Domestic Tourism Destination Choices — a Choice Modelling Analysis

Twan Huybers*
School of Business, The University of New South Wales, Australian Defence Force Academy, Canberra ACT 2600, Australia

ABSTRACT

Tourism destinations compete with each other to attract visitors. Although international tourism has received a lot of attention, domestic tourism remains the mainstay for many destinations. To inform the basis on which destinations compete, an understanding of the determinants of destination choices is required. In this paper, the discrete choice modelling method is applied to investigate the determining factors underlying the short-break holiday destination choices of prospective tourists from Melbourne, Australia. The results from an estimated nested logit model indicate the relative importance of a number of destination and trip attributes and respondent characteristics. The model results are used to simulate the effects on destinations’ market shares resulting from various changes in attributes and tourist characteristics. Copyright © 2003 John Wiley & Sons, Ltd.

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INTRODUCTION

The importance of international tourism and its contribution to the global economy is well documented. However, the emphasis on international tourism tends to obscure the continuing dominance of domestic tourism flows in many countries. For instance, in Australia — a country in the top 15 of international tourism earners (World Tourism Organization, 2002) — domestic tourism expenditure has generally been around four to five times that of international tourists. Further, increased geopolitical instability and events such as the recent SARS virus outbreak may well result in substitution effects between international and domestic tourism flows. This suggests enhanced domestic tourism opportunities for holiday destinations.

However, destinations are not equally well placed to benefit from increases in domestic tourism. The agencies responsible for destination development and promotion need to be aware of the determinants of tourists’ destination choices. That knowledge helps the agencies to identify their destination’s position within the market and the potential need to reposition themselves strategically. In this paper, the use of discrete choice modelling to analyse domestic tourists’ destination choices is reported. It concerns the choices of short-break destinations by residents from Melbourne — capital city of the state of Victoria, Australia. Short breaks are defined here as trips of two to three nights’ duration, e.g. long weekends or mid-week arrangements.
Consistent with Lancaster’s (1966, 1971) characteristics-based theory of consumer choice, the choice modelling method is based on the key premise that consumers base their purchase decisions on the comparative attributes of a relevant choice set of rival products. Applied to tourism, this refers to choices by tourists between various destinations that differ in their attributes such as their attractions, facilities and the distance from tourists’ home. The application of the characteristics approach in a discrete destination choice framework is discussed in Papatheodorou (2001).

The investigation of destination choices reported in this paper is based on an analysis of stated choices. In stated choice studies, information about decision-makers’ preferences is elicited using decision experiments. It is in this respect that stated choice models differ from models based on choices revealed in actual choice situations. To approximate actual choice situations in a stated choice model, the analyst selects an appropriate set of product attributes and a set of relevant choice options. This requires careful exploratory research and testing but does not ensure the external validity of results derived from the stated choice experiment. However, various studies have shown the external validity of stated preference models (see, for instance, Pearmain et al., 1991; Swait et al., 1994; Adamowicz et al., 1998).

Despite the above limitation of stated choice models, there are two major reasons why they may be preferred to revealed preference studies. There is often insufficient variability in the explanatory variables in revealed preference data sets. Also, those variables often show high collinearity. Hence, the statistical efficiency of measuring the variables’ effects on observed choices is compromised. The advantage of a stated preference study is that the analyst uses an experimental design that determines the variability and non-collinearity of choice determinants in the hypothetical choice scenarios.

The justification for the use of stated choice models in travel and tourism applications has been discussed by, for instance, Rugg (1973), Fesenmaier (1990) and Morley (1995). Some applications of the choice modelling method to destination choices have appeared in the literature. These include Haider and Ewing (1990) in which Canadian tourists’ choices of Caribbean islands are analysed. A further application is Morley’s (1994) investigation of the effects of different price components on Malaysia residents’ demand for travel to Sydney. Also, Huybers and Bennett (2000) use choice modelling to analyse international holiday destination choices of prospective UK tourists. Morley (1994) and Huybers and Bennett (2000) are based on the stated choices of prospective tourists to avoid the potential for selection bias often associated with surveys of tourists at their destinations. The same approach is followed in this paper.

The paper is structured as follows. In the next section, the specification of discrete choice models is discussed. This is followed by a discussion of the design of the survey instrument and the survey data. The estimation results are reported in the subsequent section, followed by the results of some model simulations. In the final section, a summary and some concluding comments are offered.

