed, the risk attitude of consumers moderates these relationships. A cluster analysis expands these findings by providing a thorough understanding of the distinct consumer segments according to their strategic behavior and risk attitude.

This study makes several contributions. First, by investigating various booking attributes, the study provides a fine-grained understanding of consumer preferences in hotel booking. Second, the study acknowledges the presence of a number of consumer segments that show different booking preferences. These segments vary according to strategic behavior and risk propensity. Third, this research notes the salience of automatic rebooking services in strategic hotel booking, thus contributing to previous studies demanding further research on pricing of these services (Xia & Suri, 2014). Consumers might use these tools to analyze price data and make informed decisions with reduced effort. Last, the findings add further evidence to the broader stream of research on strategic consumer purchase decisions (Aviv & Pazgal, 2008; Levin et al., 2009). From a practical standpoint, the study provides new insights in terms of the segmentation of consumers and their preference for refundable and non-refundable room rates.

## 2. Strategic behavior and risk attitude

The present study investigates the strategic choice behavior of consumers in online hotel booking. When choosing among room rates with different cancellation policies, consumers may opt for the free cancellation rate if they wish to protect themselves from uncertainties about future travel plans. Apart from this benefit, the free cancellation rate also enables consumers to cancel their reservation and repurchase the service. In the hotel industry, given the perishable nature of the product, several variations of prices between the booking date and the check-in date are commonly observed (Gaggero & Piga, 2011; Alderighi, Nicolini, & Piga, 2015). In this context, the expectation of a future price drop may encourage consumers to behave strategically. Hence, consumers have the opportunity to choose between an alternative with a deterministic price (i.e., non-refundable room rate) and an alternative with a probabilistic price (i.e., free cancellation room rate).

The EUT framework has been the focus of numerous theoretical and empirical works on individual information processing and decision-making involving probabilistic outcomes. In the context of choice behavior, EUT suggests that a person will choose the alternative that maximizes their expected utility. To do so, individuals tend to evaluate the consequences of choosing one alternative and of neglecting the other (Shafir & Tversky, 1992). Drawing on EUT, risk attitude can be considered a descriptive label for the shape of the utility function presumed to underlie the choices of consumers. Risk attitude denotes the standing of a person on the continuum from risk aversion to risk seeking. The terms risk averse, risk neutral, and risk seeking are conveniently represented within the EUT framework through the curvature of the utility function.

The EUT framework allows the calculation of the utility that an individual derives from a set of probabilistic outcomes. Given that the behavioral preferences of consumers toward risk affect their choice, the functional form of the utility associated with the probabilistic outcome varies with the risk attitude of consumers. Risk-taking attitude differs across service domains (Weber, Blais, & Betz, 2002). Even within the travel and recreational realm, differences in risk attitudes have an impact on tourists' choice behavior (Alvarez & Asugman, 2006). Therefore, in the hypotheses development, this study proposes the moderating effect of risk attitude.

The following sections present the two benefits associated to the free cancellation rate (insurance and expected future discount), as well as two attributes (booking window and automatic rebooking service) that may affect the preference for the free cancellation rate over the non-refundable rate.

### 2.1. Free cancellation rate: "Insurance premium" and "expected discount"

Customized services have been proved to increase consumers' perceptions of value (Dellaert & Stremersch, 2005; Jin, He, & Song, 2012). When booking a hotel room online, consumers can decide on a number of product attributes (Masiero, Heo, & Pan, 2015). One of these attributes is the cancellation policy offered by the service provider. Upgrading to free cancellation policy provides some benefits to the consumer. On the one hand, the free cancellation option offers an insurance to the consumer in the case of any unexpected risks such as future events affecting the travel plan. By paying an "insurance premium", consumers reduce the level of pre-purchase risk perception, which in turn increases the perceived utility (Riasi, Schwartz, & Chen, 2018). It follows that consumers will be willing to pay an "insurance premium" for the higher perceived utility. According to classic economic theory, price increments generate disutility (Erickson & Johansson, 1985). Therefore, the utility of the free cancellation option diminishes as the "insurance premium" increases. More formally:

H1. There is an inverse relationship between the "insurance premium" and the utility of the free cancellation rate.

On the other hand, the free cancellation option gives consumers the opportunity to speculate in the case of lower future prices. In the hotel industry, a number of studies suggest that free cancellation policies encourage some consumers to keep searching for a better deal (Schwartz 2006; Chen, Schwartz, & Vargas, 2011). If the price drops after booking the hotel room, the consumer will be able to rebook it at a lower price. In this context, the consumer will exploit the opportunity to benefit from a future discount. The "expected discount" thus has an impact on the perceived utility of the free cancellation rate. Specifically, the higher the expected savings (i.e., difference between the price paid and the expected future price), the higher the utility of the free cancellation rate. This argument leads to the following hypothesis:

H2. There is a positive relationship between the "expected discount" and the utility of the free cancellation rate.

As stated in Section 2, the preference for the non-refundable versus the free cancellation rate may vary based on the risk attitude of consumers. In particular, the free cancellation rate alleviates two types of risks: (i) the risk concerning changes in future travel plans, and (ii) the risk of not being able to speculate on lower future prices. It follows that the sensitivity for "insurance premium" and the "expected discount" may differ across consumers depending on their risk attitude. When it comes to the first type of risk, higher risk aversion involves higher perceived significance of the loss (Pizam et al. 2004). Risk-averse consumers may attach more value to the "insurance premium" as they are less inclined to risk a potential loss (i.e., future risks affecting the travel plan). This perception results in increased willingness to pay a premium to overcome those risks, that is, they show lower "insurance premium" sensitivity. In light of these arguments, the following hypothesis is proposed:

H1.1. Risk-averse consumers exhibit lower “insurance premium” sensitivity than risk-seeking consumers.

The second type of risk refers to missing the opportunity of a future gain. In hotel booking, free cancellation rates not only empower risk-seeking consumers but also expose them to the uncertainty of price dynamics. When future prices are uncertain, risk-seeking consumers may show higher willingness to gamble. Their decision is driven by the opportunity to maximize expected gains, hence becoming more sensitive to future price drops. Thus, when selecting between booking a hotel room with the free cancellation option and one that is non-refundable, a risk-seeking consumer will focus more on the “expected discount” that comes with a potential price drop. It follows that risk attitude affects the booking preferences of consumers such that risk-seeking consumers exhibit higher “expected discount” sensitivity. The above discussion leads to the following hypothesis:

H2.1. Risk-seeking consumers exhibit higher “expected discount” sensitivity than risk-averse consumers.

