Journal of Economic Theory and Econometrics, Vol. 24, No. 4, Dec. 2013, 338–365

The Determinants of Convention Site Selection: An Experimental Analysis*

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Abstract This paper examines the determinants of convention site selection with experimental data. The meetings and conventions industry is becoming more competitive and gaining importance in a national economy. However, there are only a few studies available on this issue. Moreover, analytical tools used are limited to statistical variance analysis or simple linear regressions and they lacked theoretical backgrounds. This paper tries to fill this gap and examines the determinants of site selection and their relative importance in Korean meetings and conventions industry. We employ the random utility theory to investigate individual choice decisions and estimate the mixed logit model for the choices with different selection attributes. After careful examination of previous literature, fifteen candidate factors are finally chosen and the logit and the mixed logit models are estimated. Both methods show that meeting facilities, exhibition, access to site, reputation, local support and shopping are the most important factors.

Keywords Convention, Site Selection, Discrete Choices, Mixed Logit Model, Market Share

JEL Classification C11, C25, C91, L83

*We are grateful to two anonymous referees for their helpful comments. All remaining errors are ours. This research is supported by Ministry of Culture, Sports and Tourism (MCST) and Korea Culture and Tourism Institute (KCTI) Research and Development Program 2012.

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Received August 20, 2013, Revised October 29, 2013, Accepted November 25, 2013

1. INTRODUCTION

The meetings and conventions industry is becoming one of the most competitive and lucrative market areas. Most companies, organizations, and associations hold events, meetings, and conferences every year. The direct benefits of meetings and conventions are, of course, economic effects, but indirect effects, such as international trade, cultural linkages, regional pride, political relations and etc, are also gaining importance. Many metropolitan and middle and small sized cities are competitively trying to host meetings and conventions, constructing buildings and amenities (Kim, 2010). These heated competitions triggered interest and research on the process of meetings and conventions site selection. It is thus important to find the determinants of site selection because regional communities have limited resources and time and they have to focus on a few selected factors to increase the possibility of hosting meetings and conventions.

Since the influential work of Crouch and Ritchie (1998), there have been many papers that study the determinants of convention site selections. They are Crouch and Louviere (2004), Chen (2006), Dipietro, et al. (2008), Shonk, et al. (2012), to name a few. Considering its significance in meetings and conventions industry, however, the amount of the studies on the determinants of site selection does not seem sufficient. Possible reasons are: First, appropriate data is not available. Obviously, data should be collected by survey interviews and this causes a lot of cost and time. Also, survey questions need to be carefully designed. Second, the analytical tools were mostly simple indices and they lacked theoretical backgrounds. Early methods of analysis were simple linear regressions or statistical variance analysis such as ANOVA. Rigorous econometric techniques such as logistic regressions have been applied only recently (eg., Crouch and Louviere, 2004).

This paper tries to fill this gap, and examines the determinants of site selection and their relative importance in Korean meetings and conventions industry. First, we reviewed previous literature for the choice of candidate selection factors and made up a core list of factors. Given the candidate factors, randomized experiments were designed and survey interviews were carried out for 100 meetings and conventions organizers on the choice of sites. Second, we employed the random utility theory to investigate individual choice decisions and estimated the logit as well as the mixed logit models on the choices with different selection attributes. From the results, we determine the relative importance of the selection factors that affect the decision and we compute market share for a selected survey scenario as an application.

Our results show that fifteen candidate factors are finally chosen after careful examination of previous literature on the selection factors, and the logit and the mixed logit models provide similar results. Both methods show that meeting facilities are the most important factor in selecting convention sites. Exhibition, access to site, reputation, local support and shopping are also important factors. These six factors constitute primary group factors. Secondary group factors are restaurant, hotel grade, image, activity, past experience, and access to hotel. The remaining factors, safety, participation period, and cost, do not significantly affect the decision. The results from the mixed logit model provide individual-level parameters for each factor and this information enables more rigorous and detailed analysis of the convention industry.

The rest of the paper is organized as follows. Section 2 provides an overview of the literature on the choice of meetings and conventions venues. Section 3 briefly introduces the data and methods used for our analysis. Section 4 presents empirical results and a few applications are followed in section 5. Concluding remarks are found in Section 6.

2. LITERATURE SURVEY

Fortin, Ritchie, and Arsenault (1976) pointed out that companies and associations have different motivations and decision process in determining convention sites. Hence, organizers of events must in some way reflect their own organization's intentions in determining the venue sites. Crouch and Ritchie (1998) reviewed 64 studies on convention site selection and identified several categories of site selection factors. Their review revealed that although there have been some efforts to find the determinants of convention sites, the analyses in most cases depended on anecdotal and experimental evidence, surveys, reviews, and conceptual studies. More seriously, there are only few studies on the determinants of convention sites, as Crouch and Louviere (2004) indicated.

Recently, Chen (2006) proposed the analytical hierarchy process (AHP) approach, a decision-making method based on pairwise comparisons between criteria, to construct an evaluation structure with criteria and associated weights of convention site selection for meeting planners. Seventeen factors are ranked according to this method. DiPietro, et al. (2008) examined three event organizing associations and ranked selection factors by asking respondents to rate selection variables with a scale running from 1 to 5. Shonk, et al. (2012) provided selection factors for small-scale sporting event. Respondents were asked to rate their perceived level of importance (from 1 to 7) each factor had regarding the selection of their most recent event destination. Jun and Oh (1999), Hong (2003), and Shin, et al. (2008) are a few examples of Korean studies. They used similarly simple statistical models, variance analysis, factor analysis and linear regressions.

The purpose of this paper, finding the determinants of convention site selection and estimating their relative importance, is closely related to conjoint analysis. The conjoint analysis is any decompositional method that estimates the structure of a consumer's preferences, given his or her overall evaluations of a set of alternatives (Green and Srinivasan, 1990, p.4). Theoretical developments have been made in 1960s by Luce and Tukey (1964), Krantz (1964), and Tversky (1967), for example. In 1970s, since the researches by Green and Rao (1971), Johnson (1974), and Srinivasan and Shocker (1973), among others, the conjoint analysis began to receive considerable attentions as a useful technique for empirical applications, especially in marketing area for the development of new products and the analysis of consumer behavior (Green and Srinivasan, 1990).

Convention site selection literature could be better understood as extensions or applications of the conjoint analysis because new products (in our case, convention sites) with different attributes are suggested in the form of choice scenarios to interviewees and the different weights implicitly assigned by the interviewees to each attribute are estimated by various methods. The methodologies of the conjoint analysis are very diverse (Green and Srinivasan, 1990) and many methods have been applied to measuring the relative weights of multiattributed products and services. One major trend of research methods is LINMAP, PREFMAP, and MONANOVA[1] and the other is discrete choice models such as logit and probit models. Louviere (2001) applied the multinomial logit model to develop new product strategies in fast food restaurants. Crouch and Louviere (2004) is the first to apply the logistic regression model to the convention site selection problem.

