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Understanding hotel location preference of customers: Comparing random utility and random regret decision rules

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Abstract

During hotel selection, tourists compare alternative hotels based on hotel characteristics and process such information according to a specific decision rule. This study investigates customer preference toward various hotel location attributes through the implementation of a stated choice experiment and estimation of a discrete choice model. The study further aims to compare the well-established utility-based decision rule with a recently introduced regret-based decision rule. The study analyzes the stated preferences of 719 tourists in Hong Kong for different factors, including walking time to the nearest points of interest, hotel neighbourhood, online rating, and price. The two decision rules investigated in the study provide similar estimation results with regard to the significance of the estimated coefficient of different factors, although the random regret minimization model performs significantly better than the random utility maximization model. The paper also compares and discusses the willingness to pay measures and implications.

Keywords: hotel location; stated choice experiment; discrete choice model; random utility maximization; random regret minimization.

Introduction

It has been long acknowledged that the business success of hotels depends heavily on various location factors (Canina, Enz, & Harrison, 2005; Sainaghi, 2011), such as proximity to transport hubs (Lee & Jang, 2011), access to points of interests (Gémar, Moniche, & Morales, 2016), and co-location with other hotels (Baum & Haveman, 1997). Once located, relocating is almost impossible for hotels because of the huge sunk cost (Bull, 1994). Therefore, hotel location analysis is regarded as one of the most essential tasks for hoteliers. Yang, Luo, and Law (2014) found that most hotel location models are supply-side oriented, and investigate the hotel location selection criteria from a hotelier's perspective or identify location factors that contribute to better hotel business performance. Only a handful of studies looked into the importance of hotel location attributes from the demand side and recognized the types of location preferred by customers (Lee, Kim, Kim, & Lee, 2010; Yang, Mao, & Tang, 2017). Among this stream of research, most studies only considered vague constructs of locational attributes, such as "perceived location convenience" and "market accessibility." Without rigorous analysis, the essential locational factors cannot be unveiled fully, and research outputs are of very limited value in guiding hotel location evaluation in practice. To fill the research gap, this study investigates how various hotel location attributes influence a series of behavioral outcomes of customers, including the intention to select a hotel and willingness to pay for hotel location attributes. In particular, the research aims to investigate customer preference toward various hotel location attributes through the implementation of a stated choice experiment and estimation of a discrete choice model.

The hotel selection can be a complex task, and tourists typically process information according to a defined decision rule (McCleary, Weaver, & Hutchinson, 1993). This study further aims to compare the well-established utility-based decision rule with a recently introduced regret-based decision rule. The random utility maximization (RUM) paradigm has long been used to represent the consumer decision-making process (Nicolau & Mas, 2005). Rational consumers are assumed to evaluate all possible options available and choose the one that satisfies them the most. Specifically, consumers compare different options, attach a specific utility to each one of them, and finally select the alternative/product that maximizes their utility. RUM models benefit from a solid foundation in microeconomic theory and have become widely popular since the introduction of the computational convenient multinomial logit model (McFadden, 1974). However, different theories on choice behavior have been integrated within the specification of discrete choice models in an attempt to improve the explanatory ability of the model. Among others, regret theory (Bell, 1982; Loomes & Sugden, 1982) has stimulated an important stream of literature since the initial formulation of a random regret minimization (RRM) model specification introduced by Chorus, Arentze, and Timmermans (2008) and Chorus (2010). Under the RRM paradigm, consumers are assumed to select the alternative that minimizes the anticipated regret. To the best of our knowledge, this study represents the first application to test the appropriateness of the RRM model specification in the tourism and hospitality context.

Therefore, the results are expected to provide a clear guideline for future studies on the relevance of hotel location attributes and decision-making rules of tourists.

Literature review

In this section, the relevant literature on hotel location analysis is presented and discussed from both supply and demand sides. In particular, from a demand perspective, the importance of hotel location is first emphasized, followed by a more comprehensive discussion on various location factors in shaping customers' satisfaction, selection, and willingness-to-pay. Lastly, a comparison is presented between the utility-based and regret-based decision-making rules.

Supply-side analysis of hotel location

The location choice decision is regarded as the most important decision for new hotels, and a superior location helps the hotel shape competitive advantages over competitors in both the short term and the long term (Urtasun & Gutiérrez, 2006; Yang, Tang, Luo, & Law, 2015). Various theories across different disciplines have been introduced to provide insights on hotel location choice and unveil the underlying factors that shape hotel location patterns. Yang, Luo, and Law (2014) provided a comprehensive literature review of theoretical models used in hotel location research, and four types of models were highlighted, including tourist-historic city model from urban studies (Ashworth & Tunbridge, 2000), mono-centric model from business geography (Egan & Nield, 2000; Shoval, 2006), agglomeration model from economics (Canina, Enz, & Harrison, 2005), and multi-dimensional model from marketing (Urtasun & Gutiérrez, 2006). Specifically, the tourist-historic city model presents a comprehensive spatial typology of hotel location sites in cities (Ashworth & Tunbridge, 2000), whereas the monocentric model underpins a spatial hierarchy of hotel location based on a hotel's relative capability to leverage center locations for revenue generation (Egan & Nield, 2000; Shoval, 2006). In another model, the agglomeration model, the benefits the hotel can receive from co-locating, and clustering are referred to as agglomeration effects (Luo & Yang, 2016). Seeking agglomeration benefits becomes obvious particularly when low-end hotels select the location (Canina, et al., 2005; Kalnins & Chung, 2004). Finally, the multi-dimensional model incorporates other important dimensions other than the spatial one in understanding hotel location decision, and these vital dimensions include price, capacity, and services ones (Urtasun & Gutiérrez, 2006), which are intertwined with each other in a typical location selection process.