### 2.2. Booking window

When evaluating a product, consumers consider the perceived proximity of the outcome, that is, the temporal distance (Liberman & Trope 1998). This temporal perspective (near future vs. distant future) has an impact on the value associated to the outcome. Kim, Zhang, and Li (2008) suggest that individuals are normally more sensitive to outcomes in a proximal position (i.e., near future) compared with outcomes in a distal position (i.e., distant future). Hence, distant choices are less preferred than near choices (Dhar & Kim, 2007). For travel products, advanced booking represents a situation in the distant future. A long period between the booking date and the check-in date (i.e., booking window, or equally, lead time) entails high uncertainty associated with travel. Consistent with this notion, previous studies have found that hotel-booking decisions are time sensitive (e.g., Jang, Chen, & Miao, 2019). Building up on these arguments, the booking window may have an impact on the utility of the free cancellation rate. Specifically, consumers will attach more value to this rate when the lead time is long, as it helps overcoming uncertainty toward future outcomes. Indeed, the ability to cancel or change a booking is preferred more when the booking window is longer (Arenoe & van der Rest, 2019). Therefore, we posit that the utility of the free cancellation rate increases as the booking window increases. Hence, the following hypothesis is made:

H3. The booking window has a positive effect on the utility of the free cancellation rate.

Uncertainty and perceived risk increase as a decision becomes more distant (Sagristano, Trope & Liberman, 2002). The evaluation of the distant outcome will vary across consumers depending on their attitude toward risk (Castaño, Sujan, Kacker, & Sujan, 2008; Tversky & Kahneman, 1992). Risk-averse consumers may perceive more value from the free cancellation rate when the time before the stay is longer. Instead, risk-seeking consumers may show proneness to undertake risks. Thus, they may not take into consideration the time between the booking date and the check-in date as much as risk-averse consumers may. Therefore, the impact of the lead time on the preference for the free cancellation rate is lower for risk-seeking consumers than for risk-averse consumers. Hence, the following hypothesis is made:

H3.1. The preference of risk-seeking consumers for the free cancellation rate is less affected by the booking window.

### 2.3. Cognitive effort and automatic rebooking services

As part of the purchase decision-making, consumers take into account both the required costs (efforts) and the benefits (ability) to select the best alternative (Payne, Bettman, & Johnson, 1992). Search costs are especially high when products are perishable and intangible (Yang, Mueller, & Croes, 2016), thereby increasing cognitive effort. Cognitive effort is generally considered as a barrier that may decrease perceived value (Kleijnen, De Ruyter, & Wetzels, 2007). Given that the capacity of information processing of consumers is limited, they often seek for cues to reduce the search costs required to make a decision (Park & Nicolau, 2015). In this regard, intelligent agents (i.e., shopping bots) have been developed to assist consumers in their online information searches (Ansari, Essegaier, & Kohli, 2000; Peterson & Merino, 2003).

Given the variety of rates and its dynamic nature, tracking hotel prices has become a time-consuming task entailing high cognitive effort (Lu et al., 2016). Virtual assistants that facilitate this task have emerged as an opportunity for consumers who choose free cancellation rates with the expectation to find a lower price since they are keen to keep tracking future prices (Bhattacharya, 2018). Acknowledging this trend, online travel agencies have recently launched additional services, such as constant monitoring and automatic rebooking (e.g., Pruvo). These services rely on automated methods to monitor hotel prices after the free cancellation booking and take action in the case of a price drop. From the perspective of the consumer, automatic rebooking services make the free cancellation option even more attractive as they reduce their cognitive effort. Therefore, the utility of the free cancellation rate may increase when an automatic rebooking service is available. Hence, the following hypothesis is proposed:

H4. The availability of an automatic rebooking service increases the utility of the free cancellation rate.

Previous literature on information search behavior suggests that risk perceptions prompt consumers to engage in problem-solving strategies aimed at reducing perceived risk (Dowling & Staelin, 1994). Risk-averse consumers tend to avoid perceived uncertainty and show less willingness to gamble (Castaño et al., 2008). Conversely, risk-seeking consumers perceive higher utility when they have the opportunity to take advantage of price dynamics. In this context, an automatic rebooking service will boost the utility of the free cancellation rate, which risk-seeking consumers associate with the chances to obtain a better deal. Therefore, the following hypothesis is proposed:

H4.1. The preference of risk-seeking consumers for the free cancellation rate increases if an automatic rebooking service is available.

Hypotheses H2.1 and H4.1 are particularly relevant in defining strategic behavior. The next section presents an overview of pertinent insights on the strategic behavior of consumers that will inform the discussion of our findings.

## 2.4. Strategic consumer

Theoretically, consumers can be classified into two groups according to their strategic behavior, that is, naïve (or myopic) consumers and sophisticated (strategic) consumers (Dana, 1998; Elmaghraby & Keskinocak, 2003). A myopic consumer makes a purchase without considering future prices. Markets characterized by myopic consumers allow the seller to ignore the detrimental effects of future price variations on current purchases. In contrast, a strategic consumer considers the future path of prices when taking a purchase decision. Specifically, a strategic consumer will try to maximize utility by waiting for the first markdown to make the purchase. In a market with a large proportion of strategic consumers, pricing decisions of sellers are more complex because the seller has to consider future and current prices. Su (2007) suggests that optimal price paths can involve either markups or markdowns, depending on patience levels of strategic consumers.

To deal with the opportunism of strategic consumers, sellers have implemented a number of price protection policies. These policies are also appealing to consumers as they protect them from potential price fluctuations. For instance, Levin et al. (2007) investigate a revenue management technique where sellers offer price adjustments for a fee. Furthermore, Lai, Debo, and Sycara (2010) study the impact of posterior price matching on the profit of sellers and show that the type of price protection policy and the optimal inventory level depend on the ratio of myopic and strategic consumers. In the context of retailing, Cohen-Vernik and Pazgal (2017) propose a policy under which the seller refunds a fraction of any future price difference (i.e., price difference refund policy), showing that profitability does not necessarily depend on the premise that some consumers do not request a refund.