CHOICE MODELLING

A detailed discussion of various conceptual and practical issues concerning the discrete choice modelling method is provided by, for instance, Ben-Akiva and Lerman (1985) and Louviere et al. (2000). Choice modelling is based on random utility theory in which choices are assumed to be made on the basis of the relative utilities derived from alternative options available in a choice set. The utility of a good, which cannot be observed, is assumed to consist of two components. The first is the deterministic component, \( V \), which is an indirect utility function of the options’ attributes, \( a \), as well as of the decision-maker’s characteristics, \( c \). The second component represents the random error term, \( e \), which plays a crucial role in model specifications as will be discussed shortly. Overall, then, individual \( i \)’s utility of good \( x \) is

\[
U_{ix} = V_{ix}(a_{ix}, c_i) + e_{ix}
\]  

(1)

The probability that individual \( i \) chooses good \( x \) from \( y \) goods in choice set \( S \) is
If it is assumed that the random error terms are independently and identically distributed (IID) and follow the double exponential distribution, the random utility model converts into the choice probabilities of the multinomial logit (MNL) model.

Each estimated attribute coefficient \( \beta \) comprises a weight component \( w \) and a scale component \( \mu \): \( \beta = w \cdot \mu \). The identical distribution aspect of the IID assumption constrains the scale parameter to be the same for all error terms within one data set. Hence, the value of the scale parameter does not affect the choice probabilities.

In many applications, it is restrictive to assume that the IID assumption holds across all choice alternatives. One way of relaxing this strict assumption is to assume that the IID property applies only within subsets of the choice alternatives. Adopting that assumption results in the nested logit model. In that model, the choice process can be represented by a hierarchical tree structure. An example of a simple nested structure is depicted in Figure 1. It shows that the upper level choice is made between the branches ‘No Holiday’ and ‘Holiday’. The elemental choice alternatives are shown as the lower level choices within the subsets. In this case, it is assumed that the IID property holds between destinations A and B but not between those destinations and the alternative to stay at home.

Following the laws of probability, for a two-level nested structure, the joint probability that an individual chooses option \( x \) in branch \( b \) is the product of the equivalent conditional probability and the probability that branch \( b \) is chosen:

\[
P_{xb} = P_{xb|b} P_b
\]

The conditional choice probability of option \( x \) from \( w \) options within branch \( b \) is

\[
P_{xb|b} = \frac{e^{\mu_b}}{\sum_y e^{\mu_y}}
\]

whereas in a two-level nested structure the choice probability of branch \( b \) from \( t \) branches is

\[
P_b = \frac{e^{(\mu_b IV_b)}}{\sum_y e^{(\mu_y IV_y)}}
\]

The log sum in the denominator of equation (5) is sometimes referred to as the inclusive value index (IV) of the branch, in this case the IV of branch \( b \) (IV\(_b\)). The parameter \( \mu_b \) is the IV parameter of branch \( b \). It is an indicator of the similarity of the options within the branch in terms of their error structure. As shown in equation (5), the inverse of \( \mu_b \) is used as a scale parameter to normalise the utilities of each choice alternative within a particular branch (see Koppelman and Wen, 1998; Hensher and Greene, 2002). To be globally consistent with random utility maximisation, the IV parameter must lie between 0 and 1, although Boersch-Supan (1990) demonstrates that IV parameters \( >1 \) are valid under local utility maximisation conditions. The IV parameter equals 1 if the correlation between the indirect utility functions of the options within the branch is zero. If all IV parameters are equal to 1, the model specification reduces to the MNL model (Ben-Akiva and Lerman, 1985). Hence, IV parameters that are significantly different from 1 suggest that the nested logit structure is more appropriate than MNL.

The choice model is operationalised by carrying out a survey of (prospective) decision-makers. In a choice modelling experiment, respondents are presented with a series of choice scenarios (choice sets) that approximate actual choice situations. Each choice set con-
tains a number of choice options that are described in terms of levels of selected attributes. The configuration of choice option descriptions is different in each choice set. As respondents indicate the option they would choose in each set, the effect of attribute level changes on choice can be observed. This allows the estimation of the marginal rates of substitution between attributes. The modelling results also can be used to simulate the effect of changes in attributes on the market shares of the choice options. The latter are the choice probabilities of the options included in the experiment.

SURVEY DESIGN AND DATA

As emphasised above, it is essential that the hypothetical choice scenarios in a stated choice modelling study mirror real market choices. To that end, exploratory analyses of destination choices were carried out through a series of focus groups in Melbourne in March and May 2002. The focus group discussions, in which prospective short-break tourists from Melbourne participated, yielded a relevant group of short-break destinations and a set of destination and trip attributes. Focus groups were also used to determine the attribute labels and the wording of each of the attribute levels. Finally, draft questionnaires were tested during focus group sessions.

Seven major attributes were identified in the focus groups. These attributes and their level descriptions are shown in Figure 2—the showcard used in the survey. They include two continuous variables: ‘Expenditure per person’ and ‘Travel time (transport mode)’. In the experimental design, both these attributes were varied across four levels, which were different for each destination. The expenditure levels for each destination were based on visitor expenditure data for overnight residents from Melbourne (National Visitor Survey, 2000). The other five attributes are categorical, three of which were defined at two levels (‘Amenities’, ‘Crowdedness’ and ‘Event/festival’) and the remaining two were varied across four levels.