In the logit model, the choices of the respondents are aggregated across each choice situation and relative weights of various attributes are estimated. In this process, individual choice information on the various attributes of new products are lost. As indicated by Wittink and Montgomery (1979), Moore (1980), and Green and Srinivasan (1990), however, significant improvements in predictive validity could be obtained by estimating preference models at the individual level rather than at the aggregate level. The mixed logit model, one of the most recent developments in the discrete choice model, makes it possible to estimate the preference parameters at the individual level (Train, 2001; Train, 2009). Also, if the heterogeneity of the interviewees is significant (as in our case be-

[1] For more details of these methods and their applications, refer to Green and Srinivasan (1990) and the references cited there.

low), the mixed logit model provides more efficient estimates than the standard logit model. Moreover, the mixed logit model allows for the direct comparisons of many alternatives at the same time, which is one of the major concerns in marketing area, whereas the logit model considers only whether an option is acceptable or not. Finally, the mixed logit model is a fully general discrete choice model and it can accurately approximate the random utility model as suggested by McFadden and Train (2000).

It is known that consumer's behaviors involving decision making such as for site selection could be well described by the random utility theory (Crouch and Louviere, 2004; Louviere, 2001). More formally, individual weights for each attribute are combined to represent the overall utility of a product and decisions are made to maximize the utility function. Hence, the random utility theory (RUT), originally proposed by Thurstone (1927) and significantly advanced by McFadden (1974), provides a sound, well-tested theoretical approach to address the problem in the current paper, as asserted in Crouch and Louviere (2004). RUT assumes that preferences can be decomposed into a systematic and observable component and a random and unobservable component (Louviere, Hensher, and Swait, 2000). The systematic component represents the decision strategy used by the individual(s) (known as a utility function), and the random component represents all possible unobserved influences on decisions.

The mixed logit model allows various kinds of distribution for the random components, and the random utility model can be accurately estimated by the mixed logit model, as asserted by McFadden and Train (2000). The mixed logit model can be estimated either by classical method (Revelt and Train, 1998; Brownstone and Train, 1999) or by Bayesian method (Allenby, 1997; Sawtooth Software, 1999) as well. Each method has advantages and disadvantages but a powerful set of procedures for estimating discrete choice models has been developed within the Bayesian tradition by Allenby and Lenk (1994) and Allenby (1997). (See Train (2009, Chapter 12) for more details.) Also, Rossi et al. (1996), Allenby (1997), and Allenby and Rossi (1999) showed how the procedures can be used to obtain information on individual-level parameters within a model with random taste variation.

3. DATA AND MODEL

3.1. DATA

Models on decision making requires choice data obtained either by observing real choices or by collecting stated choices made in response to hypothetical situations. Choices collected in real markets typically are known as revealed preferences (RP), whereas choices collected in hypothetical situations are known as stated preferences (SP). RP choice data offer the advantage of certainty with regard to actual choice behavior, but suitable RP data often are unavailable. Moreover, basing choice models solely on RP data can be disadvantageous because of inadequate information about choice options considered but not selected (Crouch and Louviere, 2004). In this aspect, SP data is more advantageous in that choice is made in more controlled situations. In this paper, we use the SP data to examine the determinants of site selection.

To construct candidate selection factors, we reviewed previous literature and collected all the variables considered in the literature.[2] After careful examination by experts on convention industry, we chose fifteen factors as candidate selection factors that are expected to fit Korean convention industry well.[3] Survey interviews are carried out by full profile method. Thus, a set of attributes (or factors) are used to create 'profiles' that are shown to respondents and then they evaluate these profiles. Since we have fifteen attributes and each attribute has 2 or 3 characteristics, we have total $2^{10} \times 3^5 (= 248,832)$ profiles. Among these, total 32 profiles are generated and two choice sets are made up each with 16 profiles. The profiles are constructed so that each attribute in these profiles has correlation of zero with the other attributes. Also, the 16 profiles are randomly shown to each respondent. One hundred professional convention organizers (PCO) are asked to answer whether they would recommend each profile or not.[4] Thus, we have the data set of 0/1 dependent variables and fifteen independent variables. The data is listed in Table 1.

The variables are expected to have the following results. Access to the site takes the value 1 if easily accessible, 0 if not. Easy accessibility is a good condition for a site and thus this factor is expected to have positive sign. Accessibility to hotel indicates the distance from the hotel to the convention sites. It is expected to have positive sign, but for some individuals it may have negative sign because some people may prefer to have quiet accommodations away from the

[2]Attributes are chosen based on the following ten previous foreign and Korean literature: Crouch and Ritchie (1998), Crouch and Louviere (2004), Chen (2006), DiPietro, et al. (2008), Shonk, et al. (2012), Jun and Oh (1999), Lee and Choi (2003), Hong (2003), Shin, et al. (2008), and Kwon and Lee (2006).

[3]More details of the variable selection and data collection process are found in Han and Song (2013).

[4]Total number of interviews were 103, but three persons answered the 16 questions with all yes or no. Hence their interview data did not provide any information for the identification of determining factors, and thus were discarded from the data.

Table 1: Variables Description

Category	Variable	Description	Value
Choice	choice	Selected as a venue (dependent variable)	0/1
Accessibility	site	Airport or high-speed rail available	0/1
	hotel	Hotel is within 5/7/10 minutes	5/7/10
Extra-conference opportunity	activity	Sightseeing and entertainment	0/1
	shop	Shopping	0/1
	food	Restaurants	0/1
Accommodation	grade	Accommodation grade	1/2/3
Local support	support	Local support	0/1
Meeting facility	meeting	Meeting facility	0/1
	exhibit	Exhibition facility	0/1
Information	experience	Performance of past similar events	0/1
	reputation	Reputation of previous participants	0/1/2
Environment	safe	Safety and security	0/1
	image	Image of site	0/1
Cost and period	period	Participation period	2/4/5
	cost	Participation cost per person	10/15/20

convention sites. Since large values are generally less preferred, we multiplied minus to this variable to get positive sign.

Extra conference opportunities (sightseeing/shopping/restaurant) are important supplements to convention events, thus they are expected to have positive signs. Some people, however, may be indifferent to these opportunities and the coefficients may be 0 or even negative. Accommodation is essential part of the events. Given budget constraints, high grade hotels would be obviously preferred. Since small number indicates higher grade hotels, we multiply minus to grade variable so that we would get positive sign.

Local support is popular in Korea and sometimes is an important financial source of an event. Such support may lower individual participation fees or may provide some sorts of conveniences to the participants. Hence, it would have positive sign. Meeting and exhibition facilities are essential parts of the events and well established facilities would be preferred. Hence, they would have positive signs. Experiences of past similar events and reputation of participants are important background information to the convention organizers as well as to the participants. Successful hosting of similar events would increase the likelihood of the success of the current events. Also, the information obtained from the participants of previous events about the satisfaction level is very valuable one. Hence, these factors would affect the choice in a positive way.

Safety and security are items to be checked during travels or tours. Korea, however, is one of the safest countries in the world and this factor may not be critically considered or may be simply ignored. Hence, the sign may be close to zero. The image of the site is important supplement to the convention. For example, a conference of water forum may be hosted more probably in a region with the image of clean water. Hence, this factor would be positively related.