In hotels, the free cancellation rate and the automatic rebooking service become two strategic factors to be considered as part of the booking decision. According to the Advanced Booking Decision Model (ABDM; Schwartz, 2006), the booking process of price-sensitive consumers does not end with the hotel choice. When the free cancellation rate is available, the consumer can follow the strategy “Book and Search”. Strategic consumers will then book and keep searching for a better deal (Chen, Schwartz, & Vargas, 2011). This trend has become more appealing with the emergence of websites specialized in last-minute deals (Carroll & Siguaw, 2003; Jang et al., 2019). Additionally, automatic rebooking services enable consumers to rebook the hotel room automatically in the case of a price drop. If the price decreases after the booking date and prior to the actual stay, the booking will be automatically adjusted for them. Strategic consumers will show higher preference for these services.

- FIGURE 1 ABOUT HERE -

Figure 1 illustrates the conceptual model specification and identifies, in line with the proposed research hypotheses, the expected sign of the coefficients associated with the utility of the free cancellation (FC) rate with respect to the utility of the non-refundable (NR) rate. As illustrated, each main hypothesis is followed by a sub-hypothesis that looks at the specific interaction between each investigated factor and risk propensity.

## 3. Methodology

### Data collection

The present study is based on a survey among tourists visiting Hong Kong from May to August 2019. The target population referred specifically to independent tourists who had booked their accommodation online. A trained research assistant conducted computer-assisted personal interviews in different locations of the destination. Potential participants were contacted using a systematic counting rule to ensure the representativeness of the sample but limiting the number of responses from Chinese tourists to a quota of approximately 30% to increase the demographic heterogeneity of the sample. The final sample was composed of 382 independent tourists and is described in Table 1. Despite the quota sampling, Chinese tourists represented the major market in the sample (27.7%), followed by Europe (17.8%), USA (11.8%), Korea (6.5%), and Taiwan (5.2%). These proportions correspond with the official ranking for overnight visitor arrivals by country of residence (Hong Kong Tourism Board, 2019). On average, the respondents stayed 4.3 nights at the destination and spent $141.2 per night on the accommodation. Only a small share (16.5%) of the sample reserved the accommodation via a direct channel as opposed to online travel agencies and search engines. The majority of the sample made the hotel booking either 16 to 30 days (30.4%) in advance or more than 1 month (34.3%) prior to the stay. In terms of demographics, the sample equally represented male (50.3%) and female (49.7%), mainly referring to young generations (64.4% under 35 years old) with a monthly household income above $5,000 in 28.8% of cases.

- TABLE 1 ABOUT HERE -

### Research design

The core part of the research consisted of a discrete choice experiment aimed to investigate the stated preference of respondents for refundable and non-refundable hotel room rates. In particular, respondents were asked to consider a hypothetical scenario involving the hotel booking for their current Hong Kong visit. The choice experiment included one room rate attribute for two alternatives, namely, “non-refundable rate” and “free cancellation rate,” along with four scenario attributes (Table 2). To reflect the common practice in the pricing of hotel rooms, the design of the experiment was constrained so that the free cancellation rate was always more expensive than the non-refundable rate. Furthermore, to ensure a realistic setting of the experiment for each respondent, the levels of the room rate attribute were pivoted around the actual room rate paid for their current Hong Kong visit. By tailoring the survey to their previous response –i.e., room rate paid–, the room rate variations in the stimuli are aligned with their reference price (Viglia, Mauri & Carricano, 2016). The scenario was described by four attributes related to the time before the actual stay, the probability of both a 20% and a 40% drop of the room rate after the booking was made, and the availability of a service that would automatically rebook the hotel room if its rate dropped. These figures (i.e., 20% and 40%) represent the most common discount rates in the industry (Forbes, 2020). Logically, respondents could benefit from the automatic rebooking service only if they had selected the free cancellation rate.

- TABLE 2 ABOUT HERE -

Each respondent faced 10 choice tasks generated through a fractional factorial experimental design. To facilitate the correct interpretation of the probabilities of price drops, the choice experiment was explained in detail during the face-to-face interview with the respondents. Moreover, each choice task included a pie chart illustrating the price probabilities for the two room rates. Hence, three slices were illustrated for the free cancellation rate reflecting the probability of the three possible price outcomes (i.e., current rate, 20% discount, and 40% discount). In contrast, a single deterministic price was illustrated for the non-refundable rate. Figure 2 presents an example of the choice card.

- FIGURE 2 ABOUT HERE -

To investigate the impact of the risk attitude of respondents on the selection of hotel room rates involving probabilistic outcomes, the survey included a set of four questions referring to the gambling risk attitude scale developed by Weber et al. (2002), which was defined according to a five-point Likert scale (very unlikely to very likely). Table 3 presents the descriptive statistics as well as the results of the factor analysis, which confirms the unidimensionality of the construct. In fact, the four items load on one single factor and exhibit high correlation with the factor (factor loadings greater than 0.7). The resulting risk attitude factor explains a considerable portion (78.3%) of the variability in the original data and presents a good level of internal consistency (Cronbach’s alpha equal to 0.90). Standardized factor scores are derived through the regression method and are used in the following analysis as unidimensional indicators of risk attitude. Negative factor scores indicate consumers with greater than average risk aversion, whereas positive factor scores denote a risk propensity above average.

- TABLE 3 ABOUT HERE -

**Empirical model specification**

Considering that respondents faced a choice between an alternative with a deterministic price (i.e., non-refundable rate) and an alternative with a probabilistic price (i.e., free cancellation rate), the model specification is based on an integration of the expected utility theory (EUT) and non-EUT into the random utility maximization (RUM) model (Liu & Polak, 2007; Latinopoulos, Sivakumar, & Polak, 2017).