Based on past literature, a set of hotel location factors have been highlighted from the supply-side analysis. Chou, Hsu, and Chen (2008) stressed two categories of location factors in hotel location choice, namely, geographical conditions (e.g., surrounding environment and rest resources) and traffic conditions (e.g., accessibility and transport convenience). In general, Adam and Amuquandoh (2013) found six dimensions of hotel location, namely, "economic," "neighborhood characteristics," "transport," "laws and regulations," "physical site characteristics," and "socio-cultural characteristics of the neighborhood." Different hotels demonstrate heterogeneous location selection preferences. For example, various hotel-specific characteristics have been unveiled, such as hotel class (Yang, Wong, & Wang, 2012), hotel age (Luo & Yang, 2016), hotel size (McCann & Vroom, 2010), and hotel brand (Kalnins, 2004). Furthermore, location choice decision is primarily determined by a set of location-specific factors. First, the location's accessibility to major tourist attractions and transport facilities is an essential factor. For example, Shoval, McKercher, Ng, and Birenboim (2011) show that most hotel guests limit their activities within the immediate vicinity of the hotel, and Li, Fang, Huang, and Goh (2015) highlighted the importance of access to tourist attractions and transport facilitation on explaining the location pattern of hotels in Hong Kong. Second, the level of competition/agglomeration associated with a particular location site is paramount. On the one hand, hotels try to avoid locations with intense competition, especially within-brand/chain competition (Kalnins, 2004). On the other hand, hotels are attracted by the agglomeration benefits from their neighbors. Luo and Yang (2016) investigated the impact of two types of agglomeration economies, localization economies (benefits from intra-industrial clustering) and urbanization economies (benefits from inter-industrial clustering), on hotel location choice in Beijing. The results confirmed the impact of the former for star-rated and non-rated budget hotels, and the impact of the latter on non-rated budget hotels only. Lastly, other location-specific factors have also been examined in shaping hotel location choices, including local lodging market structure (Lado-Sestayo, Otero-González, Vivel-Búa, & Martorell-Cunill, 2016), environmental quality (Crecente, Santé, Díaz, & Crecente, 2012), local tourism demand (Luo & Yang, 2013), and local infrastructure (Assaf, Josiassen, Woo, Agbola, & Tsionas, 2017).

Various hotel investors and consultancy service providers developed specific feasibility models for newly proposed hotel properties, and location evaluation is one of the vital components (O'Neill, 2013). In a typical feasibility model, location evaluation includes hotel site and neighborhood description, market area analysis to understand the local economic vitality, and supply and demand analysis of local sites (HVS Consulting and Valuation Services, 2009; U.S. Hotel Appraisals, 2011). Based on the location factors highlighted, feasibility models elaborate a set of simulation/prediction to project future operation and financial performance. In some feasibility analysis, the analysis of local competitive set is thoroughly conducted to better understand the competition landscape (RK Consulting Services, 2018).

Demand-side analysis of hotel location

Location perception and satisfaction

An extensive review of the hotel guest satisfaction suggests convenient location is rated among the top attributes by both business and leisure travelers in hotel satisfaction because hotel guests prefer a convenient location where various services and facilities are easily accessible (Tsai, Yeung, & Yim, 2011). Hotel location has been long confirmed empirically as an indispensable component of overall hotel experience (Carneiro & Costa, 2000; Lockyer, 2005; Ren, Qiu, Wang, & Lin, 2016). Kim, Kim, and Heo (2016) analyzed hotel reviews from social media and found the most popular satisfier is "location" for both full-service and limited-service hotels in New York. Radojevic, Stanisic, and Stanic (2017) found hotels located close to the city center tend to receive higher TripAdvisor ratings from guests' feedback. However, Liu, Teichert, Rossi, Li, and Hu (2017) investigated TripAdvisor reviews of hotels in China and found location to be the least important factor among six TripAdvisor rating factors. They explained that hotel location had been evaluated when guests were making the reservation, and thus, its influence diminished when evaluating the actual experiences.

Hotel guests' perception and satisfaction toward hotel location consist of multiple dimensions. Using factor analysis, Lee, et al. (2010) unveiled six dimensions explaining hotel location perception, namely, "tourism attraction," "convenience," "safety," "surrounding environment," "traffic," and "accessibility." In a more recent study by Xiang and Krawczyk (2016), six location-related factors were extracted from text mining on hotel reviews. These factors include "shopping and attractions," "transportation," "noise," "view," "convenience," and "dining." Yang, et al. (2017) developed a comprehensive framework to understand the factors shaping guests satisfaction toward urban hotel location, and in general, location attributes can be classified into three categories: 1) accessibility to points of interest, customers prefer a hotel location close to various attractions, services, and facilities in a destination, and it is an economically rational choice for hotel guests to minimize their transportation costs in terms of time and money (Chaves, Gomes, & Pedron, 2012); 2) transport convenience, which measures the ease with which the guests can go out and come back to the hotel location (Canina, et al., 2005); and 3) the surrounding environments, which refer to the environmental elements, such as public goods and services, exogenous to the hotel but endogenous to the surrounding area where the hotel is physically located (Bull, 1994). Yang, et al. (2017) also recognized the heterogeneity of location satisfaction across different types of guests; for example, business travelers focus more on transport convenience whereas family travelers care more on the surrounding environment.

Location and hotel selection

Previous literature has long recognized the importance of location on customers' hotel selection/choice (Cobanoglu, Corbaci, Moreo, & Ekinci, 2003). McCleary, et al. (1993) suggested hotel location as the most important factor influencing business travelers' hotel selection, and Rivers, Toh, and Alaoui (1991) revealed location convenience drew the highest attention from both members and non-members of frequent guest programs in hotels. Among frequent individual travelers to Hong Kong, Chan and Wong (2006) found convenient hotel location is the most influential factor without considering the factor of price, and the result still holds for many different market segments. Many other empirical studies have confirmed that hotel location is among the top-ranked factors shaping guests' decision on hotel selection (Ananth, DeMicco, Moreo, & Howey, 1992; Barsky & Labagh, 1992; Tsaur & Tzeng, 1996;

Yavas & Babakus, 2005). Moreover, some studies investigated the roles that different location attributes play in shaping hotel selection. In an econometric modeling effort by Ghose, Ipeirotis, and Li (2012), several location characteristics were estimated to be significantly associated with customer's hotel choice, and include local crime rate, external amenities, and proximity to public transportation, beach, interstate highway, and downtown.

Location and willingness to pay

The traditional hedonic pricing model framework has been used to identify location factors associated with a premium on hotel room rate (Lee & Jang, 2011). The model disentangles the hedonic value of every single locational attribute under demand-supply equilibrium and calibrates the willingness to pay (WTP) of different attributes in an implicit manner (Papatheodorou, Lei, & Apostolakis, 2012). Location advantages have been highlighted with their significant hedonic values. Zhang, Ye, and Law (2011) investigated the impact of TripAdvisor location rating on hotel price in New York, and the results suggest a one point higher location rating is associated with a 12.4 percent increase in room rate. This effect is more substantial for midscale and luxury hotels but is insignificant for economy hotels.

According to previous hedonic pricing analyses of hotel room rates, various location attributes have been recognized to have a hedonic value on hotel room rates. In particular, distance to the city center has been reported to be a vital variable contributing to the WTP of a hotel room (Bull, 1994; Monty & Skidmore, 2003; Schamel, 2012). Other location attributes include distance to beach (Coenders, Espinet, & Saez, 2003; Espinet, Saez, Coenders, & Fluvi, 2003; Rigall-I-Torrent, Fluvià, Ballester, Saló, Ariza, & Espinet, 2011; Saló, Garriga, Rigall-I-Torrent, Vila, & Fluvià, 2014; Thrane, 2005), distance to airport (Lee & Jang, 2011), interstate access (White & Mulligan, 2002), and proximity to railway station (Abrate, Capriello, & Fraquelli, 2011; Thrane, 2007). Hotel location is also linked directly to the surrounding scenery from hotel rooms, and many empirical studies have confirmed different amounts of WTP among hotel rooms with different views based on stated choice analysis (Masiero, Heo, & Pan, 2015; Wong & Kim, 2012).