Preferences for participation period would differ from person to person. Some may prefer short and compact schedule and others may like long and loose schedule. Hence, the sign cannot be predicted in advance. Low participation cost per person would be obviously welcome. However, event organizers are often financially sponsored by local societies or they may get group discount. Thus, the participation cost may not be practically a big burden to the participants. Moreover, the participants may have to participate the events irrespective of the cost, i.e., the decision for participation may be inelastic to the cost. Hence, the sign of cost may be insignificant. Since high value of cost is less preferred, we multiplied minus to this variable.

Table 2 shows summary statistics of the variables used in the estimation. Total 100 convention organizers answered the survey questions for 16 choice situations. We thus have 1,600 observations. Since there are a few missing data with no response, we finally have 1,589 observations.

Survey respondents were asked to evaluate the relative importance of each attribute of each site and answer the question: “Would you recommend the convention host to consider this site as a venue?” Thus, the dependent variable in our data set is 0/1 dummy variable, as used in Crouch and Louviere (2004). This data set is suitable for the estimation of the logit model and the results will give us overall contribution of each attribute toward the choice of convention site. During this process, however, individual choice information is lost and the results cannot be used, for example, for the purpose of market segmentation strategy. Also, the estimation results from single choice problem (i.e., 0/1 problem) does not provide enough information for the comparison of two (slightly) different sites, which is the usual situation faced by the planners and also is one of the main concerns in marketing area. For example, we need to know how better one option is against another alternative to calculate market share of a convention site. To solve this problem, as mentioned above, we employ the mixed logit model and, accordingly, data needs to be reconfigured.

Table 2: Data Description

Variable	Obs	Mean	SD	Min	Max
choice	1589	0.4380	0.4963	0	1
site	1589	0.5053	0.5001	0	1
hotel	1589	-6.7766	2.0549	-10	-5
activity	1589	0.5072	0.5001	0	1
shop	1589	0.5003	0.5002	0	1
food	1589	0.4997	0.5002	0	1
grade	1589	-1.7376	0.8245	-3	-1
support	1589	0.5009	0.5002	0	1
meeting	1589	0.5047	0.5001	0	1
exhibit	1589	0.5009	0.5002	0	1
experience	1589	0.5179	0.4998	0	1
reputation	1589	1.2303	0.8314	0	2
safe	1589	0.5135	0.5000	0	1
image	1589	0.5060	0.5001	0	1
period	1589	3.2486	1.2988	2	5
cost	1589	-13.6942	4.1284	-20	-10

To apply the mixed logit model to our data set, we transform the current 0/1-type dependent variable into the one with the paired comparison, i.e., the choice data where one alternative is chosen against another alternative. Thus, we reconfigure the structure of the data set as follows. That is, we first separate the profiles into two groups that have choice variables 1 and 0. Then, we select profiles one by one from each group and match them as a pair. Since the profile with the choice variable 1 is above each individual's threshold and the profile with 0 is below the threshold, when we compare these two profiles, the profile with 1 would be again preferred to the one with 0.[5] In this way we can mimic the situation where each individual compare two alternatives and choose one among them, as is assumed in the mixed logit model.

We thus apply the logit model to the original data set and the mixed logit model to the reconfigured data set. When we construct the reconfigured data set, we lose a few observations. Since the numbers of 1's and 0's for each individual are different, when we match two alternatives, there remain a few unmatched

[5]That is, person n recommends alternative i if $U_{nit} > c_n$ where c_n is person n's threshold and does not recommend alternative j if $U_{njt} < c_n$. Therefore, we know that $U_{nit} > U_{njt}$ is true as long as the person's utility function is fixed.

profiles, which are thrown away. More precisely, from the 1,589 observations, we lose about 26.4% data and are left with 1,170 matched observations. Notice also that this matching process is random. Hence, to reduce the randomness in the final results, we repeated this process fifty times and provided the averages of the repetitions. This data transformation method would be practically useful but may suffer from increased uncertainty due to data loss.

3.2. MODELS

Logit model

Logit model can be applied to the situation where the dependent variable is discrete choice variable and enables probabilistic interpretation of the coefficients. Consider independent variable x and dependent variable Y. Then, the probability of $Y = 1$ given x is as follows:

$$\begin{aligned} P(Y = 1|x) &= F(x, \beta) \\ P(Y = 0|x) &= 1 - F(x, \beta) \end{aligned}$$

where β is the coefficient of x and $F(\cdot)$ is the transformation function that relates x to the probability of Y. For $F(\cdot)$, probability distribution functions are usually used. Probit model uses normal distribution and logit model uses logistic distribution function. Logit model is:

$$P(Y = 1|x) = \frac{e^{x'\beta}}{(1 + e^{x'\beta})} = \Lambda(x'\beta).$$

Estimation is made by the maximum likelihood estimation.

Mixed logit model[6]

The decision maker faces a choice among J alternatives. The utility of a person n from alternative j at t-th choice situation is specified as

$$U_{njt} = x'_{njt}\beta_n + \varepsilon_{njt}$$

where x_{njt} are observed variables that relate to the alternative and decision maker, β_n is a vector of coefficients (or partworths) of variables for person n representing that person's tastes, and ε_{njt} is a random term that is iid extreme value.[7] The

[6]The derivation of the mixed logit model in this subsection closely follows Train (2001), Train and Sonnier (2003) and Train (2009).

[7]In the study of site selection, the coefficients of factors indicate the strength of preferences each organizer assigns to the selection factors and they are sometimes called 'partworth'.

decision maker knows the value of his own β_n and ε_{njt}'s for all j and chooses alternative i if and only if $U_{nit} > U_{njt}, \forall j \neq i$. More generally, if we denote individual n's sequence of choices at t-th choice situation as y_{nt}, the probability for various t is:

$$L(y_n|\beta_n) = \prod_t \frac{\exp a(x'_{ny_{nt}}\beta_n)}{\sum_j \exp a(x'_{njt}\beta_n)}.$$

The researcher observes the x_{nj}'s but not β_n or the ε_{nj}'s. If the researcher observed β_n, then the choice probability would be standard logit. However, the researcher does not know β_n and therefore cannot condition on β_n. The unconditional choice probability is therefore the integral of L over all possible values of β_n:

$$P_n(y_n|b,\Omega) = \int L(y_n|\beta_n)g(\beta_n|b,\Omega)d\beta_n$$

where $g(\cdot)$ is the probability distribution function of multivariate normal distribution, b and Ω are mean and variance. This unconditional probability is called the mixed logit choice probability. Standard logit is a special case where $g(\beta_n) = 1$.

A choice situation consists of several alternatives described collectively by variables x. Suppose everyone in the population faces the same choice situation described by the same variables x. Some portion of the population will choose each alternative. Consider the people who choose alternative i. The tastes of these people are not all the same: there is a distribution of coefficients among these people. Let $h(\beta|i,x,\theta)$ denote the distribution of β in the subpopulation of people who, when faced with the choice situation described by variables x, would choose alternative i. Let $g(\beta|\theta)$ is the distribution of β in the entire population. We can generalize the notation to allow for repeated choices. Let y denote a sequence of choices in a series of situations described collectively by variables x. The distribution of coefficients in the subpopulation of people who would make the sequences of choices y when facing situations described by x is then denoted $h(\beta|y,x,\theta)$. Note that $h(\cdot)$ conditions on y, while $g(\cdot)$ does not. It is sometimes useful to call h the conditional distribution and g the unconditional distribution. Here, our main interest is the coefficients of the variables, β_n, and it could be estimated either by the classical approach or the Bayesian approach.