According to EUT, the utility that an individual $n$ derives from a set $q$ of outcomes $x_q$ occurring with probability $p_q$ is expressed as $U_{nj} = \sum_q p_q u(x_q)$. The functional form of the utility associated with the $x_q$ outcome ($u(x_q)$) allows the specification of different behavioral preferences toward risk, such as risk aversion (concave utility function), risk propensity (convex utility function), and risk neutrality (linear utility function). Immediately intuitive functional forms refer to logarithmic transformation to express risk aversion (i.e., ($u(x_q)=ln(x_q)$), quadratic transformation to express risk propensity (i.e., ($u(x_q)= (x_q)^2$), and linear expected value to express risk neutrality (i.e., ($u(x_q)=x_q$). A commonly used nonlinear functional form is based on the assumption of Constant Absolute Risk Aversion (CARA) and is defined as $(1-e^{-ax_q})/a$, where different values of $a$ identify risk aversion ($a < 0$), risk propensity ($a > 0$) and risk neutrality ($a = 0$). The main critique of EUT resides on the observation that individuals tend to perceive probabilities subjectively (Kahneman & Tversky, 1972; Karmarkar, 1978). Several probability weighting functions have been proposed in the literature leading to the development of non-EUT theories, such as rank-dependent utility theory (Quiggin, 1982) and prospect theory (Kahneman & Tversky, 1979), which accommodate the commonly observed characteristic of consumers addressing risky outcomes by overweighting low probabilities and underweighting high probabilities. A widely used probability weighting function is the form proposed by Tversky and Kahneman (1992), defined as follows: $w(p_q) = p_q^{\gamma} \Big/ \left[ p_q^{\gamma} + (1-p_q)^{\gamma} \right]^{1/\gamma}$, where $\gamma$ represents the distortion of probabilities. The values of $0 < \gamma < 1$ lead to an inverse s-shaped functional form where low probabilities are over-weighted and high probabilities are under-weighted. A linear probability weighting function is identified if $\gamma = 1$, leading to the case where subjective probabilities coincide with objective probabilities (i.e., $w(p_q) = p_q$). The values of $\gamma > 1$ indicate an underweighting of low probabilities and an overweighting of high probabilities. The integration of both the weighting probability function and the nonlinear transformation of the utility associated with probabilistic outcomes into a single expression is straightforward.

A RUM model is typically specified according to a linear-additive function so that the utility associated with individual $n$ for alternative $j$ is $U_{nj} = V_{nj} + \varepsilon_{nj} = \sum_k \beta_k x_k + \varepsilon_{nj}$. The systematic part of the utility ($V_{nj}$) is composed of coefficients $\beta_k$ associated with the observed attributes $x_k$, whereas the random part of the utility ($\varepsilon_{nj}$) is assumed to be independent and identically distributed following an extreme value distribution. Hence, the individual preference for alternative $j$ reveals the utility weights attached to each attribute. To integrate EUT in which the nonlinear transformation of the utility includes a risk attitude parameter, such as in the CARA, and non-EUT into the RUM model it is necessary to specify a nonlinear utility model. Hensher, Greene, and Li (2011) provide the formulation of the nonlinear logit model.

To investigate the impact of both "insurance premium" and "expected discount" associated with the free cancellation alternative, the room rate for the non-refundable alternative is normalized to zero. The "insurance premium" is defined as the percentage increase between the non-refundable rate and the free cancellation rate, whereas the "expected discount" is defined as the percentage change between the free cancellation rate and the expected value of future rate. The expression of both "insurance premium" and "expected discount" in terms of relative changes ensures consistent values across individuals with different levels of actual room rate.

The first model proposed in the current study (Model 1) refers to a linear EUT specification embedded into a random parameters logit model. The utility for the two alternatives is defined as follows:

$$V_{NR} = ASC_{NR}$$
$$V_{FC} = \beta_1\left(\frac{price_{FC} - price_{NR}}{price_{NR}} \times 100\right) + \beta_2\left(\frac{price_{FC} - E\left[price_{FC}\right]}{price_{FC}} \times 100\right) + \beta_3 time + \beta_4 auto \tag{1}$$
$$where,$$
$$E\left[price_{FC}\right] = p_{D20\%}(1-0.2)\,price_{FC} + p_{D40\%}(1-0.4)\,price_{FC} + (1 - p_{D20\%} - p_{D40\%})\,price_{FC}$$

The alternative specific constant associated with the non-refundable rate ($ASC_{NR}$) and the random parameters $\beta_k$ are specified as random, so that $\beta_{nk} = \beta_k + \sigma_k \eta_{nk}$, where $\eta_{nk}$ is the individual specific heterogeneity with mean zero and standard deviation one, $\beta_k$ and $\sigma_k$ are the mean and standard deviation of the random parameter, here assumed to follow a normal distribution. The coefficients $\beta_1$ and $\beta_2$ capture individual sensitivity toward "insurance premium" and "expected discount", respectively. In particular, individuals are assumed to perceive the "insurance premium" as a loss (with respect to the non-refundable rate) and the "expected discount" as a gain (with respect to the free cancellation rate).

The second model (Model 2) incorporates a probability weighting function into the definition of expected price for the free cancellation alternative, resulting in a non-EUT specification:

$$E\left[price_{FC}\right] = w(p_{D20\%})(1-0.2)\,price_{FC} + w(p_{D40\%})(1-0.4)\,price_{FC} + w(1 - p_{D20\%} - p_{D40\%})\,price_{FC}$$
$$where,\ w(p_q) = p_q^{\gamma} \Big/ \left[p_q^{\gamma} + (1-p_q)^{\gamma}\right]^{1/\gamma} \tag{2}$$

Model 2 further aims at revealing sources of random heterogeneity in the coefficients through the risk attitude indicator. Therefore, the random parameters ($ASC_{NR}$ and $\beta s$) in Model 2 are specified as follows:

$$\beta_{nk} = \beta_k + \delta risk_n + \sigma_k \eta_{nk} \tag{3}$$

where δ is the coefficient associated with the factor scores of the gambling risk attitude scale.

The specification of a random parameters logit model allows the estimation of individual-specific parameters through the application of the Bayes' theorem (Hensher & Greene, 2003).

Given that differentiated profiles can arise from consumers with different sensitivities toward the choice attributes as well as with different attitudes toward risk, the empirical analysis is followed by a segmentation of the sample with respect to individual-specific parameters.