To the best of our knowledge, past studies have incorporated only few location attributes as control variables in various types of demand-side analysis, and failed to scrutinize a set of location factors. Moreover, no known studies have examined the effect of location attributes on customers' willingness-to-pay through stated choice experiments and discrete choice modeling.

Utility-based and Regret-based decision rules

While various location factors affect customers' hotel choice, the decision rule that determines the choice is also crucial. The utility-based decision rule, that is, the random utility maximization (RUM) paradigm, represents the most popular and conventional decision rule (Nicolau & Mas, 2005). Rational consumers are assumed to evaluate the potential alternatives and choose the alternative that provides them with the maximum utility. The theoretical foundation of RUM models is built on the expected utility theory which can be traced back to the 18^{th} century (Bernoulli, 1738). The use of RUM models in the choice modeling literature is also widely popular ever since the introduction of the multinomial logit model (McFadden, 1974).

However, the violation of the expected utility theory can be observed in different contexts (e.g., Allais, 1953). At this regard, Hess, Stathopoulos, and Daly (2012) discuss the specification of discrete choice models that allow alternative decision rule paradigms. Among others, the random regret minimization (RRM) paradigm has received increasing interest as a semi-compensatory decision rule for discrete choice analysis (Hensher, Greene & Ho, 2016). RRM paradigm nests its foundation on the Regret Theory (Bell, 1982; Loomes & Sugden, 1982), in which decision-makers are assumed to experience regret as a consequence of a decision and to take into account the anticipation of such regret when making decisions. The anticipated regret is related to the negative feeling perceived by the decision-maker when the chosen alternative underperforms the unchosen alternatives in certain attributes. Therefore, in contrast to RUM, the unchosen alternatives can potentially influence the evaluation of the chosen alternative (Dhar & Wertenbroch, 2012). Under the RRM paradigm, individuals are assumed to minimize the anticipated regret when selecting among alternatives (Chorus, Arentze & Timmermans, 2008). The RRM model (Chorus, Arentze & Timmermans, 2008; Chorus, 2010) is as tractable and parsimonious as the RUM model (Chorus, 2010).

In hospitality context, the anticipated regret is found to be influential on the intentions to select an eco-friendly restaurant (Kim, Njite, & Hancer, 2013) and on the purchase of restaurant membership (Jang, Mattila, & Bai, 2007). However, to the best of our knowledge, no previous studies have analyzed the regret-based decision rule in the tourism and hospitality choice context.

Data

The data refer to a survey conducted among tourists in Hong Kong. Hong Kong is among the top 10 destinations in terms of international tourist receipts (World Tourism Organization, 2017) and houses a large variety of tourist attractions. Its hotel industry comprises a wide selection of 277 hotels and 1469 guesthouses (Hong Kong Tourism Board, 2018), located mainly in urban areas. Hence, Hong Kong is an ideal destination in terms of investigating tourist preferences for urban hotel location.

The first part of the questionnaire collected information on tourists' current visit and hotel stay. The central part of the questionnaire included the stated choice experiment where respondents were asked to state their preference among a hypothetical set of alternative hotels. Since RRM reduces to RUM in case of binary choice (i.e., two alternatives) tasks (Chorus, 2010), we set the number of hypothetical alternatives to three. This ensures a meaningful comparison between utility-based and regret-based decision rules, without adding undesirable complexity (DeShazo

& Fermo, 2002; Louviere, Carson, Burgess, Street, & Marley, 2013) to the choice tasks. Table 1 reports the list of attributes and levels used in the choice experiment. In particular, each hypothetical hotel was described according to the walking distance to three points of interest, namely the nearest metro station (Li, et al., 2015), the nearest top-tier shopping district (Oppermann & Brewer, 1996), and the nearest top-tier sightseeing site (Yang, et al., 2017). The range of the attribute levels was determined by considering the actual distances to the relevant points of interest from a comprehensive set of hotels at the destination. In particular, the data was compiled from a major OTA (hotels.com) for 181 three-star and above hotels located at walking distance to metro stations, top-tier shopping districts, and sightseeing attractions. The average walking distance to the nearest metro station and to the nearest shopping district and sightseeing site was about 7 minutes and 15 minutes, respectively. The attribute associated with hotel neighborhood distinguished among hotels located on the main road, commercial street, pedestrian square, and waterfront promenade (Fleischer, 2012; Lange & Schaeffer, 2001; Masiero, et al., 2015). To facilitate respondents' comprehension, a sample image of the four hotel neighborhoods accompanied the textual description. The overall quality of the hotel was captured by the online rating (Yang, Park, & Xu, 2018), which varied from two to five stars. The price of the hypothetical hotel was pivoted around the room rate of the current stay revealed by respondents in the previous section of the questionnaire. The practice of "pivoting" not only makes the scenario more realistic (Train & Wilson, 2008) and meaningful to the respondent (Hensher, 2006), but it is also supported by behavioral and cognitive psychology theories (Rose, Bliemer, Hensher, & Collins, 2008).

- TABLE 1 ABOUT HERE -

The combination of attributes and their levels in the hypothetical hotel alternatives was generated through experimental design techniques. Initially, a fractional factorial design was implemented in a pilot test that aimed at verifying the validity of the experiment and obtaining preliminary information on respondents' preferences. An efficient design was generated using the preliminary estimates from the pilot data and implemented in the main survey. In fact, although efficient designs have the advantage of improving the reliability of the estimates, they require prior information on the respondents' sensitivity toward the variable under investigation (Rose & Bliemer, 2009). The experiment design was duly inspected prior to its implementation in order to ensure that no strictly dominant alternatives were present (i.e., better location, better rating and cheaper rate) and verify the validity of the proposed alternatives. Each respondent in the main survey faced eight choice tasks. The selected number of choice tasks ensured attribute level balance without affecting respondents' ability to process the entire choice exercise (Rose, Hensher, Caussad, de Dios, Ortúzar, & Jou, 2009). A description of the choice scenario accompanied the choice exercise. In particular, respondents were informed that while the hotel alternatives differed in terms of location attributes, customer rating and price, the hotel category as well as purpose and length of stay were assumed to be the same as in their current trip. Figure 1 illustrates an example of the choice card.