The Bayesian procedures, as an alternative to classical approach, avoid two of the most prominent difficulties associated with classical procedures (Train, 2009). First, the Bayesian procedures do not require maximization of any function, thus avoid typical problems encountered in maximization process such as convergence failures, choice of starting values, or local versus global maxima issues. Second, desirable estimation properties, such as consistency and efficiency, can be attained under more relaxed conditions. Moreover, the Bayesian procedures provide an estimator whose properties can be examined and interpreted in purely classical ways and under certain conditions, the estimator that results from the Bayesian procedures is asymptotically equivalent to the maximum likelihood estimator. Thus, below, we introduce the Bayesian approach.

We can derive $h(\beta|y_n,x_n,\theta)$. By Bayes' rule, we have

$$h(\beta|y_n,x_n,\theta) \times P(y_n|x_n,\theta) = P(y_n|x_n,\beta) \times g(\beta|\theta).$$

This equation simply states that the joint density of β and y_n can be expressed as the probability of y_n times the probability of β conditional on y_n (which is the left-hand side), or with the other direction of conditioning, as the probability of β times the probability of y_n conditional on β (which is the right-hand side). Rearranging,

$$h(\beta|y_n,x_n,\theta) = \frac{P(y_n|x_n,\beta) \times g(\beta|\theta)}{P(y_n|x_n,\theta)}.$$

We know all the quantities on the right-hand side. From these, we can calculate h.

The mean of β in the subpopulation of people who would choose y_n when facing x_n is

$$\bar{\beta}_n = \int \beta \cdot h(\beta|y_n,x_n,\theta)d\beta.$$

This mean generally differs from the mean β_n in the entire population. Substituting the formula for h,

$$\bar{\beta}_n = \frac{\int \beta \cdot P(y_n|x_n,\beta) \times g(\beta|\theta)d\beta}{P(y_n|x_n,\theta)} = \frac{\int \beta \cdot P(y_n|x_n,\beta) \times g(\beta|\theta)d\beta}{\int P(y_n|x_n,\beta) \times g(\beta|\theta)d\beta}.$$

The integrals in this equation do not have a closed form. However, they can be readily simulated. We take draws of β from the population density $g(\beta|\theta)$ and calculate the weighted average of these draws, with the weight for draw β^r being proportional to $P(y_n|x_n,\beta^r)$. The simulated subpopulation mean is

$$\breve{\beta}_n = \sum_r w^r \beta^r$$

where the weights are

$$w^r = \frac{P(y_n|x_n,\beta^r)}{\sum_r P(y_n|x_n,\beta^r)}.$$

If the number of choice situations that a person faces can be considered to rise, then the estimate of $\bar{\beta}_n$ can be considered to be an estimate of β_n. Let T be the number of choice situations that person n faces. If we observe more choices by the person (i.e., T rises), then we are better able to identify the person's coefficients. By the Bernstein-von Mises theorem, the mean of h is an estimator of β_n that is asymptotically equivalent to the maximum likelihood estimator of β_n, where the asymptotics are defined as T rising (Train, 2009, p.288). Also, the standard deviation of the draws provides the classical standard errors of the estimates.[8]

Until now, we assumed that all the coefficients vary across individuals. However, there are various reasons that the researcher might choose to specify some of the coefficients as fixed. Ruud (1996) argues that a mixed logit with all random coefficients is nearly unidentified empirically, since only ratios of coefficients are economically meaningful. He recommends holding at least one coefficient fixed, particularly when the data contain only one choice situation for each decision maker. In this paper, we fixed the cost variables.[9]

Lognormal or truncated normal distributions are often specified when the analyst wants to assure that the coefficient takes the same sign for all people. There is little change in either procedure when some or all of the coefficients are distributed lognormal or truncated normal instead of normal. Normally distributed coefficients are drawn, and then the ones that are lognormally or truncated normally distributed are transformed when they enter utility.

More generally, denote the partworths of person n as c_n, which is a vector with the same length as β_n. The partworths are defined by $c_n = T(\beta_n)$, where T is a transformation that depends only on β and is weakly monotonic (such that $\partial c_n^k / \partial \beta_n^k \geq 0$ for each element k of c_n and β_n).[10] The distribution of c_n is determined by the transformation. Little is changed in the estimation procedure by this transformation. Normally distributed β_n's are drawn as before but then transformed to c_n's when they enter utility. Utility is thus specified as

$$U_{njt} = x'_{njt} T(\beta_n) + \varepsilon_{njt}.$$

[8]See Chapter 12 of Train (2009) for the numerical issues of how to calculate the mean of the posterior distribution, the Gibbs sampling and, more generally, the Metropolis–Hastings algorithm that are used to obtain draws from the posterior distribution.

[9]The willingness to pay (wtp) for an attribute is the ratio of the attribute's coefficient to the price coefficient and the concept is popularly used in marketing literature. If the price coefficient is held fixed, the distribution of wtp is simply the scaled distribution of the attribute's coefficient. For this reason, we specified the cost (or the price of participation in our setup) as a fixed variable.

[10]Lognormal uses $c_n = \exp a(\beta_n)$ and is appropriate when all people like a specific attribute. Truncated normal uses $c_n = \max(0, \beta_n)$ and is appropriate when some people does not care about the attribute. This distribution has a probability mass at $\beta_n = 0$ and has the same normal distribution for $\beta_n > 0$.

The probability of the person's choice sequence given β_n is

$$L(y_n|\beta_n) = \prod_t \frac{\exp a(x'_{ny_{nt}} T(\beta_n))}{\sum_j \exp a(x'_{njt} T(\beta_n))}.$$

The Bayesian approach has additional advantage in that lognormal or truncated normal distributions can be easily accommodated. In MLE, optimum is not easily obtained and sometimes the inverse of Hessian does not exist. On the other hand, in the Bayesian approach, we do not have such problems because the Bayesian approach does not need maximization process.

4. ESTIMATION

4.1. LOGIT RESULTS

In this section, we provide the estimation results of convention site selection analysis using the logit and mixed logit models. Table 3 shows the estimation results from the logit model. The results show that thirteen out of fifteen variables are significant. Meeting, access to site, and exhibition facilities are three the most important determinants. Access to hotel and safety were not significant in the results of linear regression model (not shown here) but they are significant in the logit model. Participation period and cost are not significant at the 10% level. This means that convention organizers do not seriously consider period and cost factors when they determine the sites of events as we discussed in Section 3. The signs of the variables are all as expected. Thus, all the variables, except the period variable which is insignificant, have positive signs. This indicates that higher values of these factors increase the probability of hosting events.

4.2. MIXED LOGIT RESULTS

The logit model estimates the average effects of the variables on the choice of convention site. However, different organizers such as associations, companies, and regional communities have different preferences for site selection. Also, there are many types of events such as meeting, exhibitions, and conferences and these different events have different weights for the determinants of site selection. If organizers have different preferences, they will choose differently under the same set of alternatives. This is because organizers put different weights on different characteristics of the venue. Therefore, we might have better estimation results if we allow individuals to have different weights for determining factors.