The focus group feedback yielded a set of six relevant destinations. The choice set comprises four Victorian regions (Goldfields of Victoria, Great Ocean Road, Mornington Peninsula and Phillip Island/Gippsland) and two interstate capital cities (Canberra and Sydney). The four Victorian regions and their names follow the classification developed by Tourism Victoria, the State’s tourism development and marketing authority. This regional classification differs from the one adopted by the Australian Bureau of Statistics and used for the purpose of the National Visitor Survey. Focus group participants clearly indicated that they were more familiar with, and hence preferred, the regions identified by Tourism Victoria.

Table 1 shows the number of overnight trips for each of the six destinations and the shares of each destination as a percentage of total overnight trips by Melbourne residents (National Visitor Survey, 2000). As shown in the table, the six regions in the survey cover 49% of all overnight visitors from Melbourne. Focus group discussions revealed that six was the maximum number of destinations to be included with a view to the complexity of the survey task. In addition, participants indicated that a mix of two interstate and four Victorian destinations was appropriate. In that light, coverage of 49% of current overnight visitors appears acceptable.

A fractional factorial main effects design was used to construct 16 different versions of the choice experiment. Each questionnaire contained eight choice sets for which respondents indicated their preferred option from the alternatives presented. The orthogonal, main effects design allowed the estimation of the independent attribute effects on utility assuming negligible two-way or higher-order interactions between attributes. Main effects generally explain between 70 and 90% of the variance in response data (Louviere, 1988; Louviere et al., 2000).

Each choice set in the questionnaire (available from the author) included the six destinations described in terms of the attributes discussed above. A seventh alternative was also included. To enhance the reality of the choice situation, respondents were given the option to choose not to go on a holiday if they preferred this to any of the six described destinations in a choice set.

The survey was administered in August 2002. Potential respondents were approached
Amenities
This indicates the general standard of the amenities (e.g. accommodation, food outlets).
- Low to medium (2 to 3 stars)
- Medium to high (3 to 4 stars)

Crowdedness
This tells you how busy it is at the destination and its attractions.
- Pleasantly busy (there are quite a few people around, but it does not feel overcrowded)
- Crowded (there are vast numbers of people around)

Environment
This is the setting of the main activities that you undertake during your holiday.
- Natural (you are out and about e.g. walking in a national park, swimming/surfing at a beach, playing golf or other sports)
- Cultural/historical (e.g. you visit museums/galleries, heritage sites)
- You engage in activities in even mix of natural and cultural/historical settings
- Other (you spend most of your time relaxing in or around the accommodation, enjoying food/wines in restaurants/winery, going to cinema/casino, etc.)

Event/festival
This tells you whether there is a special event or festival at the destination (e.g. cultural/heritage, music, sports).

Expenditure per person
This is the all-inclusive expenditure per adult person that you would incur for your holiday, based on a trip of three nights. This includes transport, accommodation and food/drinks/entertainment.

Season
This tells you the time of year of your visit to the destination.
- Spring
- Summer
- Autumn
- Winter

Travel time (transport mode)
This is the time it takes to reach the destination from your home (with the mode of transport indicated as well). The difference in time is related to distance, and to factors such as congestion and delays during your trip.

Figure 2. Attributes and attribute levels (questionnaire showcard).

Table 1. Melbourne residents, overnight holiday/leisure trips (2000). Source: National Visitor Survey (2000)

| Destination region          | Number | Share (%) |
|-----------------------------|--------|-----------|
| Canberra                    | 117,000| 2         |
| Goldfields of Victoria      | 269,000| 4         |
| Great Ocean Road            | 791,000| 12        |
| Mornington Peninsula        | 701,000| 11        |
| Phillip Island/Gippsland    | 864,000| 13        |
| Sydney                      | 475,000| 7         |
| Other destinations           | 335,300| 51        |
| Total                       | 6,570,000| 100      |

by interviewers at three geographically dispersed shopping malls across Melbourne (both on weekdays and weekends) and screened on the basis of two criteria. They were recruited if they were contemplating a short-break holiday within the next 3 months, and if they were a major decision-maker within their travel party. Respondents were then given the questionnaire, a showcard with the information about the attributes and a map showing the destinations. Interviewers were available for help while respondents completed their questionnaires. The questions in the choice experiment
had been rotated sequentially to avoid any order bias.