- FIGURE 1 ABOUT HERE –

The survey was administered by a professional survey company that conducted computer-assisted personal interviews among tourists in the main tourist areas of Hong Kong in June 2017. Potential respondents were approached according to a systematic sampling technique whereas the sample size was decided by compromising the desire to represent different segments of tourists and the disposable budget for the research project. Among the 750 tourists interviewed, 31 observations were excluded from the sample because of poor quality data, resulting in 719 valid observations. Table 2 reports the descriptive statistics of the sample. The tourists in the sample spent, on average, four nights in Hong Kong, and sightseeing (3.12) and dining experiences (3.09) were the most important travel motivation, followed by cultural and historical attractions (2.98) and experiencing different cultures (2.96). The majority (41%) of the tourists were traveling with friends, while 24% were alone. The remaining 35% were either traveling with their family (22%) or relatives (13%). A considerable share (52%) of tourists was familiar with the destination as they were at their second or more visit to Hong Kong. Regarding the current hotel stay, tourists spent an average of US$198 per room per night, although the magnitude of the standard deviation indicates considerable variability in hotel room rates. The majority (66%) of the tourists selected accommodations located in the Kowloon district whereas 29% of the sample stayed at hotels in the Hong Kong Island district.

- TABLE 2 ABOUT HERE -

Methodology

Consumer choice among a set of finite and discrete alternatives is modeled typically under the random utility maximization (RUM) paradigm. In particular, the utility derived by individual *n* for alternative *j* is specified as follows:

$$U_{nj} = V_{nj} + \varepsilon_{nj} = \sum_k \beta_k x_{jk} + \varepsilon_{nj} \quad , \tag{1}$$

where V_{nj} represents the observed part of the utility captured by a linear combination of coefficients β_k associated with k attributes x_k and ε_{nj} refers to the error term representing the unobserved part of the utility assumed to be independent and identically distributed (iid) following an extreme value distribution. Under the RUM paradigm, individuals are expected to select the alternative j that maximizes their utility. Considering that only part of the utility is observed, individual choices can be predicted only up to a probability. Therefore, the probability that individual n chooses alternative i is equal to $P_{ni} = P(V_{ni} + \varepsilon_{ni} > V_{nj} + \varepsilon_{nj}, \forall j \neq i)$. Given the distributional assumption of the error term, the multinomial logit (MNL) choice probability for a RUM model is computed conveniently as follows:

$$P_{ni} = \frac{\exp(V_{ni})}{\sum_j \exp(V_{nj})} \quad . \tag{2}$$

As previously discussed, the RRM paradigm is considered as an alternative decision rule assuming that individuals minimize the anticipated regret when selecting between alternatives (Chorus, Arentze & Timmermans, 2008). Here, regret is intended as what the individual experiences when an unchosen alternative performs better than the chosen one (Chorus, 2010). Therefore, the assumption is that consumers aim to avoid regret rather than seek utility when choosing among different products. Formally, the anticipated regret experienced by individual n for alternative j is specified as follows:

$$RR_{nj} = R_{nj} + \varepsilon_{nj} = \sum_{i \neq j} \sum_k \ln\left(1 + \exp\left[\beta_k (x_{ik} - x_{jk})\right]\right) + \varepsilon_{nj} \ , \tag{3}$$

where R_{nj} represents the observed regret, β_k refers to the coefficient associated with attribute x_k, and x_{jk} and x_{ik} are the values of the attribute k for the considered alternative j and another alternative i. The unobserved regret is captured by the error term with its negative following an iid extreme value distribution. As indicated in the regret function, a pairwise comparison is made for each attribute k between its level in the considered alternative j and in any other alternative i in the choice set. A close inspection of the utility and regret functions suggests a fundamental conceptual difference in the decision-making process assumed in the two approaches. In the utility approach, the individual is assumed to assess alternatives separately by attaching weight to each alternative attribute. The utility values, which are derived through summation, are then compared, and the alternative with the highest value is selected. Therefore, the comparison between alternatives takes place at the aggregate level, making RUM models fully compensatory. That is, a decrease in one alternative attribute can be offset fully by an equal increase in another equally important attribute. In the regret approach, the individual is assumed to assess alternatives collectively by attaching a weight to the differences between attributes across all alternatives. The overall regret is obtained through summation, and the alternative with the lowest value is selected. Therefore, the alternatives are compared at both attribute and aggregate levels, making the RRM model semi-compensatory. That is, the level of compensation needed to offset a decrease in one alternative attribute depends on the relative performance of the attribute compared to the other alternatives.

Under the RRM paradigm, the probability that individual n selects alternative i is equal to $P_{ni} = P(R_{ni} + \varepsilon_{ni} < R_{nj} + \varepsilon_{nj}, \forall j \neq i)$. Mathematically, minimizing the regret is equivalent to maximizing the negative regret (Chorus, 2010). Hence, the same probability can be rewritten as $P_{ni} = P(-(R_{ni} + \varepsilon_{ni}) > -(R_{nj} + \varepsilon_{nj}), \forall j \neq i)$. Considering the distributional assumption of the negative error, the MNL choice probability of an RRM model can be computed conveniently as follows:

$$P_{ni} = \frac{\exp(-R_{ni})}{\sum_j \exp(-R_{nj})} \quad . \tag{4}$$

The extension of the MNL choice probabilities to account for random preference heterogeneity and panel structure of the data (i.e., correlation across choice tasks for the same respondent) is straightforward, leading to the so-called mixed logit (MXL) probabilities (Train, 2009). The MXL choice probabilities for the RUM and RRM models, respectively, are specified as follows:

$$P_{ni} = \int \prod_s \frac{\exp(V_{ni})}{\sum_j \exp(V_{nj})} f(\beta) d\beta \quad , \tag{5}$$

$$P_{ni} = \int \prod_s \frac{\exp(-R_{ni})}{\sum_j \exp(-R_{nj})} f(\beta) d\beta \quad , \tag{6}$$

where s = 1,…, S refers to the choice tasks per respondent, and *f(β)* is a density function typically specified to follow a normal distribution. The integrals in equations (5) and (6) have no close form, and the choice probability for MXL models are approximated through simulation. As shown in the equations above, the MNL-RRM and MXL-RRM models share the same type of choice probabilities of the MNL-RUM and MXL-RUM models. This characteristic makes the RRM class of models easy to estimate through maximum (simulated) likelihood estimator commonly used in software packages for discrete choice analysis. In fact, investigation of the RRM models is reported in a growing number of applications in several contexts, including transport mode choice (Chorus, 2010; Boeri & Masiero, 2013; Hess & Stathopoulos, 2013; Leong & Hensher, 2015; Hensher, Greene & Ho, 2016), shopping-centre choice (Chorus, 2010; Rasouli & Timmermans, 2017) outdoor recreation site choice (Boeri, Longo, Doherty & Hynes, 2012; Thiene, Boeri & Chorus, 2012), and leisure activities (Dekker, Hess, Arentze & Chorus, 2014). Chorus, Rose, and Hensher (2013) introduced a hybrid model specification where attributes are processed according to either utility-based or regret-based decision rules. Chorus, van Cranenburgh, and Dekker (2014) provide a comprehensive review of 43 empirical comparisons between RUM and RRM models that appeared in 21 articles. Their analysis shows quite clearly the absence of a dominant approach in terms of model fit because 13 comparisons resulted in a statistical tie, 15 in favor of RUM model and 15 in favor of RRM model.