The choice probabilities for the random parameters logit models defined above are specified as follows:

$$P_{ni} = \int \prod_s \frac{\exp(V_{ni})}{\sum_j \exp(V_{nj})} f(\beta)\, d\beta\,, \tag{4}$$

where $s = 1,\ldots, S$ denotes the presence of multiple-choice tasks per respondent. Given that the integral in Equation (4) does not have a closed form, the estimation of the model coefficients is performed through the maximization of the following simulated log-likelihood:

$$\log L_{nj} = \sum_n \log \frac{1}{R} \sum_r \prod_s \frac{\exp(V_{nj})}{\sum_j \exp(V_{nj})} f(\beta) d\beta, \qquad (5)$$

where $r = 1, \ldots, R$ refers to the number of draws used in the simulation. The models in the current study are estimated using 600 Halton draws.

## 4. Model results

Table 4 presents the results for two random parameters logit models. Model 1 defines the probabilistic price outcome according to a linear EUT specification and represents the base model. Model 2 relies on a non-EUT specification through the introduction of the probability weighting function proposed by Tversky and Kahneman (1992) and incorporates the interaction between random parameters and risk attitude indicator in the attempt to explain the sources of preference heterogeneity. A model with the weighting probability function and the CARA transformation of utility associated with probabilistic outcomes has also been tested in our data. However, the value of alpha, which is associated with the CARA formulation, was not significant (results available upon request). The models are assessed through the log-likelihood value at convergence (LL (model)) as opposed to the log-likelihood value with the constant term only (LL (constant)). The McFadden pseudo $R^2$ and the Adjusted McFadden pseudo $R^2$ are defined respectively as $1 - LL(model)/LL(constant)$ and $1-(LL(model)-k)/LL(constant)$, where the latter favors model parsimony by penalizing a model with a higher number of parameters (k). Greater values of the Adjusted McFadden pseudo $R^2$ indicate better models.

The results for Model 1 indicate a positive alternative specific constant for the "non-refundable" rate (*$ASC_{NR}$(mean)*), suggesting an intrinsic preference for the cheaper alternative, though the standard deviation estimate (*$ASC_{NR}$(st.dev.)*) denotes significant preference heterogeneity within the sample. The coefficient associated with the "insurance premium" is negative and significant, thus confirming the hypothesis H1 of the inverse relationship between "insurance premium" and utility of the free cancellation rate. The hypothesis H2 is supported by the estimate for the "expected discount", which indicates a positive and significant relationship between the "expected discount" and the utility of the free cancellation rate. The sensitivity for both "insurance premium" and "expected discount" varies across the sample, as indicated by the significant standard deviation coefficients. The time window between the date of booking and the date of stay has a positive effect on the utility of the "free cancellation" rate over the "non-refundable" rate. As the booking window increases, consumers tend to attach greater value to the "free cancellation" option to protect themselves against the increased uncertainty associated with potential changes in the travel plan. This finding supports hypothesis H3. Also for this attribute, the standard deviation coefficient indicates a significant heterogeneity among the respondents. The estimate for the automatic rebooking service is positive and significant, thus providing support for hypothesis H4.

- TABLE 4 ABOUT HERE -

Regarding Model 2, the mean and standard deviation estimates associated with the experiment's attributes are consistent with the estimates obtained for Model 1. The gamma parameter associated with the probability weighting function is statistically smaller than one (as confirmed by the 95% confidence interval), indicating a tendency to overweight low probabilities and underweight high probabilities. This is in line with the assumptions proposed by rank-dependent utility theory and prospect theory. The introduction of the risk attitude indicator is proven highly effective in capturing sources of preference heterogeneity in the attributes under investigation, as indicated by the significance of the interaction coefficients. The model performance exhibits a considerable increase in the Adjusted McFadden pseudo $R^2$, which increases from 0.211 for Model 1 to 0.226 for Model 2. As expected, the positive sign associated with the interaction between the alternative specific constant and the risk attitude (Risk | $ASC_{NR}$) indicates that the intrinsic preference for the non-refundable rate increases as the risk propensity increases. Evidence in favor of hypothesis H1.1 is provided by the sensitivity toward the "insurance premium", which increases as the risk propensity increases. The interaction between the "expected discount" and the risk attitude is positive and significant indicating that the weight attached to "expected discount" increases as the risk propensity increases, and thus supporting hypothesis H2.1. Moreover, as the risk propensity increases, the time window between the date of booking and the date of stay affects to a lesser extent the preference for free cancellation rate (over non-refundable rate). This finding supports the hypothesis H3.1. Risk-seeking consumers attach greater preference to the free cancellation rate (over the non-refundable rate) if the automatic rebooking service is available. Therefore, the hypotheses mostly related to strategic behavior (i.e., H2.1 and H.4.1) are supported by the findings.

### 4.1. Segmentation on individual estimates

The individual estimates obtained from Model 2 are further classified into different segments through cluster analysis. The identification of the optimal number of segments relied on the hierarchical Ward's method, whereas the non-hierarchical k-mean method was used to finalize the classification of the cases in the segments. The solution with four segments was considered the most appropriate given that it maintains a good level of homogeneity within the clusters, explaining a considerable amount (81%) of original variability. Table 5 reports the descriptive statistics of the segments, including their characterization and profile. Statistical difference among segments' profile is tested by using F-test for continuous variables (i.e. risk attitude, current room rate, and length of stay) and $\chi^2$ test for categorical variables (i.e. advance booking, booking channel, gender, and income). The $\eta^2$ (associated with the F-test) and Cramer's V statistics (associated with the $\chi^2$ test) are also provided as indicators of the effect size. Small, medium and large effects are associated with value of $\eta^2$ (V) greater than 0.01 (0.20), 0.06 (0.50), and 0.14 (0.80), respectively.

- TABLE 5 ABOUT HERE -

Segment one: Loss avoiders. This segment is the largest, representing approximately 37% of the sample. Consumers in this segment are characterized by a small sensitivity to the "insurance premium" and a high sensitivity to the time distance between the booking date and the date of stay. They also exhibit a small sensitivity to both "expected discount" and automatic re-book service. Hence, these consumers are likely to select the free cancellation rate as a means to protect themselves from a change in the travel plans. As expected, this group registers the highest risk aversion among the four segments. The consumers in this segment tend to book the hotel room with greater lead time and for a longer stay.

Segment two: Strategic gamblers. This is the smallest of the four segments and is characterized by a high preference for both "expected discount" and automatic rebooking service. They also show a low sensitivity for temporal distance and a high sensitivity to "insurance premium". Therefore, the consumers in this group are likely to choose the free cancellation rate if attracted by potential gains. As expected, the consumers in this segment exhibit the highest risk propensity among the sample, in accordance with the research hypotheses related to strategic behavior (i.e., H2.1 and H4.1). Strategic gamblers are mostly male and are wealthier than the consumers in other groups. They use direct booking in much greater proportion than other consumers, book with short lead time and stay for a relatively short period at the destination.