A total of 384 questionnaires were completed. A small number of questionnaires were incomplete. However, all of those were partially useable for model estimation purposes. In addition to the responses to the choice scenarios, other data were collected using the questionnaire. They included various socio-demographic and attitudinal characteristics of respondents. Some of these sample characteristics are included in Table 2. Slightly over half the respondents were female and the average age of respondents was 37. Nearly half the survey respondents indicated that they used hotel/motel facilities as their usual choice of accommodation. The vast majority of respondents indicated that they used hotel/motel facilities as their usual choice of accommodation. The vast majority of respondents indicated that they use their own vehicle as the main mode of transport for holiday purposes. This is consistent with visitation data that show that about 73% of Melbourne residents’ short-break destinations are within the state of Victoria (National Visitor Survey, 2000); most intrastate destinations are within driving distance from Melbourne. Finally, all income categories were reasonably well represented in the sample. The income classification shown in Table 2 is a truncated version of the one used in the 2001 Census by the Australian Bureau of Statistics.

Respondents were also asked to provide some information specific to each of the destinations, the results of which are shown in Table 3. All six destinations had been visited previously by a large proportion of respondents. This particularly was the case for Great Ocean Road, Phillip Island/Gippsland and Sydney, with around two-thirds of the respondents. Sydney was the destination at which most respondents had grown up and in which ‘a lot of their friends and relatives’ still lived. The relevance of these destination-specific data to the model results is considered shortly.

ESTIMATION RESULTS

Initially, various MNL model specifications were estimated (LIMDEP (version 7.0) was used for all estimations). The indirect utility function specification for each destination consisted of an alternative-specific constant (ASC), the destination attributes and respondents’ socio-economic and attitudinal characteristics. The latter were included in the utility specification to capture preference heterogeneity among individuals. The ASC represents the
mean of the difference between the unobserved factors in the error term of one destination and that of an arbitrarily selected base case.

The inclusion of individuals’ characteristics and ASCs in the model can help to achieve compliance with the independence of irrelevant alternatives (IIA) property of the MNL model (Train, 1986; Louviere, 1994). The IIA property, directly related to the IID assumption of the error terms, implies that the relative choice probabilities between any two alternatives within the choice set are not affected by the inclusion or exclusion of other alternatives in that set. The procedure proposed by Hausman and McFadden (1984) can be used to test MNL models for compliance with the IIA property. This involves testing for the equivalence between the parameters of the full model and a model in which one of the options is deleted. The MNL models failed the Hausman-McFadden test, which suggests that the IIA property was violated. Hence, alternative model specifications incorporating different assumptions about the distribution of the error terms were investigated.

The estimation results presented below are those of a nested logit model. Estimations of alternative model specifications other than nested logit, including the heteroscedastic extreme value model, were attempted. However, these were unsuccessful using LIMDEP 7.0. A large number of different nested logit model specifications were estimated. In terms of the hierarchical tree structure, this included various configurations that appeared plausible in a behavioural sense. For instance, a structure with the three branches ‘Victoria’, ‘Interstate’ and ‘Home’ appeared plausible a priori. However, it should be kept in mind that the tree structure in a nested logit model is not necessarily consistent with behavioural expectations (Louviere et al., 2000).

The tree structure of the nested logit model specification reported below is shown in Figure 3. It does not appear to have an obvious behavioural foundation. However, there is reason to believe that the destinations in the non-degenerate branches display some correlation associated with common unobserved destination attributes. This is due to the derivation of the tree structure from a choice frequency experiment that was included in the questionnaire. In that experiment, respondents were asked to indicate their destination choices on the basis of the names of the six destinations and the option to stay at home. Offering only the names of the destinations ensured that the choices would be determined by respondents’ perceptions of the various destinations and their attributes. The experiment consisted of eight choice sets of different sizes and compositions, allowing an assessment of choices in different choice contexts (cross-effects). The choice sets were constructed using an ortho-

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**Table 3. Destination-specific respondent characteristics a**

| Destination region               | Previous visit to the destination (%) | Destination is home base (%) |
|----------------------------------|---------------------------------------|-----------------------------|
| Canberra                         | 43                                    | 3.3                         |
| Goldfields of Victoria           | 45                                    | 5.2                         |
| Great Ocean Road                 | 69                                    | 4.9                         |
| Mornington Peninsula             | 57                                    | 6.2                         |
| Phillip Island/Gippsland         | 64                                    | 5.9                         |
| Sydney                           | 65                                    | 11.7                        |

*a Sample proportions.*

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gonal 2^n present–absent design. Half the respondents received the main design, whereas the other half were presented with its foldover version.