The RUM model has solid microeconomics foundation that facilitates the derivation of compensation measures, such as the marginal rate of substitution (MRS), defined as the ratio of two marginal utilities ($MRS_{(RUM)} = (\partial U_i / \partial x_i) / (\partial U_i / \partial y_i) = \beta_x / \beta_y$). If one of the two marginal utilities is associated with a monetary attribute (typically price), the marginal rate of substitution is interpreted as the very useful and popular WTP measure ($WTP_{(RUM)} = \beta_x / \beta_{price}$). In the RRM model, the derivation of the MRS lacks theoretical support of the microeconomics axiom (Chorus, 2012). However, it is possible to compute the MRS (or WTP) counterpart for an RRM model, although the derivation is less straightforward than for a RUM model because of the semi-compensatory nature of the RRM approach. As discussed in Chorus (2012), the RRM counterpart of the MRS is derived as follows:

$$MRS_{(RRM)} = \frac{\partial RR_i / \partial x_i}{\partial RR_i / \partial y_i} = \frac{\sum_{j \neq i} \beta_x / (1 + 1/\exp[\beta_x (x_j - x_i)])}{\sum_{j \neq i} \beta_y / (1 + 1/\exp[\beta_y (y_j - y_i)])} \quad . \qquad (7)$$

Therefore, the MRS (and WTP where y refers to the price attribute and $\beta_y = -\beta_{price}$) counterpart for an RRM model is not a single constant as in the linear RUM model but varies based on the attribute levels in the chosen and unchosen alternatives in the choice set. In particular, high (low) values of $MRS_{(RRM)}$ are expected when the chosen alternative performs relatively worse (better) than the unchosen alternatives. This argument is an intuitive one and reflects the behavioral appeal of the RRM semi-compensatory paradigm. Chorus, Rose, and Hensher (2013) provide a comprehensive comparison of WTP measures derived from attributes processed under different decision rules, being utility-based, regret-based, or a combination of the two.

The following section proposes a comparison between RUM and RRM approaches regarding MNL and MXL models. Willingness to pay measures derived from the MNL models are illustrated and discussed further in terms of practical implications.

Results

Table 3 presents the results for the MNL and MXL models estimated under the RUM and RRM decision rules. Several hybrid MNL model specifications were tested, thereby allowing the attributes to be processed under different combinations of utility-based and regret-based decision rules without obtaining any apparent improvement in the model fit. The MXL models were estimated using 500 Halton draws and assuming a Normal distribution for the random coefficients. The models are evaluated according to the log-likelihood at convergence and the

Akaike information criterion (AIC). The Ben-Akiva & Swait (1986) test for non-nested models is also performed to compare statistically the model fit for the two proposed specifications.

- TABLE 3 ABOUT HERE -

The coefficients of the RUM and RRM models are expected to have the same sign, although their interpretation differ. In a RUM model, a coefficient represents the change in utility associated with an alternative given by a one-unit increase in the value of the attribute. Therefore, it is reasonable to expect positive coefficients for quality attributes (such as "online rating") and negative coefficients for undesirable attributes (such as "distance" and "price"). In an RRM model, a coefficient represents the change in regret given by a one-unit increase in the attribute value of an unchosen alternative compared with the attribute value of the considered alternative. Therefore, the results for the RRM models suggest that regret increases as online rating increases in an unchosen alternative compared with the online rating of the selected alternative. Meanwhile, regret decreases as the price (or distance) increases in the unchosen alternative in comparison with the values in the chosen one.

The model estimates for the attributes associated with distance, online rating, and price attributes are highly significant and consistent across RUM and RRM decision rules for both MNL and MXL models. The only exception is for the coefficient associated with the distance to the nearest top tier sightseeing site which is significant for the MNL models but not significant (prob. > 0.05) for the MXL models. Looking at the magnitude of the coefficients associated with distance attributes, we note that by far, individuals value vicinity to the metro station as the most important feature. Regarding the neighborhood location of the hotel, it is evident that a waterfront location is highly preferred, while some contrasting results emerge for attributes related to the other location attributes. In particular, both RUM- and RRM-MNL models do not detect any significant difference in preference for "commercial street" and "pedestrian square" locations over "main road" location. However, the MXL models indicate "main road" location is preferred to "commercial street" and "pedestrian square" (RUM-MXL only) locations.

The consideration of the panel structure and random preference heterogeneity in MXL has the effect of improving substantially the model fit from the MNL version. In particular, the log likelihood for the MXL specification increased by 255 and 268 points for the RUM and RRM models, respectively. Indeed, all coefficients report significant estimates for the standard deviation, with the exception of the coefficients associated with "commercial street" and "pedestrian square" location attributes.

Regarding the comparison between RUM and RRM, we observe a better fit for the RRM specification in both MNL and MXL models. In particular, the RRM-MNL model has a 17-point lower AIC than its RUM counterpart, while the RRM-MXL model outperforms the RUM-MXL by 43 points. The Ben-Akiva and Swait (1986) test for non-nested models confirms the model fit improvement registered for the RRM model is statistically significant (prob.<0.01) for both MNL and MXL model specifications.

To enhance the comparison between the RUM and RRM decision rules, the WTP measures derived for MNL models are reported in Table 4. As discussed in the previous section, the WTP measures for the RUM model are single constants whereas those for the RRM model depend on the attribute levels in the chosen and unchosen alternatives. In general, the WTP estimates are in line with the findings of previous literature, where the geographical convenient rooms (Chou, Hsu, & Chen, 2008), waterfront promenade (as harbour view room in Masiero, Heo, & Pan, 2015; Wong & Kim, 2012) and higher quality rooms (as room class in Chou & Chen, 2014) are considerably more attractive than other type of rooms. According to the RUM-MNL model, on average, tourists are willing to pay US$ 5.9 per every minute of walking time saved to reach the nearest metro station. In other words, if Hotel A and Hotel B are located, respectively, at 5 and 10 minutes walking distance to the nearest metro station, tourists are willing to pay US$ 30 more for Hotel A than for Hotel B. Similarly, on average, the vicinity to a top-tier shopping district (sightseeing site) is valued at US$ 1.2 (US$ 0.7) per every minute of walking time saved. Compared with a hotel located on the main road, tourists are willing to pay US$ 58 more for a hotel located on a waterfront promenade. One additional star in the online rating is valued, on average, US$ 18.