Segment three: Moderately strategic consumers. This segment is composed of consumers with relatively high sensitivity to "expected discount" and automatic rebooking service. They are also characterized by a relatively high sensitivity to "insurance premium" and attach a relatively low weight to lead time. The consumers in this segment have a higher propensity to risk than the average of the sample. Similar to Segment 2, the booking profile of consumers in this segment indicates shorter lead time and length of stay, as well as a prevalence of male.

Segment four: Opportunistic cost minimizers. This segment is characterized by a relatively high sensitivity to temporal distance. Similar to Segment 1, consumers in this group are only marginally attracted by the automatic rebooking service and register a relatively low sensitivity to "expected discount". However, they also show a relatively high sensitivity to "insurance premium". The consumers in this segment are slightly more risk averse than the average of the sample and have lower income than the consumers in other segments. They book their hotel room with long lead time and mainly through indirect channels.

To provide further insights into the consumer preference for the two alternatives (i.e., non-refundable rate and free cancellation rate), the average parameter estimates for the four segments are used to simulate the choice probabilities under a specific scenario. The simulated scenario provides a visual illustration of the condition underlying strategic consumer behavior. In particular, the scenario considers a 20% premium for the free cancellation rate (a 20%

premium for free cancellation represents the common practice in the destination under investigation) and a 30-day booking window. The scenario further assumes three probabilities for a 20% price drop (30%, 40% and 50%) and a 40% price drop (10%, 20% and 30%). Figure 3 reports the choice probabilities (y-axis) at different probability levels of price drop (x-axis) for the four segments (panels A to D). The choice probabilities associated with the non-refundable rate (blue lines) and the free cancellation rate (red lines) are plotted by assuming that the automatic rebooking service is either available (solid lines) or unavailable (dotted lines). Figure 3 shows that for relatively low probabilities of price drop (i.e. probability of 20% and 40% price drop equal to 30% and 10%, respectively), only consumers in Segment one would select the free cancellation rate. In fact, under the given assumptions, consumers in Segment one (i.e., loss avoiders) prefer the free cancellation regardless the probability of a price drop. Segment two (i.e., strategic gamblers) will switch to the free cancellation rate if there is at least a medium probability of price drop (i.e. probability of 20% and 40% price drop equal to 40% and 20%, respectively) and under the condition that the automatic rebooking service is available. If the automatic rebooking service is not available, consumers in Segment two require a medium-high probability of price drop to switch to free cancellation rate, and hence to compensate for the effort of monitoring the room rate manually. Consumers in segment three (i.e., moderately strategic consumers) prefer the free cancellation rate for medium probabilities of price drop with a noticeable difference with respect to the availability of the automatic rebooking service. Segment four (i.e., opportunistic cost minimizers) prefers a non-refundable rate even at medium-high probabilities of price drop, whilst seeking for gain opportunity at high probabilities of price drop (i.e. probability of 20% and 40% price drop equal to 50% and 30%, respectively) by switching to a free cancellation rate.

- FIGURE 3 ABOUT HERE -

## 5. Discussion and conclusion

Dynamic pricing policies have become increasingly popular in the hotel industry (Abrate, Fraquelli, & Viglia, 2012). These techniques enable sellers to adjust prices according to different factors (e.g., demand forecast, competitors' price, and occupancy rates) with the ultimate goal of boosting revenue. However, this dynamic pricing context has also affected consumer decision-making. Consumers are aware of these practices, and strategic behaviors have started to flourish. When booking a hotel room, consumers normally face the choice between refundable and non-refundable rates. Consumers can see free cancellation options not only as an insurance but also as an opportunity to rebook at a lower rate in the event that the price drops before the actual consumption. This scenario presents new challenges for hospitality managers. To shed some light into this phenomenon, the present study adopts a discrete choice experiment to investigate consumer strategic behavior in hotel-booking decisions.

Free cancellation rates enable consumers to cancel the booking at no cost any time between the booking date and the checking date. The benefits of free cancellation rates are twofold. First, these rates offer protection against uncertainties about the future travel plan (i.e., insurance value). Second, consumers have the opportunity to rebook the hotel room should the price drops (i.e., expected discount). The present study seeks to extend the current understanding of consumer preferences for free cancellation rates by investigating the interplay between these two benefits, two attributes of the booking process (i.e., lead time and automatic rebooking service) and the risk attitude of the consumer. The empirical results show that the "insurance premium" decreases the utility of the free cancellation rate, which is in line with classic economic theory. Instead, the "expected discount" has a positive effect on the utility of the free cancellation rate. Interestingly, as risk propensity increases, consumers are more sensitive towards the insurance premium (i.e., less willing to pay the premium to avoid a potential future loss) and attach greater value to the expected discount (i.e., the opportunity to find a better deal is more salient). The inclusion of the booking window and automatic rebooking service in the model also shows interesting results. As the lead time increases, consumers perceive greater value from the "free cancellation" option. Risk attitude also moderates this effect, so that the preferences of risk-seeking consumers are less affected by the booking window. Finally, the free cancellation rate is more attractive for risk-seeking consumers when an automatic rebooking service is available. Thus, the findings support the presence of strategic behavior in the context of online hotel booking and explain this behavior as a function of risk attitude.

The findings of this study contribute to previous literature in a number of ways. First, our results continue the research avenue on strategic decision-making (Aviv & Pazgal, 2008; Levin et al., 2009). Specifically, our study extends Schwartz's (2006) model on strategic behavior in hotel booking. Integrating EUT and non-EUT into a random utility model, this study provides new insights on the trade-off between deterministic and probabilistic outcomes in this context. The results reveal the presence of various consumer segments that differ in their preference for non-refundable and free cancellation rates. Second, although price protection policies have been widely discussed in the context of retail (e.g., Cohen-Vernik & Pazgal, 2017), the recent popularity of automatic rebooking services in the hotel industry opens up a new research avenue for scholars (Bhattacharya, 2018; Xia & Suri, 2014). To the best of the authors' knowledge, this study presents the first attempt to investigate the interplay between the utility of free cancellation rates and the availability of automatic rebooking services, thereby expanding research opportunities in tourism and hospitality management research. Third, our findings provide additional empirical support for recent studies in hotel-booking behavior. By introducing the role of risk attitude, our study adds further evidence to previous works that outline the time dependency of hotel booking decisions (Arenoe & van der Rest, 2019).