Table 3: Results of Logit Model

Variable	Estimate	Stan. Err.	t-value	p-value	Low Limit	Upp. Limit
site	0.8540***	0.1152	7.42	0.000	0.6283	1.0797
hotel	0.0668**	0.0290	2.30	0.021	0.0099	0.1237
activity	0.4670***	0.1156	4.04	0.000	0.2405	0.6935
shop	0.6613***	0.1196	5.53	0.000	0.4270	0.8957
food	0.5256***	0.1190	4.42	0.000	0.2924	0.7588
grade	0.3867***	0.0714	5.42	0.000	0.2467	0.5266
support	0.6622***	0.1197	5.53	0.000	0.4275	0.8968
meeting	1.2652***	0.1190	10.63	0.000	1.0320	1.4985
exhibit	0.8481***	0.1178	7.20	0.000	0.6172	1.0790
experience	0.3022***	0.1160	2.60	0.009	0.0748	0.5296
reputation	0.4437***	0.0740	6.00	0.000	0.2988	0.5887
safety	0.1981*	0.1156	1.71	0.087	-0.0285	0.4246
image	0.5135***	0.1186	4.33	0.000	0.2809	0.7460
period	-0.0477	0.0460	-1.04	0.299	-0.1378	0.0424
cost	0.0063	0.0150	0.42	0.677	-0.0232	0.0358
chi2(15)	273.86	Log-lik	-909.014	N	1589	
Prob>chi2	0.000	Pseudo R2	0.1654			

Note: 1. Constant is not reported. 2. Columns 6 and 7 provide the lower and upper limits of confidence interval. 3. ***, **, and * indicates the statistical significance at the 1%, 5% and 10% level, respectively.

The mixed logit model makes this possible. Below, we provide the results from the mixed logit model.[11]

Table 4 shows the results from the mixed logit model assuming that the part-worths follow normal distribution. Notice first that we have estimates of the variance of $\hat{\beta}$ as well as the estimates of the mean of $\hat{\beta}$. This is because $\hat{\beta}$ is assumed to vary across individuals. Hence, by checking the significances of the estimates of variance we can evaluate the presumption that organizers have heterogeneous preferences. Notice that cost variable does not have variance estimates because it is assumed to be fixed across individuals as we discussed in Section 3.

Columns 5 to 7 present the results for variance estimates. t-values in column 7 show that most variables are significant at the 10% level. The least significant variable, access to site, has significance level of 12%. Therefore, we can reject

[11] We thank Train for sharing his MATLAB codes with us.

Table 4: Results for Mixed Logit Model: Normal Distribution for Partworths

	$\hat{\beta}$	Stan. Err.	t-value	Var($\hat{\beta}$)	Stan. Err.	t-value	$\hat{\beta} < 0$
site	5.7379***	1.1705	4.9019	19.5401	12.4013	1.5757	0.0900
hotel	0.6050*	0.3453	1.7522	4.2863**	1.7507	2.4483	0.3829
activity	2.3577**	1.0589	2.2265	18.5277*	10.6988	1.7318	0.2847
shop	5.4183***	1.1294	4.7974	17.8552*	10.5145	1.6982	0.0934
food	4.1563***	1.0754	3.8651	13.0640	8.1328	1.6063	0.1228
grade	2.6530***	0.7538	3.5196	14.9833*	7.7347	1.9371	0.2429
support	5.6706***	1.1259	5.0366	15.5692*	9.2651	1.6804	0.0768
meeting	8.7946***	1.4174	6.2045	38.5778*	20.6423	1.8689	0.0695
exhibit	6.7903***	1.1123	6.1049	15.2355*	8.9351	1.7051	0.0446
experience	1.8730*	1.1146	1.6803	19.7920*	11.5874	1.7081	0.3372
reputation	4.5684***	0.8638	5.2886	13.8255**	6.8498	2.0184	0.1035
safety	0.1612	1.1306	0.1426	25.3256*	14.2688	1.7749	0.4847
image	3.9582***	1.1469	3.4512	30.8228**	15.3859	2.0033	0.2272
period	-0.1988	0.4712	-0.4220	6.7652**	2.9696	2.2781	0.5308
cost	0.0894	0.1295	0.6901				
log-lik	-262.57						

Note: ***, **, and * indicates the statistical significance at the 1%, 5% and 10% level, respectively.

the assumption that the preferences of organizers are homogeneous and we conclude that the mixed logit model provides better results than the logit model. Particularly, access to hotel, reputation, image, and period have more significant variance estimates. This means that organizers have more diverse preferences for these variables than others.

Columns 2-4 show the results for $\hat{\beta}$ estimates. Although the estimates are different from those of the logit model, qualitative results are similar. That is, the ranking of factors in terms of t-value is similar to that of the logit model. Thus, meeting, exhibition, reputation, and access to site are important selection factors. The other variables show similar patterns. One reason that the rankings of variables are similar across different models might be due to the uncorrelatedness of variables. As discussed above, selection factors are randomized by construction and their statistical independence may have caused these results. Unlike the logit results, however, safety is insignificant in the mixed logit results in addition to period and cost. It was marginally significant in logit.

Last column presents the ratio of people who has $\hat{\beta}$ estimates less than zero.

Large values of ratios below zero imply that the variables may be insignificant and also reflects diverse preferences of convention organizers. More specifically, about 34% of the estimates of experience are below zero and this means that 34% of people assign negative values to previous experience. This may be because some organizers may try to find new places for an event instead of well-known and popular places. In this case, previous experience may affect the decision negatively. Therefore, the low significance of experience does not simply mean that it is less important. Rather, it means that the preferences of organizers are diverse and we need to approach them more strategically.

The results in Table 4 assume that the partworths are normal and thus the coefficients of variables are allowed to have positive and negative values. However, as we discussed above, the theory indicates that the variables are expected to have positive signs. Therefore, if we restrict the variables to have only positive signs, we might have better results. For this, lognormal and truncated normal distributions are popularly employed. Bhat (1998, 2000), Train (1998), Revelt and Train (1998), and Johnson (2000) utilized lognormal distributions and Johnson (2000) examined censored normals and found that they provided more reasonable results and better fit than uncensored normals in his application. Both distributions are possible in our setup. But our experiences indicate that reasonable estimates are hard to get with lognormal distribution and that truncated normal works better in our case. Therefore, we provide results of truncated normal only. Lastly, we did not restrict period to have positive sign because the theory does not say clearly about its sign.

Table 5 shows the results of truncated normal partworths. We have slightly different results from the normal case. Thus, in addition to period and cost variables, activity, hotel grade, experience, and image are also insignificant. Safety became significant in this model. Important variables in the normal case are still significant: meeting, exhibition, site, and reputation are strongly significant. Variance estimates are less significant and t-values are lower than in the normal case. But, they are still significant at the 20% level and we can marginally reject the hypothesis that variances of coefficients are zero.