- TABLE 4 ABOUT HERE -

It is interesting to note the mean WTP values obtained by the RRM-MNL model are very similar to the WTP values calculated on the RUM-MNL model. This result reinforces the robustness of the model specification estimated under the two different decision rules. However, the RRM model provides additional information on the relative distribution of WTP because the WTP value varies based on the attribute levels in the chosen and unchosen alternatives in the choice set. For example, the WTP for walking time to the nearest metro station can be as low as US$ 2.9 per minute in the case of a hotel which, compared to other hotels in the choice set, already performs well on this attribute and has a relatively high price. Meanwhile, if the considered hotel had lower performance in walking time to the nearest metro station as well as a lower price than competing hotels, tourists would be willing to pay as much as US$ 25.6 per every minute of walking time saved. In other words, if Hotel A is located closer to the metro station and is already more expensive than competing hotels, then it can expect potential guests to be willing to pay US$ 2.9 per every minute of walking time saved over competing hotels. A similar interpretation applies to other attributes associated with walking time distance and online rating.

Regarding the neighborhood location, the interpretation of the WTP minimum and maximum values for a hotel facing the waterfront promenade is less straightforward because the attribute is nominal instead of continuous. In general, the WTP for waterfront location (with respect to the main road) is reduced from US$ 332.40 to US$31.70 if the unchosen hotels are respectively located or not located on waterfront promenades.

A numerical example provided below illustrates the properties of the WTP values derived from the RRM-MNL model and compares them with those from the RUM-MNL model. Assume the following choice scenario: an individual faces three hotels A, B, and C, which are evaluated regarding all the attributes from Table 1. The preference-weighting of the individual on each attribute is equal to the corresponding MNL model estimate presented in Table 3. The revealed price for the individual is assumed to be equal to the mean room rate (i.e., US$ 198) in the sample. To enable the numerical example to be presented in a three-dimensional figure (Figure 2), the two unchosen alternatives are fixed to A (relatively low quality and low price) and B (relatively high quality and high price). Here, the evaluation of low/high quality and low/high price follows the variation in the choice experiment. That is, the measures of walking time to the nearest metro station, the nearest shopping district, and the nearest tourist attraction range from 2 to 20 minutes, 5 to 30 minutes, and 5 to 30 minutes, respectively. The measure of online rating ranges from 2 stars to 5 stars, and the measure of price ranges from 70% to 140% of the mean price in the sample (i.e. from US$ 138 to US$ 277).

- FIGURE 2 ABOUT HERE –

The unchosen alternatives A and B are located at the left and right polars in each graph, respectively. In the figure, the red plane identifies the WTP value for the RUM-MNL model, which is constant across different attribute and price levels in the unchosen alternatives. Instead, the blue plane reflects the WTP values for the RRM-MNL model based on different attribute levels of the chosen alternative (with respect to the attribute levels in the unchosen alternatives). Considering the walking time to the nearest metro station (top left graph), the constant WTP value derived from the RUM-MNL model is equal to US$ 5.9 per minute. Instead, the RRM-MNL model indicates that the WTP can amount to as much as US$ 7.2 per minute when the chosen alternative is relatively cheaper (i.e., US$ 138 compared to US$ 277 for the unchosen alternatives) and farther from the metro station (i.e., 20 minutes compared to 5 minutes for the unchosen alternatives). The WTP decreases to about US$ 4.6 per minute when the chosen alternative is relatively expensive (i.e., US$ 277 compared to US$ 138 for the unchosen alternatives) and located nearer the metro station (i.e., 5 minutes compared to 20 minutes for the unchosen alternatives).

- TABLE 5 ABOUT HERE -

In order to further investigate the comparison between RUM and RRM across different profiles of tourists, both RUM-MNL and RRM-MNL models were estimated for appropriate segments in the sample. In particular, three main tourist characteristics were dichotomized and considered as potential sources of deterministic heterogeneity, namely, familiarity with the destination (first-time versus repeat visit), country of residence (China versus outside China), and income (low versus mid-high). Low income is categorized as a household annual income below US$20,000. Table 5 reports the WTP measures derived from the significant model estimates along with the statistics for model evaluation (the full set of model estimates is omitted for brevity but available from the authors upon request). The model fit statistics reveal a better performance for the RRM model specification, especially for the first-time visit, outside China residence, and mid-high income segments. Nevertheless, the superiority in RRM model fit is marginal for the repeat visit segment and negligible for the China residence and low-income segments. In terms of the WTP measures, similar values are obtained for RUM and RRM model specifications within the same segments. In particular, first-time visitors, non-Chinese residents, and mid-high income travelers exhibit higher WTP values than their segment counterparts. These findings are in line with the assumption that first-time visitors and long distance travelers tend to spend more on their trip (McKercher, 2008; Oppermann, 1996).

Conclusions

Based on a stated choice experiment on 719 tourists to Hong Kong, we applied discrete choice models to gain a better understanding of the various location factors explaining hotel selection of tourists. In the experiment, we created hypothetical sets of alternative hotels after randomizing the levels of different factors, such as walking time to the nearest metro station, walking time to the nearest top-tier shopping district, walking time to the nearest top tier sightseeing and cultural/historical site, hotel neighbourhood, online rating, and price. The utility-based decision rule (based on random utility maximization) and the regret-based decision rule (based on random regret minimization) provide similar estimation results with regard to the significance of the estimated coefficient of different factors. In general, location factors including walking distances to the nearest metro station, top-tier shopping district and top-tier sightseeing site, and neighborhood type are found to be statistically significant. After incorporating the random preference heterogeneity into the choice model, we further obtained significant estimates for the standard deviation, highlighting a significant level of heterogeneity in tourists' hotel location preferences. Based on the estimates from the choice models, we derived the WTP with regard to various location factors. For example, according to the results from the RUM-MNL model, every minute of walking time saved to reach the nearest metro station, top-tier shopping district, and top-tier sightseeing site is estimated to be associated with a WTP of 5.9 US$, 1.2 US$, and 0.7 US$, respectively. The RRM-MNL model generated similar mean WTPs and captured the variation in the WTP values depending on the attributes featured by chosen and unchosen hotels. For example, tourists would be willing to pay as much as 25.6 US$ per every minute of walking time saved to the nearest metro station in a situation where the chosen hotel is located relatively far from the metro station but relatively cheap as compared with competing hotels.