From a managerial perspective, the results of the cluster analysis offer actionable implications. The identification of four different segments (i.e., loss avoiders, strategic gamblers, moderately strategic consumers, and opportunistic cost minimizers) according to their hotel-booking behavior allows practitioners to have a greater understanding of consumer preferences. Loss avoiders strongly prefer the free cancellation rate over the non-refundable rate. Therefore, leveraging on the free cancellation rate may pay off as a pricing strategy for this group of consumers. Strategic gamblers instead seek to take advantage of the free cancellation rate and automatic rebooking services depending on the probability of future discounts. Hotels and online travel agencies can exploit the revenue potential of making such information available.

Disclosing this information may encourage this group of consumers to choose free cancellation rates as a price protection policy (Levin et al., 2007), which translates in higher margins for service providers. Moreover, the results suggest that not every consumer perceives the automatic rebooking service as particularly attractive (e.g. loss avoiders and opportunistic cost minimizers). This preference may be due to the generalized suspicion that typically characterizes online buyers (Benedicktus, Brady, Darke, & Voorhees, 2010). Thus, platforms providing automatic rebooking services should build credibility and trustworthiness among consumers. The findings also reveal some characteristics of different consumer profiles, such as length of stay, booking behavior and gender, thereby providing rich insights for practitioners. Managers can use this information to achieve more efficient price discrimination by integrating it into dynamic pricing systems.

The study is not without limitations. First, respondents were informed about the probabilities of a future price drop while this information is often unavailable on booking platforms. Although this manipulation may pose a concern regarding the realism of the choice experiment, it allows advancing some insights into the potential of disclosing future price probabilities. Second, the study is based on hotel booking decisions for a relatively short stay in an urban destination. Thus, caution should be exercised in generalizing the findings of this study to other types of tourist destinations. Third, this study considered a 20% and a 40% price reduction. It remains to be seen what would have been the consumer response outside these boundaries (e.g., 10% to 20% price drop).

This study also raises some questions that may enrich the future research agenda. Investigating a wider range of scenario attributes could be beneficial to extend the findings of this empirical study. For instance, OTAs often use scarcity messages to increase consumer pressure to book. Further experimental research could enhance the current findings by exploring the effect of scarcity messages on strategic consumer behavior. Finally, future studies can also explore the strategic role that hotel price drops might play in gaining or losing market share to competitors.

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Table 1. Descriptive statistics of the sample.

| | | | | |
|---|---|---|---|---|
| **Length of stay (nights)** | 4.3 | 2.9 | 1 | 20 |
| **Actual room rate (US$)** | 141.2 | 59.5 | 50 | 300 |
| **Booking channel (direct)** | 16.5% | | | |
| Advanced booking | | | | |
| **One to five days** | 11.5% | | | |
| **Six to 15 days** | 23.8% | | | |
| **16 to 30 days** | 30.4% | | | |
| **One to two months** | 22.3% | | | |
| **More than two months** | 12.0% | | | |
| **Gender (male)** | 50.3% | | | |
| Age | | | | |
| **16 to 25** | 28.3% | | | |
| **26 to 35** | 36.1% | | | |
| **36 to 45** | 23.6% | | | |
| **46 to 55** | 7.6% | | | |
| **56 to 65** | 1.8% | | | |
| **66 or older** | 2.6% | | | |
| Monthly household income (US$) | | | | |
| **Below 1000** | 8.6% | | | |
| **1000 to 2000** | 9.9% | | | |
| **2000 to 3000** | 17.5% | | | |
| **3000 to 4000** | 21.2% | | | |
| **4000 to 5000** | 13.9% | | | |
| **5000 to 6000** | 11.0% | | | |

| | |
|---|---|
| **>6000** | 17.8% |
| Nationality | |
| **China** | 27.7% |
| **Korea** | 6.5% |
| **Taiwan** | 5.2% |
| **USA** | 11.8% |
| **Europe** | 17.8% |

Table 2. Attributes and attribute levels

| | |
|---|---|
| Scenario attributes | |
| Probability of a 20% price drop ($p_{D20\%}$) | 20%; 30%; 40%; 50%; 60% |
| Probability of a 40% price drop ($p_{D40\%}$) | 10%; 15%; 20%; 25%; 30% |
| Time before stay (*time*) | 3 days; 7 days; 20 days; 30 days; 45 days |
| Automatic rebook (*auto*) | Not available; available |
| | |
| Alternative attribute | |
| Room rate (*NR*) | Actual room rate; ±10%; −20% |
| Room rate (*FC*) | Actual room rate; ±10%; +20% |

Table 3. Gambling risk attitude.

| | Mean | St. dev | Factor loading | Variance explained | Cronbach's alpha |
|---|---|---|---|---|---|
| **Risk attitude** | | | | 78.3% | 0.904 |
| **Betting a day's income at the horse races** | 2.08 | 1.30 | 0.908 | | |
| **Betting a day's income at a high stake poker game** | 1.97 | 1.18 | 0.894 | | |
| **Betting a day's income on the outcome of a sporting event** | 2.08 | 1.21 | 0.826 | | |
| **Gambling a week's income at a casino** | 1.58 | 0.87 | 0.745 | | |

Table 4. Model results.