A choice model with choice frequencies as dependent variables and ASCs as independent variables was estimated and the results are shown in Table 4. The relative magnitudes of the estimated ASCs suggest the subsets of destinations as depicted in Figure 3 (a nested structure with Canberra and ‘None’ was tried but showed inferior estimation results). The ‘Inland’ branch comprising Canberra and Goldfields of Victoria appears plausible because they are the only two non-coastal destinations and, hence, may share unobserved attributes that cause correlations among the error components within the subset. The common denominator for the branch containing Mornington Peninsula, Phillip Island/Gippsland and Sydney is not obvious. Hence, the first tier in the structure is labelled ‘M–P–S’. The results in Table 4 suggest that Great Ocean Road is perceived as sufficiently different from the other three coastal destinations and appears separately in the tree structure as does the ‘None’ option.

In the selection of the nested logit tree structure, estimated IV parameters were tested for compliance with random utility maximisation. Also, likelihood ratio tests were carried out to compare nested logit and MNL specifications. The maximum likelihood estimation results for the statistically superior nested logit model specification are shown in Table 5. The log-likelihood of the nested logit model is significantly higher than that of the equivalent MNL specification (−5280.436) at a significance level of 0.01 using the likelihood ratio test. Twice the difference between these log-likelihood values is greater than the critical Chi-squared value with four degrees of freedom (13.277). The IV parameters for the two degenerate branches in the model are necessarily equal to 1. The two estimated IV parameters are both between 0 and 1, which implies that the model is globally consistent with random utility maximisation. Statistical t-tests showed that both IV parameters are significantly different from unity. In combination with the failed Hausman–McFadden test of the MNL models, this supports the use of the nested logit model.

The model specification is elaborate. It includes the choice attributes in the experiment, ASCs for each of the six destinations, the respondent characteristics of Table 3, two socio-demographic variables (‘Age’ and ‘Income’) and respondents’ ‘own vehicle’ travel mode characteristic. Likelihood ratio tests revealed that the effects of most attribute levels are statistically significantly different between destinations. Hence, these destination-specific attribute levels are shown separately for each destination. The other attribute levels are included generically, that is, they apply to each destination equally, and appear in the first four rows of the table. The respondent characteristics are included in a destination-specific fashion. The characteristics ‘Age’ and ‘Income’ are included for each destination. The other respondent characteristics (‘Home base’, ‘Been before’ and ‘Own vehicle’) are included only for those destinations for which their effects are significant.

The number of 21,455 observations mentioned in the table is derived from 384 responses of eight choice sets each, with seven choice options in each choice set minus 49 missing choice data. The goodness-of-fit of the model specification can be gauged by its adjusted $\rho^2$ value and the $\chi^2$ value. As adjusted $\rho^2$ values that exceed 0.20 are evidence of an extremely good fit of the data in disaggregated logit models (Hensher and Johnson, 1981), the overall fit of the model appears good. This is supported by the high $\chi^2$ value (equivalent to

### Table 4. Estimation results of frequency model (name-only experiment)

| Variable | Coefficient | p-value |
|----------|-------------|---------|
| ASC_Cb  | 0.14861     | 0.112   |
| ASC_Gf  | 0.44027     | 0.000   |
| ASC_GOR | 1.78695     | 0.000   |
| ASC_MP  | 1.07397     | 0.000   |
| ASC_PG  | 1.10325     | 0.000   |
| ASC_Syd | 1.13583     | 0.000   |

**Summary statistics**

| Observations | LL (convergence) | $\rho^2_{adj}$ |
|--------------|------------------|-----------------|
| 64           | $-3500.217$      | 0.317           |

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Table 5. Estimation results of nested logit model.