This study contributed to the current knowledge in tourism location, hotel selection, and tourism pricing analyses. This study represents the very first research effort to investigate the location factors from a demand perspective using rigorous micro-econometric analysis. Therefore, quantitative simulation can be conducted to evaluate the hotel location site for new hotel entrants (Yang, et al., 2015), and tourist heterogeneity can be incorporated into the model to avoid any one-fit-all solution for a typical hotel location analysis. We applied a stated choice experiment to understand customer preference for hotel selection factors and uncover the value of the various location attributes. Unlike past studies that applied hedonic pricing to estimate the value of various hotel characteristics, the stated preference approach allows the analyst to focus on a variety of attributes and attribute levels in a controlled setting. This method facilitates the avoidance of the omitted variable bias levied against the hedonic pricing method. Future studies that compare the hedonic pricing model and discrete choice model can provide further insights into the preference of tourists on hotel location factors. Ultimately, this study investigated tourists' decision rules on hotel choice regarding the location factors.

In contrast to the commonly adopted random utility maximization model, the random regret minimization model is examined, and its results show promising explanatory power. Our results reveal that in selecting a hotel in an urban context such as Hong Kong, tourists are more likely to minimize anticipated regret rather than maximize expected utility when they are processing information related to the location of available hotels. In particular, the findings suggest that the regret-based decision rule is particularly appropriate for segments such as first-time visitors, mid-high income tourists, and tourists residing outside China.

Our results also provide insights to hotel investors and real estate appraisals. First, as an important step in the hotel feasibility study, future property performance can be predicted using the WTP estimates we obtained from the discrete choice analysis. Specifically, a Web-GIS platform can be developed to demonstrate potential location sites that are particularly promising for new hotel entrants (Kisilevich, Keim, & Rokach, 2013). Second, the results can help hoteliers to better formulate the pricing strategy based on the specific characteristics of the hotel. Facing price changes of competing hotels, the hotelier could conduct simulations in developing the best response.

Some limitations may temper the generalizability of our results. First, the results were obtained from data collected in Hong Kong, and may not be transferable to other geographic settings, especially to a non-urban environment. Second, because of the capacity limitation of the stated choice experiments, some less essential location factors (for urban hotels in Hong Kong) were not considered in our research design, such as security (Chu & Choi, 2000), access to the airport (Lee & Jang, 2011), and region life convenience (Aliagaoglu & Ugur, 2008). Therefore, we call for future research efforts to consider other location factors when collecting data in other areas and further investigate the location preferences of different customer segments.

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Tables

Table 1. Attributes and levels

Attribute	Level
Walking time to the nearest metro station	2 minutes; 5 minutes; 10 minutes; 20 minutes
Walking time to the nearest top tier shopping district	5 minutes; 10 minutes; 20 minutes; 30 minutes
Walking time to the nearest top tier sightseeing and cultural/historical site	5 minutes; 10 minutes; 20 minutes; 30 minutes
Hotel neighbourhood *(with visual aid)*	Main road; Commercial street; Pedestrian square; Waterfront promenade
Online rating	**; ***; ****; *****
Price	Room rate (– 30%; Room rate; + 20%; +40%)

Table 2. Descriptive statistics of the sample

	Mean (or %)	Std. dev.	Min	Max
Current visit				
Length of stay	4.08	5.096	1	60
Motivation for this trip [a]				
Experience different cultures	2.96	.887	1	4
Visit cultural and historical attractions	2.98	.836	1	4
Visit most popular attractions	3.12	.771	1	4
Visit entertainment parks	2.41	.977	1	4
Experience nightlife	2.43	1.022	1	4
Experience dining out	3.09	.802	1	4
Go shopping	2.81	.959	1	4
Travel party				
Alone	24%			
Friends	41%			
Relatives	13%			
Partner with or w/o kids	22%			
Destination familiarity				
First-time visit	48%			
Repeat visit	52%			
Current hotel stay				
Room rate (US$)	198	166	32	1000
Hotel area				
Hong Kong Island	29%			
Kowloon	66%			
New Territories	5%			
Socio-demographics				
Household Annual Income				
Below US$10,000	17%			
Between US$10,000 and US$19,999	16%			
Between US$20,000 and US$29,999	18%			
Between US$30,000 and US$49,999	17%			
Between US$50,000 and US$69,999	15%			
Above US$70,000	17%			

[a] Four-point scale (1 = Not at all important; 4 = Very important)

Table 3. Model results

	MNL				MXL			
	RUM		RRM		RUM		RRM	
	Coeff.	(Prob.)	Coeff.	(Prob.)	Coeff.	(Prob.)	Coeff.	(Prob.)
Mean estimates								
Walking time to the nearest:								
Metro station	-0.033	(0.000)	-0.023	(0.000)	-0.031	(0.000)	-0.024	(0.000)
Top tier shopping district	-0.007	(0.000)	-0.005	(0.000)	-0.007	(0.000)	-0.005	(0.000)
Top tier sightseeing site	-0.004	(0.015)	-0.003	(0.008)	-0.002	(0.337)	-0.002	(0.093)
Neighbourhood (ref: main road)								
Commercial street	0.021	(0.647)	0.021	(0.483)	-0.155	(0.003)	-0.073	(0.049)
Pedestrian square	0.046	(0.340)	0.039	(0.225)	-0.112	(0.041)	-0.043	(0.239)
Waterfront promenade	0.324	(0.000)	0.224	(0.000)	0.312	(0.000)	0.234	(0.000)
Online rating	0.100	(0.000)	0.070	(0.000)	0.073	(0.000)	0.061	(0.000)
Price	-0.006	(0.000)	-0.004	(0.000)	-0.011	(0.000)	-0.008	(0.000)
Standard deviation estimates								
Walking time to the nearest:								
Metro station					0.060	(0.000)	0.041	(0.000)
Top tier shopping district					0.013	(0.004)	0.009	(0.002)
Top tier sightseeing site					0.019	(0.000)	0.014	(0.000)
Neighbourhood (ref: main road)								
Commercial street					0.075	(0.594)	0.011	(0.980)
Pedestrian square					0.002	(0.985)	0.017	(0.967)
Waterfront promenade					0.527	(0.000)	0.358	(0.000)
Online rating					0.280	(0.000)	0.193	(0.000)
Price					0.013	(0.000)	0.010	(0.000)
Log likelihood (no parameters)	-6319.2		-6319.2		-6319.2		-6319.2	
Log likelihood (at convergence)	-5840.6		-5831.9		-5585.8		-5564.1	
AIC	11697.1		11679.9		11203.7		11160.2	

Table 4. WTP measures (in US$)

	RUM-MNL	RRM-MNL			
	Mean = Min = Max	Mean	Std.dev.	Min	Max
Walking time to the nearest:					
Metro station	5.9	6.0	1.9	2.9	25.6
Top tier shopping district	1.2	1.2	0.4	0.6	6.6
Top tier sightseeing site	0.7	0.8	0.2	0.4	4.1
Neighbourhood (ref: main road)					
Commercial street	-	-	-	-	-
Pedestrian square	-	-	-	-	-
Waterfront promenade	58.3	59.1	19.3	31.7	332.4
Online rating	18.1	18.4	5.8	9.0	105.0