Table 6 shows the results of the partworths when we assume that the partworths follow the truncated normal distribution. Last column indicates the ratio of $\hat{\beta}$ that are below zero. Estimates are slightly different from the normal case, but the ranking is similar. Thus, meeting, exhibit, support, site, reputation, and image are important determinants. Note that these partworths are calculated under the restriction that they are positive. Also, t-values are lower than the normal case. This may be because the standard errors of the partworths, $T(\beta_n)$, are es-

Table 5: Results for Mixed Logit Model: Truncated Normal Distribution for Part-worths

	$\hat{\beta}$	Stan. Err.	t-val.	Var($\hat{\beta}$)	Stan. Err.	t-val.
site	3.1397***	1.2152	2.5836	25.9402	18.3322	1.4150
hotel	-3.5203**	1.5599	-2.2568	24.2037*	14.1865	1.7061
activity	-1.5069	1.6063	-0.9381	28.5608	18.4605	1.5471
shop	2.2741*	1.1771	1.9320	18.1790	13.0255	1.3956
food	2.0724	1.2853	1.6124	22.8463	17.1516	1.3320
grade	0.0436	1.3623	0.0320	31.7263	21.7283	1.4601
support	3.4482***	1.2436	2.7727	23.8268	17.2384	1.3822
meeting	5.6619***	1.2988	4.3592	48.5975*	29.1233	1.6687
exhibit	4.1699***	1.1435	3.6468	19.6943	14.4654	1.3615
experience	-2.7068	1.9252	-1.4060	34.8582	22.8674	1.5244
reputation	2.3884**	1.0087	2.3679	25.9617	17.2320	1.5066
safety	-4.7741**	1.9544	-2.4427	35.5793	22.4351	1.5859
image	1.5645	1.3149	1.1898	35.5283	21.9027	1.6221
period	-0.0451	0.3342	-0.1351	3.2196**	1.3890	2.3178
cost	0.0308	0.0783	0.3935			
log-lik	-274.47					

Note: ***, **, and * indicates the statistical significance at the 1%, 5% and 10% level, respectively.

timated after $\hat{\beta}$ is first estimated and hence additional estimation errors caused lower significances.

Now we have two models for the estimation: normal and truncated normal. The two models show similar results in terms of the rankings of the important variables, but also show slightly different significance levels. One measure to select a better model or the measure of the goodness of fit is the value of the log-likelihood function. When the partworths follow the normal distribution, the value of log-likelihood is -262.56 and when the partworths follow the truncated normal, it is -274.47. This implies that allowing the individual partworths to have negative values provides better fit to the data than restricting them to have only positive values.[12] Therefore, from the criterion of goodness of fit, we select the

[12]We also tried hybrid case where some of the partworths follow normal and the others follow truncated normal. But the values of log-likelihood function of these hybrid cases are still lower than that of all normal case. Hence, we present only the case where all the partworths (except that of period) follow truncated normal.

Table 6: Results of Partworth: Truncated Normal Distribution

Variable	Distribution	Estimate	Stan. Err.	t-value	$\hat{\beta}=0$
site	Truncnormal	3.9915	3.7807	1.0650	0.2509
hotel	Truncnormal	0.6296	1.4895	0.4058	0.7575
activity	Truncnormal	1.5670	2.4602	0.6092	0.5720
shop	Truncnormal	3.0805	2.9611	1.0649	0.2683
food	Truncnormal	3.1395	3.2039	0.9905	0.2979
grade	Truncnormal	2.2145	3.1056	0.7189	0.4765
support	Truncnormal	4.0833	3.6269	1.1382	0.2200
meeting	Truncnormal	6.3565	5.2529	1.2643	0.1678
exhibit	Truncnormal	4.6051	3.6055	1.2946	0.1656
exper	Truncnormal	1.4631	2.3790	0.5147	0.6509
repu	Truncnormal	3.3413	3.3844	1.0178	0.2760
safety	Truncnormal	0.8161	1.7781	0.3774	0.7741
image	Truncnormal	3.1609	3.7198	0.8532	0.3777
period	Normal	-0.0463	1.7770	-0.0270	0

Note: ***, **, and * indicates the statistical significance at the 1%, 5% and 10% level, respectively.

model where the partworths follow the normal distribution and below we present the results of normal case only.

Table 7 shows the correlation of the individual partworths when they follow normal distribution. The signs and magnitudes of correlations indicate how organizers assign values to each selecting factors when they decide convention sites. Hence, for example, the organizers who think meeting facilities important also put positive values to local support, experience, reputation, and images of the site and put negative values to shopping facilities. The organizers who think access to hotel important also put positive values to hotel grade and reputation of the sites. Local support is closely related to meeting and exhibition facilities, good food, and reputation of the site. These observations suggest that different patterns among organizers could be categorized and, based on this information, regional communities or institutions may approach the convention organizers more strategically to fit their needs.[13]

Table 8 summarizes the results of the logit and the mixed logit models. The

[13]This may be a possible extension of our results, but we do not pursue it here. One example of such categorization of organizers is found in Han and Song (2013).

Table 7: Correlation between Partworths: Normal Distribution for Partworths

	site	hotel	activity	shop	food	grade	support	meeting
hotel	0.1127	1						
activity	0.0641	0.0144	1					
shop	-0.0305	-0.0227	-0.0739	1				
food	0.0603	0.1381	-0.0013	-0.0011	1			
grade	0.1810	0.3086	-0.0455	0.1047	0.1289	1		
support	0.0699	0.1164	-0.0918	0.0152	0.2664	0.0661	1	
meeting	0.0750	0.1494	0.0129	-0.2746	0.1630	0.0183	0.2798	1
exhibit	-0.0343	0.0388	-0.0974	0.1823	0.2530	0.0464	0.3558	0.0761
exper	0.2168	0.1025	0.0352	-0.0981	0.1278	0.0400	0.1506	0.3662
repu	0.1941	0.1926	-0.1209	-0.0355	0.1377	0.2457	0.3116	0.3885
safe	-0.1045	0.0397	-0.0698	0.1416	0.0060	0.1028	0.0669	0.0511
image	-0.0188	0.1137	-0.0763	0.1009	0.1017	0.1772	0.1536	0.4190
period	0.0522	-0.0565	-0.1854	0.0938	-0.0170	-0.0119	0.0878	-0.0158

	exhibit	exper	repu	safety	image	period
exhibit	1					
exper	0.1187	1				
reup	0.1817	0.2530	1			
safety	0.0838	0.0532	0.1145	1		
image	0.0628	0.1983	0.3850	0.1999	1	
period	0.0336	-0.0300	0.1379	0.0577	0.1093	1

estimates of both results are sorted in an ascending order of t-values. The table shows that the rankings of the two results are similar so that the Spearman rank correlation is 0.965. Both models indicate that meeting facilities are the most important factor of site selection. Exhibition facilities, access to site, reputation, local support and shopping are the next important factors. We may regard these top six factors as the primary group factors for the convention site selection, and their cumulative relative importance is 62% in the logit and 65% in the mixed logit model.[14] Therefore, to be selected as a convention site, these primary group factors should be satisfied above all. Next six factors, restaurant, hotel grade, im-

[14]We define relative importance of each variable by the ratio of the t-value to the sum of all the t-values in absolute value terms. Hence, for example, relative importance of meetings facilities is 15.5%(=10.63/68.6) in the logit model.

age, activity, experience, and access to hotel are secondary group factors. These factors explain about 34% in the logit model and 33% in the mixed logit model. Hence, the explanatory power of the primary group factors is about twice that of the secondary group. Lastly, safety, period, and cost are insignificant and do not have any explanatory power.