| Variable             | Coefficient | p-value | Variable         | Coefficient | p-value |
|----------------------|-------------|---------|------------------|-------------|---------|
| Gen_Exp              | -0.0014     | 0.000   | Syd_LowMed       | -0.1348     | 0.014   |
| Gen_Mix              | 0.0661      | 0.092   | Syd_PiBusy       | 0.1356      | 0.014   |
| Gen_Autumn           | -0.0547     | 0.173   | Syd_Nat          | -0.1829     | 0.051   |
| Gen_Time             | -0.0422     | 0.175   | Syd_Cult/His     | 0.0912      | 0.309   |
| Cb_LowMed            | 0.0423      | 0.644   | Syd_Event        | 0.0990      | 0.072   |
| Cb_PiBusy            | 0.2609      | 0.008   | Syd_Spring       | 0.1365      | 0.126   |
| Cb_Nat              | -0.2030     | 0.186   | Syd_Summer       | 0.1857      | 0.036   |
| Cb_Cult/His          | 0.0113      | 0.939   | ASC_Cb           | 0.5121      | 0.298   |
| Cb_Event             | 0.0241      | 0.788   | ASC_Gf           | 0.2850      | 0.383   |
| Cb_Spring            | 0.4233      | 0.002   | ASC_GOR          | 1.6621      | 0.000   |
| Cb_Summer            | 0.2428      | 0.107   | ASC_MP           | 1.3715      | 0.000   |
| Gf_LowMed            | -0.1082     | 0.081   | ASC_PG           | 1.1924      | 0.000   |
| Gf_PiBusy            | 0.3573      | 0.000   | ASC_Syd          | 2.1291      | 0.000   |
| Gf_Nat              | 0.0562      | 0.580   | Cb_Age           | 0.0104      | 0.168   |
| Gf_Cult/His          | -0.0596     | 0.563   | Cb_Inc           | 0.6672      | 0.005   |
| Gf_Event             | 0.1395      | 0.025   | Cb_Home          | 1.8809      | 0.000   |
| Gf_Spring            | 0.2980      | 0.002   | Cb_Before        | 0.5089      | 0.007   |
| Gf_Summer            | 0.0641      | 0.526   | Cb_Own           | -0.9195     | 0.000   |
| GOR_LowMed           | -0.1094     | 0.015   | Gf_Age           | -0.0035     | 0.571   |
| GOR_PiBusy           | 0.1876      | 0.000   | Gf_Inc           | 0.7641      | 0.000   |
| GOR_Nat             | 0.0685      | 0.355   | Gf_Before        | 1.0280      | 0.000   |
| GOR_Cult/His         | -0.1853     | 0.016   | GOR_Age          | -0.0187     | 0.001   |
| GOR_Event            | 0.0801      | 0.076   | GOR_Inc          | 0.9409      | 0.000   |
| GOR_Spring           | 0.1466      | 0.046   | GOR_Before       | 0.6685      | 0.000   |
| GOR_Summer           | 0.3014      | 0.000   | MP_Age           | -0.0189     | 0.001   |
| MP_LowMed            | -0.1178     | 0.023   | MP_Inc           | 0.6073      | 0.001   |
| MP_PiBusy            | 0.1949      | 0.000   | MP_Home          | 1.0114      | 0.000   |
| MP_Nat              | 0.1193      | 0.158   | MP_Before        | 0.5748      | 0.000   |
| MP_Cult/His          | -0.1179     | 0.182   | PG_Age           | -0.0196     | 0.001   |
| MP_Event             | 0.1291      | 0.013   | PG_Inc           | 0.8712      | 0.000   |
| MP_Spring            | 0.0658      | 0.443   | PG_Before        | 0.4503      | 0.000   |
| MP_Summer            | 0.3795      | 0.000   | Syd_Age          | -0.0092     | 0.122   |
| PG_LowMed            | -0.1038     | 0.065   | Syd_Inc          | 0.8348      | 0.000   |
| PG_PiBusy            | 0.2418      | 0.000   | Syd_Home         | 0.4632      | 0.002   |
| PG_Nat              | 0.0975      | 0.291   | Syd_Before       | 0.8081      | 0.000   |
| PG_Cult/His          | -0.3638     | 0.000   | Syd_Own          | -1.2096     | 0.000   |
| PG_Event             | -0.0017     | 0.975   |                  |             |         |
| PG_Spring            | 0.1511      | 0.102   |                  |             |         |
| PG_Summer            | 0.5146      | 0.000   |                  |             |         |

Summary statistics

| Summary Measure        | Value     |
|------------------------|-----------|
| Observations           | 21,455    |
| LL (convergence)       | -5273.603 |
| $\chi^2$               | 2313.549  |
| $\rho^2_{adj}$         | 0.176     |

*Significantly different from unity.
the F-statistic in regression analysis), which shows the high overall significance of the model specification.

The categorical choice attributes were included in the data set using effects coding. This involves selecting, arbitrarily, for each attribute one base level that is not included in the model specification. The other levels are included using binary coding and the coefficient for the base level can be derived from the coefficients estimated.

As shown in the table, of the four generic variables, the attribute ‘Expenditure’ and the ‘Mix of natural and cultural/historical’ level of the ‘Environment’ attribute are statistically significant at the 0.10 significance level. The coefficient of the ‘Expenditure’ attribute has a negative sign as expected a priori: a one-dollar increase in expenditure reduces destination utility by 0.0014. This expenditure coefficient can be used to estimate implicit prices of changes in attribute levels as discussed below.

The ‘Amenities’ attribute is statistically significant for all destinations except Canberra. Because of the use of effects coding, the coefficient of the non-included base level of an attribute is the negative of the sum of the level coefficients that are estimated. For instance, the coefficient for the ‘Medium to high’ level of the two-level attribute ‘Amenities’ is equal to $-\left( -0.1082 \right) = 0.1082$ for Goldfields of Victoria. The signs of the significant estimated coefficients are negative for each destination, which implies, as would be expected, that the utility of a short-break at the destination increases with a higher level of amenities.