Table 5. MNL-WTP measures (in US$) for main segments

	Familiarity				Residence				Income			
	First-time		Repeat		China		Outside China		Low		Mid-High	
	RUM	RRM	RUM	RRM	RUM	RRM	RUM	RRM	RUM	RRM	RUM	RRM
Walking time to the nearest:												
Metro station	6.3	6.3	5.7	5.9	3.5	3.6	7.2	7.3	2	2.2	8.3	8.4
		(2.4)		(1.5)		(0.6)		(2.7)		(0.5)		(2.8)
Top tier shopping district	1.2	1.2	1.2	1.2	1.3	1.3	1.2	1.2	0.8	0.9	1.4	1.4
		(0.5)		(0.3)		(0.2)		(0.4)		(0.2)		(0.4)
Top tier sightseeing site	-	-	0.8	0.9	-	-	0.7	0.8	-	-	0.8	0.9
				(0.2)				(0.3)				(0.3)
Neighborhood (ref: main road)												
Commercial street	-	-	-	-	-	-	-	-	-	-	-	-
Pedestrian square	-	-	-	-	-	-	18.8	20.9	-	-	-	-
								(6.7)				
Waterfront promenade	72.8	73.3	45.3	46.5	52.8	53.9	62.7	63.5	46.5	48.9	62.5	62.9
		(31.9)		(10.7)		(8.8)		(24.0)		(12.4)		(20.9)
Online rating	22.7	22.6	13.9	14.6	-	-	26.2	26.5	6.7	7.6	24.6	24.7
		(9.5)		(3.3)				(10.0)		(1.7)		(8.1)
Log-likelihood	-2741.7	-2733	-3093	-3092.5	-1837	-1837.2	-3986	-3975.6	-1965	-1965.3	-3851.4	-3843.1
AIC	5499.5	5482	6202.7	6201	3690.5	3690.4	7987	7967.2	3946.9	3946.6	7718.7	7702.2
Observations	345	345	374	374	217	217	502	502	237	237	482	482

Note: standard deviations in brackets

Figures

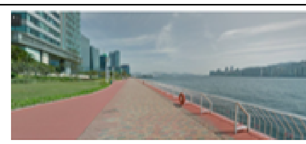
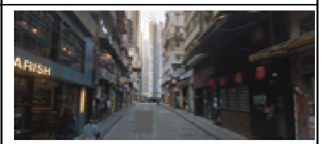
1	HOTEL A	HOTEL B	HOTEL C
Walking time to the nearest MTR	2 minutes	20 minutes	20 minutes
Walking time to the nearest top tier shopping district	20 minutes	20 minutes	5 minutes
Walking time to the nearest top tier sightseeing and cultural/historical site	30 minutes	20 minutes	5 minutes
Hotel neighborhood	 Pedestrian square	 Waterfront promenade	 Commercial street
Online rating	**	***	*****
Price	$70	$120	$140
Which hotel would you choose?			

Figure 1. Example of choice card (assuming a revealed price of $100)

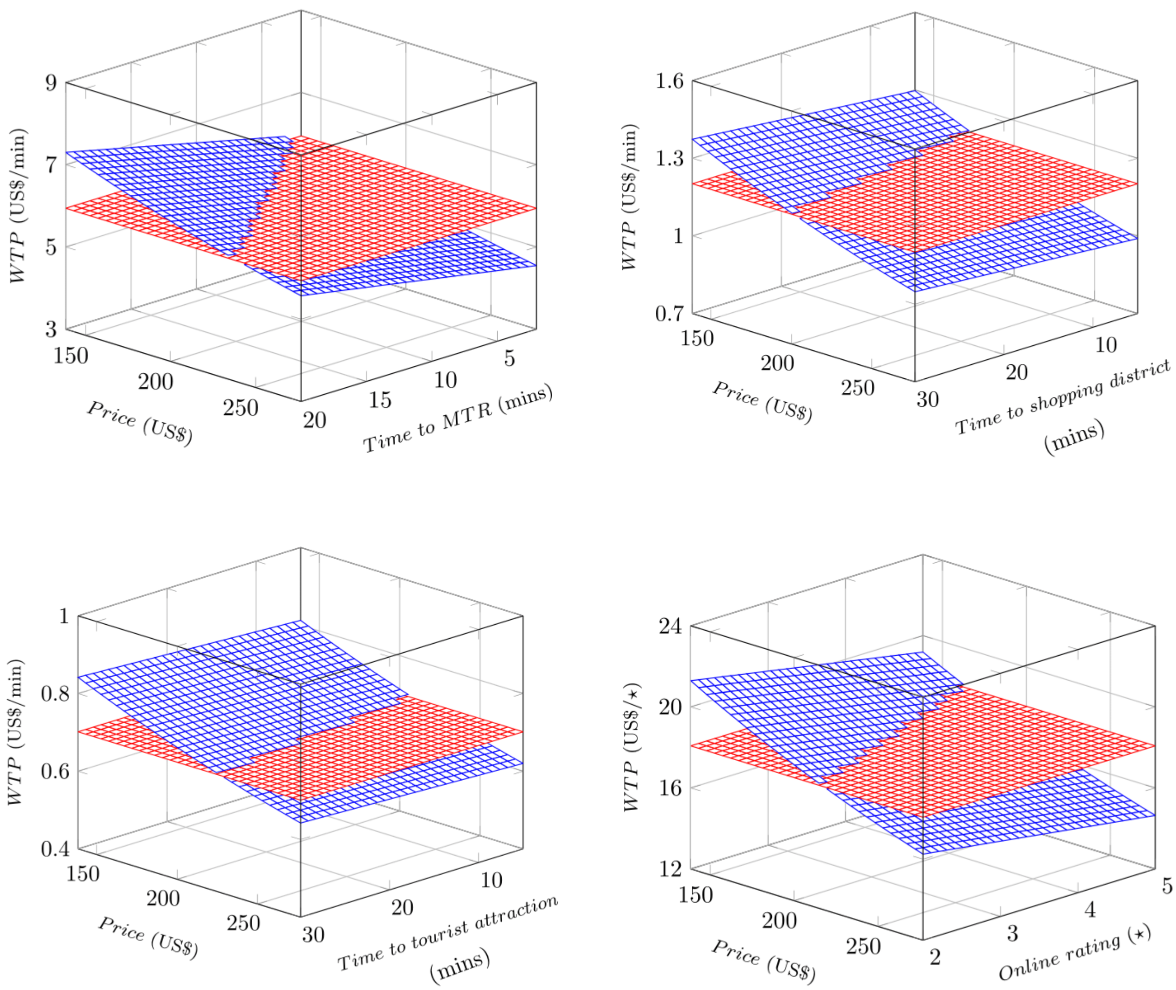


Figure 2. WTP values for RUM-MNL (red plane) and RRM-MNL (blue plane) models