Table 8: Summary of Logit and Mixed Logit Models

	Logit				Mixed Logit			
	Variable	$\hat{\beta}$	s.e.	t-value	Variable	$\hat{\beta}$	s.e.	t-value
1	meeting	1.2652***	0.1190	10.63	meeting	8.7946***	1.4174	6.20
2	site	0.8540***	0.1152	7.42	exhibit	6.7903***	1.1123	6.10
3	exhibit	0.8481***	0.1178	7.20	reputation	4.5684***	0.8638	5.29
4	reputation	0.4437***	0.0740	6.00	support	5.6706***	1.1259	5.04
5	support	0.6622***	0.1197	5.53	site	5.7379***	1.1705	4.90
6	shop	0.6613***	0.1196	5.53	shop	5.4183***	1.1294	4.80
7	grade	0.3867***	0.0714	5.42	food	4.1563***	1.0754	3.87
8	food	0.5256***	0.1190	4.42	grade	2.6530***	0.7538	3.52
9	image	0.5135***	0.1186	4.33	image	3.9582***	1.1469	3.45
10	activity	0.4670***	0.1156	4.04	activity	2.3577**	1.0589	2.23
11	experience	0.3022***	0.1160	2.60	hotel	0.6050*	0.3453	1.75
12	hotel	0.0668**	0.0290	2.30	experience	1.8730*	1.1146	1.68
13	safety	0.1981*	0.1156	1.71	cost	0.0894	0.1295	0.69
14	period	-0.0477	0.0460	-1.04	period	-0.1988	0.4712	-0.42
15	cost	0.0063	0.0150	0.42	safety	0.1612	1.1306	0.14

Note: ***, **, and * indicates the statistical significance at the 1%, 5% and 10% level, respectively.

As a robustness check, individual information of the respondents such as gender, age, job experience, and firm size are considered and used in the estimation. These individual characteristics may affect the choice of convention site because, for example, the organizers with different ages may have different weights for the attributes of the convention sites. To check this possibility, we included the characteristic variables and the interaction terms of the attribute variables with the characteristic variables, respectively, in the regression. The results[15] (not shown here) show that none of the characteristic variables are significant separately. This implicitly means that the organizers try to select the

[15]The results are available from the authors upon request.

convention site on behalf of the companies or the associations, not reflecting their own personal characteristics. Also, the interaction terms did not affect the results. That is, the regression results with the interaction terms are almost the same with the ones without the interaction terms. Therefore, we conclude that the considered 15 candidate variables have predictive abilities over individual characteristic variables.

5. APPLICATIONS

In this section, we provide two applications using the results in the logit and the mixed logit models. Table 9 presents some of the prediction results of experimental profiles using the logit model. That is, the values represent $P(Y = 1|x)$, the probability of being selected as a venue given the factors x. Profiles are sorted in a descending order of prediction values in column 2. The other columns show the values of the six primary group factors.

Table 9: Prediction for Experimental Profiles: Logit Model

Profile	Prediction	meeting	site	exhibit	reputation	support	shop
17	0.97	1	1	1	2	1	1
1	0.85	1	1	1	1	0	1
14	0.83	1	1	1	2	0	1
27	0.78	1	1	1	2	1	0
10	0.76	1	1	1	0	1	1
7	0.65	1	0	0	2	0	1
20	0.63	1	0	0	2	1	1
24	0.63	1	1	1	1	1	0
4	0.62	1	1	1	0	0	0
9	0.48	1	0	0	2	1	0
30	0.46	0	0	1	2	1	1
3	0.45	1	0	0	1	1	1
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
16	0.20	0	0	1	0	1	0
23	0.18	1	0	0	0	0	1
22	0.12	0	0	1	1	0	0
32	0.05	0	1	0	0	0	0

Notice that Profile 17 has the highest prediction value of 97% and all the primary group factors get full scores. Profiles 1, 14, 27 and so on are competing with Profile 17 and have similar values of primary group factors. On the other hand, Profile 32 has the lowest prediction value of 5% and almost all the primary group factors have values of zero. This observation shows that getting high values for the primary group factor is important to have high prediction values. Notice also that management factors such as reputation and local support are important as much as the infrastructure factors such as meeting and exhibition facilities. When we use the 50% of prediction values as a threshold to be selected as a venue, only 9 profiles exceed this threshold and survive in the market. The other 23 profiles fail to pass over this threshold and are weeded out of the market.

The information of relative importance of determinants is useful to regional communities who want to host events. That is, they can use limited resources more efficiently to host events. Also, information on the preferences of organizers enables us to increase the probability of being selected as a venue. Investigation of choices made by organizers gives clues for the determining factors of site selection and the mixed logit model provides richer information to the researcher than the standard logit model. Thus, as an application, we compare Profiles 10 and 7 below.

In Table 10, logit probability for Profile 10 is 0.76 and that for Profile 7 is 0.65. Both Profiles have probabilities higher than 0.5 and have potentials to survive in the market. This information, however, does not provide any clue on the possible market share of each profile if there are only two profiles in the market. The mixed logit model enables direct comparison of such two profiles. Thus, when we calculate the probability that Profile 10 is selected against Profile 7, we get 99%. This information actually, however, does not help much. More reasonable results can be obtained by observing the decisions made by each convention organizer.

The mixed logit model produces the partworths of each convention organizer. Then, from this, we can decide which profile would be chosen by each organizer. Since each organizer has different partworths, their choices would be different for given profiles. Our calculation shows that 77% of the organizers choose Profile 10 and the other 23% choose Profile 7. Thus, we can conclude that potential market share of Profile 10 is 77%. This analysis of market share is important from the perspective of convention site providers because it is directly related to returns of investment to convention facilities.

Information on individual organizers provides further implications. That is, it suggests a way to increase the probability of being selected as a host. For example, Profile 7 is inferior to Profile 10 under the current situation. However,

Table 10: Comparison of Two Profiles

Variable	Profile 10	Profile 7	Variable	Profile 10	Profile 7
Logit Prob.	0.76	0.65	meeting	1	1
site	1	0	exhibit	1	0
hotel	5	7	experience	1	1
activity	1	1	reputation	0	2
shop	1	1	safety	0	1
food	0	1	image	0	0
grade	2	1	period	2	2
support	1	0	cost	10	20

careful examination of the determining factors tells us that by upgrading the exhibition facility, which is the second most important factor in the mixed logit results, Profile 7's market share against Profile 10 increases from 23% to 73%. This exercise shows that the analysis of the mixed logit results provides useful information about efficient allocation of investment resources for the purpose of hosting events.

6. CONCLUSION

This paper studies the determinants of convention site selection using the data collected by survey interviews for professional convention organizers in Korea. After careful examination of previous literature on the selection factors, fifteen candidate factors are finally chosen, and we applied the logit and the mixed logit models to evaluate the relative importance of candidate factors. The logit and the mixed logit models provide similar results. Both methods show that meeting facilities are the most important factor in selecting convention sites. Exhibition, access to site, reputation, support and shopping are next important factors. These six factors form primary group factors. Secondary group factors are restaurant, hotel grade, image, activity, experience, and access to hotel. The other factors, safety, period, and cost, did not significantly affect the decision.