The signs of the estimated coefficients of the ‘Pleasantly busy’ level of the ‘Crowdedness’ attribute are positive for each destination and highly significant. This indicates that destination utility increases with lower levels of crowdedness. The estimated coefficient is relatively high for Goldfields of Victoria and relatively low for Sydney, which suggests that Melbourne tourists are more inclined to accept larger crowds during a short-break holiday in a large city such as Sydney compared with the generally less crowded Goldfields.

The coefficients of the destination-specific ‘Environment’ levels are generally insignificant. The only exceptions are the ‘Cultural/historical’ level for Great Ocean Road and Phillip Island/Gippsland and the ‘Natural’ level for Sydney. Hence, tourists’ involvement in the above activity settings in the associated destinations enhances their utility of a holiday at those destinations. For instance, Melbourne tourists with a propensity to engage in activities in a natural environment are more likely to choose Sydney as their short-break destination ceteris paribus. This is somewhat surprising because destinations such as Mornington Peninsula and Phillip Island/Gippsland, more so than Sydney, are generally regarded as destinations for natural type activities (see below).

The estimation results show that the staging of an event or festival increases destination utility and, hence, the probability of Melbourne tourists choosing that destination. However, that is not the case for Canberra and Phillip Island/Gippsland. This suggests that destination development agencies in the latter two destinations should look for other ways to attract Melbourne tourists to their regions for short-break holidays.

Most destination-specific coefficients of the ‘Season’ levels are statistically significant. The signs indicate that destination utility is generally highest during summer, in particular for Phillip Island/Gippsland. However, this is not the case for Canberra for which springtime appears to be the most attractive time for a short-break holiday. This implies that Canberra’s efforts to bring in visitors from Melbourne should focus on the spring months.

Table 5 shows that the ASCs are positive and significantly different from zero for four of the six destinations. A non-zero ASC implies a significant mean effect of the unobserved factors in the error term for a destination compared with the ‘None’ option (the base case). In other words, the destination attracts a higher utility ceteris paribus than the option to stay at home.

The effects of the socio-demographic variables ‘Age’ and ‘Income’ vary between destinations. The effect of tourists’ age on destination utility is significantly negative for Great Ocean Road, Mornington Peninsula and Phillip Island/Gippsland, i.e. the utility of those destinations falls as age increases. Income data were collected by the income categories shown in Table 2. The income variable included in the model specification applies to
a threshold household income of more than $52,000; that is, middle-income and high-income households (other income thresholds were tested but estimation results were inferior). The estimated income coefficients are significantly positive for all destinations. This suggests that households with incomes above the threshold level of $52,000 have a relatively high propensity to undertake short-break holidays, in particular at the destinations Great Ocean Road, Phillip Island/Gippsland and Sydney.

The two destination-specific respondent characteristics of Table 3 generally make a significant difference to destination choices. As shown in Table 5, having the destination as a home base has a positive effect on tourists' destination utility, particularly for Canberra but also for Mornington Peninsula and Sydney. This suggests a potential benefit to these destinations of enticing Melbourne residents for a short-break holiday to the region where they grew up and to visit their friends and relatives who still live there. Tourists’ previous visit to the destination is a significant visitation determinant for all destinations. Goldfields of Victoria and, to a lesser extent, Sydney are particularly expected to generate relatively high levels of repeat visitation.

The final respondent characteristic included in the model specification is the one related to the use of the own vehicle as the usual means of transport for holidays. Table 5 shows that this characteristic has a significantly negative effect on the utility of Canberra and Sydney. This would be expected since both of those destinations are a substantial driving distance away from Melbourne.

The estimated coefficients of the choice attribute levels can be used to calculate the implicit prices of the attribute level changes. For instance, the results show that respondents are willing to pay more to visit a destination if there is an event or festival on at the time of their visit. For Goldfields of Victoria, Great Ocean Road, Mornington Peninsula and Sydney — for which the ‘Event/festival’ coefficients are statistically significant — the estimated implicit prices for a three-night holiday are $206, $119, $191 and $147, respectively. The estimation results also can be used to evaluate market share effects owing to changes in market conditions. That is the focus of attention in the remainder of the paper.

MARKET SHARE SIMULATIONS

The model estimation results can be used to simulate the market share effects of changes in destination attributes and respondent characteristics. This could, for instance, serve destination developers’ strategic positioning purposes. To carry out model simulations, a base case comprising the actual attribute levels for each destination and the relevant respondent characteristics is required. To that purpose, survey responses were used. Respondents indicated, for each destination, their perception of four attributes: crowdedness, environment, expenditure per person and travel time. For the expenditure and travel time attributes, the sample means were used, whereas the sample modes were used for the categorical attributes. The other three attributes were derived from the sample responses regarding general holiday preferences; once again, sample modes were used. The resulting composition of attribute levels in the base case is depicted in Table 6. For the respondent characteristics, the sample mean age was used, whereas the sample proportions were used for the other characteristics (see Tables 2 and 3).