| | Model 1 | | Model 2 | |
|---|---|---|---|---|
| | Coeff (st.err.) | Sig. | Coeff (st.err.) | Sig. |
| **$ASC_{NR}$ (mean)** | 2.416 (0.204) | <0.001 | 3.089 (0.533) | <0.001 |
| **$ASC_{NR}$ (st.dev.)** | 0.563 (0.108) | <0.001 | 0.646 (0.127) | <0.001 |
| **Insurance premium (mean)** | −0.117 (0.008) | <0.001 | −0.091 (0.008) | <0.001 |
| **Insurance premium (st.dev.)** | 0.068 (0.006) | <0.001 | 0.038 (0.004) | <0.001 |
| **Expected discount (mean)** | 0.209 (0.013) | <0.001 | 0.279 (0.031) | <0.001 |
| **Expected discount (st.dev.)** | 0.078 (0.006) | <0.001 | 0.097 (0.008) | <0.001 |
| **Time before stay (mean)** | 0.058 (0.003) | <0.001 | 0.059 (0.004) | <0.001 |
| **Time before stay (st.dev.)** | 0.036 (0.003) | <0.001 | 0.031 (0.003) | <0.001 |
| **Automatic re-book (mean)** | 0.279 (0.105) | 0.008 | 0.136 (0.114) | 0.231 |
| **Automatic re-book (st.dev.)** | 0.227 (0.149) | 0.127 | 0.439 (0.150) | 0.004 |
| **$\gamma$** | | | 0.778 (0.067) | <0.001 |
| **Risk \| $ASC_{NR}$** | | | 0.763 (0.338) | 0.024 |
| **Risk \| Insurance premium** | | | −0.013 (0.007) | 0.043 |
| **Risk \| Expected discount** | | | 0.127 (0.021) | <0.001 |
| **Risk \| Time before stay** | | | −0.016 (0.003) | <0.001 |
| **Risk \| Automatic re-book** | | | 0.201 (0.106) | 0.057 |
| **LL (constant)** | −2647.8 | | −2647.8 | |
| **LL (model)** | −2079.4 | | −2033.6 | |

| | | |
|---|---|---|
| **Pseudo $R^2$** | 0.215 | 0.232 |
| **Adjusted Pseudo $R^2$** | 0.211 | 0.226 |

Table 5. Descriptive statistics of the segments.

| | One | Two | Three | Four | F or $X^2$ | Sig. | $\eta_2$ or V |
|---|---|---|---|---|---|---|---|
| **Segment size** | 143 | 36 | 88 | 115 | | | |
| **Segment share** | 37.4% | 9.4% | 23.0% | 30.1% | | | |
| *Characterization* | | | | | | | |
| **$ASC_{NR}$** | 2.245 | 4.603 | 3.792 | 3.027 | 1134.48 | <0.001 | |
| **Insurance premium** | −0.064 | −0.125 | −0.105 | −0.096 | 67.22 | <0.001 | |
| **Expected discount** | 0.156 | 0.479 | 0.379 | 0.209 | 203.14 | <0.001 | |
| **Time before stay** | 0.073 | 0.024 | 0.036 | 0.060 | 87.18 | <0.001 | |
| **Automatic rebooking** | 0.049 | 0.471 | 0.299 | 0.071 | 35.99 | <0.001 | |
| *Profile* | | | | | | | |
| **Risk attitude** | −0.75 | 1.68 | 0.98 | −0.34 | 486.91 | <0.001 | 0.794 |
| **Current room rate** | 143.6 | 158.6 | 138.3 | 134.9 | 1.62 | 0.185 | 0.013 |
| **Length of stay** | 4.88 | 3.36 | 3.35 | 4.56 | 6.85 | <0.001 | 0.051 |
| **Advance booking (above 30 days)** | 40.6% | 16.7% | 19.3% | 43.5% | 20.52 | <0.001 | 0.232 |
| **Channel (direct)** | 15.4% | 38.9% | 19.3% | 8.7% | 18.82 | <0.001 | 0.222 |
| **Gender (male)** | 42.7% | 75.0% | 60.2% | 44.3% | 17.22 | <0.001 | 0.212 |
| **Income (above US$ 3000)** | 58.7% | 83.3% | 76.1% | 54.8% | 17.39 | 0.001 | 0.213 |

Fig. 1 - Conceptual model and proposed hypotheses

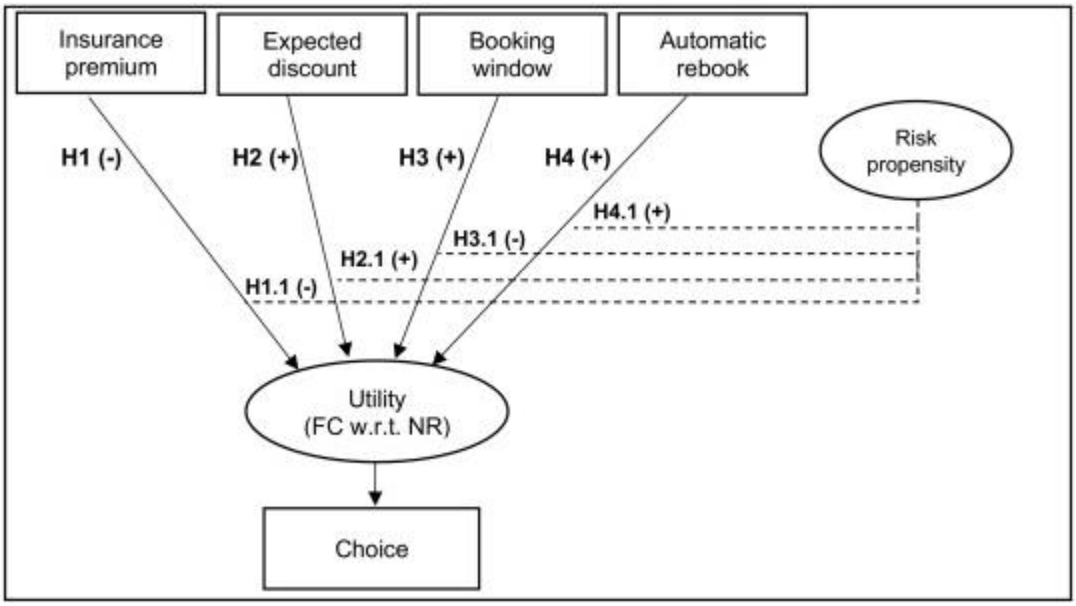


Fig. 2 - Example of choice card

| | Scenario 1 | |
|---|---|---|
| Time before check-in date | 20 days | |
| Probability of a 40% price drop | 20% | |
| Probability of a 20% price drop | 40% | |
| Monitoring and rebooking | Manual | |
| **Room rates** | **NON-REFUNDABLE** | **FREE CANCELATION** |
| Current Rate | US$ 96 | US$ 132 |
| |  |  |

Fig. 3 - Segment choice probabilities (y-axis) over low, medium and high probability of price drop (x-axis) at 30-day booking window