The mixed logit model provides richer information to the researcher than the standard logit model. The mixed logit model produces the partworths of each convention organizer. Then, from this, we can decide the market share of one profile against another. This analysis of market share is important from the perspective of convention site providers because it is directly related to returns of investment to convention facilities. Information on individual organizers provides further implications. By strategically focusing limited resources and time on the most important selection factors, the probability of hosting the events will rise. Section 5 showed some of the applications of the mixed logit model.

REFERENCES

Allenby, G. (1997). An introduction to hierarchical Bayesian modeling, Tutorial Notes, Advanced Research Techniques Forum, American Marketing Association.

Allenby, G., and P. Lenk (1994). Modeling household purchase behavior with logistic normal regression, Journal of the American Statistical Association 89, 1218–1231.

Allenby, G., and P. Rossi (1999). Marketing models of consumer heterogeneity, Journal of Econometrics 89, 57–78.

Bhat, C. (1998). Accommodating variations in responsiveness to level-of-service variables in travel mode choice models, Transportation Research A 32, 455–507.

Bhat, C. (2000). Incorporating observed and unobserved heterogeneity in urban work mode choice modeling, Transportation Science 34, 228–238.

Brownstone, D., and K. E. Train (1999). Forecasting new product penetration with flexible substitution patterns, Journal of Econometrics 89, 109-129.

Chen, C. (2006). Applying the Analytical Hierarchy Process (AHP) approach to convention site selection, Journal of Travel Research 45, 167-174.

Crouch, G. I., and J. R. B. Ritchie (1998). Convention site selection research: A review, conceptual model, and propositional framework, Journal of Convention and Exhibition Management 1, 49–69.

Crouch, G. I., and J. J. Louviere (2004). The determinants of convention site selection: A logistic choice model from experimental data, Journal of Travel Research 43, 118–130.

Dipietro, R. B., D. Breiter, P. Rompf, and M. Godlewska (2008). An exploratory study of differences among meeting and exhibition planners in their destination selection criteria, Journal of Convention and Event Tourism 9, 267–268.

Fortin, P. A., J. R. B. Ritchie, and J. Arsenault (1976). A study of the decision process of North American Associations concerning the choice of a convention site, Quebec, Canada: Quebec Planning and Development Council.

Green, P. E., and V. R. Rao (1971). Conjoint measurement for quantifying judgmental data, Journal of Marketing Research 8, 355–63.

Green, P. E., and V. Srinivasan (1990). Conjoint analysis in marketing: New developments with implications for research and practice, Journal of Marketing 54, 3-19.

Han, S., and W. Song (2013). Development of Optimal Planning Skill in Tourism Facilities and Service Programs, Korea Culture and Tourism Institute (in Korean).

Hong, S. (2003). The analysis for perception gap of competitiveness of Jeju convention industry between professional convention organizer and convention participants, Tourism Research 18, 275–287 (in Korean).

Johnson, R. M. (1974). Trade-off analysis of consumer values, Journal of Marketing Research , 121–127.

Johnson, R. M. (2000). Monotonicity constraints in choice-based conjoint with hierarchical bayes, Research paper, Sawtooth Software.

Jun, J. K., and H. C. Oh (1999). The study of the image of Korea as an international meeting destination using importance-performance analysis, Tourism-Leisure Research 11, 57–67.

Kim, E. (2010). A Study of the evaluation of competitiveness considering selective attributes of international convention destination: Focused on 16 provinces, Tourism-Leisure Research 22, 501–520 (in Korean).

Krantz, D. H. (1964). Conjoint measurement, Journal of Mathematical Psychology 1, 248–77.

Kwon, Y., and I. Lee (2006). Developing a measurement scale of convention city competitiveness focusing on the selection attributes of convention destination, Seoul City Research 7, 17-31 (in Korean).

Lee, A., and W. Choi (2003). The study of choice attribute on hotel convention: Convention planner in Seoul, Hotel Management Research 12, 73–87 (in Korean).

Louviere, J. J. (2001). Using discrete choice experiments and multinomial logit choice models to forecast trial in a competitive retail environment: A fast food restaurant illustration, Journal of Retailing 60, 81–107.

Louviere, J. J., D. A. Hensher, and J. D. Swait (2000). Stated Choice Methods: Analysis and Application, Cambridge, UK: Cambridge University Press.

Luce, R. D. and J. W. Tukey (1964). Simultaneous conjoint measurement : A new type of fundamental measurement, Journal of Mathematical Psychology 1, 1–27.

McFadden, D. (1974). Conditional logit analysis of qualitative choice behaviour, In Frontiers in Econometrics, edited by P. Zarambka, New York: Academic Press.

McFadden, D., and K. E. Train (2000). Mixed MNL models of discrete response, Journal of Applied Econometrics 15, 447-470.

Moore, W. L. (1980). Levels of aggregation in conjoint analysis: An empirical comparison, Journal of Marketing Research 17, 516–23.

Revelt, D., and K. E. Train (1998). Mixed logit with repeated choices, Review of Economics and Statistics 80, 647–657.

Rossi, P., R. McCulloch, and G. Allenby (1996). The value of household information in target marketing, Marketing Science 15, 321–340.

Ruud, P. (1996). Simulation of the multinomial probit model: An analysis of covariance matrix estimation, Working Paper, Department of Economics, University of California, Berkeley.

Sawtooth Software (1999). The CBC/HB module for hierarchical Bayes, at www .sawtoothsoftware.com.

Shin, Y., G. Yang, and Y. Kim (2008). Intentions to revisit and recommendation of convention destination according to the convention site attributes, Culture and Tourism Research 10, 99–111 (in Korean).

Shonk, D. J., T. C. Greenwell, G. Brabo, and D. Won (2012). Site selection, satisfaction, and intent to return: An exploratory study of the perceptions of rights holders of small-scale sporting events, Journal of Convention and Event Tourism 13, 1-15.

Srinivasan, V., and A. D. Shocker (1973). Estimating the weights for multiple attributes in a composite criterion using pairwise judgments, Psychometrika 38, 473–493.

Thurstone, L. L. (1927). A law of comparative judgment, Psychological Review, 273–286.

Train, K. E. (1998). Recreation demand models with taste variation, Land Economics 74, 230–239.

Train, K. E. (2001). A comparison of hierarchical Bayes and maximum simulated likelihood for mixed logit, Working Paper, Department of Economics, University of California, Berkeley.

Train, K. E. (2009). Discrete Choice Methods with Simulation, 2nd edition, Cambridge University Press.

Train, K. E. and G. Sonnier (2003). Mixed logit with bounded distributions of partworths, Working Paper.

Tversky, A. (1967). A general theory of polynomial conjoint measurement, Journal of Mathematical Psychology 4, 1–20.

Wittink, D. R. and D. B. Montgomery (1979). Predictive validity of trade-off analysis for alternative segmentation schemes, in Educators' Conference Proceedings, Series 44, eds., Neil Beckwith et al., Chicago: American Marketing Association, 69–73.