The joint choice probabilities in the nested logit model represent the implied market shares of the destinations in the choice experiment. Market shares derived from stated choice models generally do not accurately reflect actual market shares. This is confirmed by Table 7, which shows each destination’s share of the total of the six destinations. For the first three destinations, the implied market share exceeds the actual share whereas the reverse applies to the others. In order to make the implied market shares consistent with the actual share whereas the reverse applies to the others. In order to make the implied market shares consistent with the actual shares, the destinations’ ASCs were adjusted (Louviere et al., 2000). The simulation results for that calibrated model are reported below. The percentage changes in market shares reported in Table 8 are very similar to the simulation results using the model with unadjusted ASCs.

A number of scenarios are presented in Table 8 to illustrate the model simulations. They provide the estimated market share changes...
Table 6. Base case for model simulations

| Amenities          | Canberra | Goldfields of Victoria | Great Ocean Road | Mornington Peninsula | Phillip Island/Gippsland | Sydney |
|--------------------|----------|------------------------|------------------|----------------------|--------------------------|--------|
| Low to medium      | Low to medium | Low to medium        | Low to medium    | Low to medium        | Low to medium            | Low to medium |
| Crowdedness        | Pleasantly busy | Pleasantly busy      | Pleasantly busy  | Pleasantly busy      | Crowd                  | Pleasantly busy |
| Environment        | Cultural/historical | Mix of natural and cultural/historical | Natural | Natural | Natural | Mix of natural and cultural/historical |
| Event/festival     | No       | No                     | No               | No                   | No                       | No     |
| Expenditure per person | $602    | $352                   | $368             | $338                 | $340                    | $740   |
| Season             | Summer   | Summer                 | Summer           | Summer               | Summer                   | Summer |
| Travel time (hours)| 1.9      | 2.6                    | 3.3              | 2.2                  | 2.5                      | 2.1    |

Table 7. Market shares: implied versus actual

| Destination region | Implied market share (%) | Actual market sharea (%) |
|--------------------|--------------------------|--------------------------|
| Canberra           | 8.4                      | 3.6                      |
| Goldfields of Victoria | 10.1                | 8.4                      |
| Great Ocean Road   | 30.8                     | 24.6                     |
| Mornington Peninsula | 19.1                | 21.8                     |
| Phillip Island/Gippsland | 21.4              | 26.9                     |
| Sydney             | 10.2                     | 14.8                     |

aMelbourne residents, overnight holiday/leisure trips (National Visitor Survey, 2000).

Owing to the IID condition that applies within each branch, the cross-expenditure effects are identical for all destinations in the same branch as Sydney (Mornington Peninsula and Phillip Island/Gippsland). Similarly, the cross-effects for the destinations not in the same branch as Sydney are also the same. As expected, all cross-effects are positive. It is important to exercise caution in interpreting the cross-effects because they are subject to the selection of the nesting structure in the model.

In the second scenario, a double change in the base case attributes for Mornington Peninsula is simulated. The staging of an event at that destination combined with a general perception among prospective visitors that this could lead to crowded situations with large numbers of people results, perversely, in a fall in market share of around 11%. However, the simulation of the organisation of an event at Mornington Peninsula which is expected to result in an unchanged ‘pleasantly busy’ situation (not shown in Table 8) shows a market share increase of around 24%. This reflects how visitors from Melbourne attach great importance to lower levels of crowdedness at Mornington Peninsula.

As observed earlier, Canberra is a destination that Melbourne short-break tourists prefer to visit in spring rather than in winter. The
### Table 8. Model simulation results (market share effects)

| Destination region       | Scenario 1 | Scenario 2 | Scenario 3 |
|--------------------------|------------|------------|------------|
|                           | Pre (%)    | Post (%)   | Change (%) | Pre (%)    | Post (%)   | Change (%) | Pre (%)    | Post (%)   | Change (%) |
| Canberra                  | 3.58       | 3.58       | +0.15      | 3.58       | 3.67       | +2.74      | 3.58       | 4.42       | +23.6      |
| Goldfields of Victoria    | 8.43       | 8.44       | +0.15      | 8.43       | 8.66       | +2.74      | 8.43       | 8.22       | -2.5       |
| Great Ocean Road          | 24.56      | 24.59      | +0.15      | 24.56      | 25.23      | +2.74      | 24.56      | 24.38      | -0.7       |
| Mornington Peninsula      | 21.81      | 21.85      | +0.18      | 21.81      | 19.39      | -11.08     | 21.81      | 21.65      | -0.7       |
| Phillip Island/Gippsland  | 26.87      | 26.92      | +0.18      | 26.87      | 27.79      | +3.40      | 26.87      | 26.68      | -0.7       |
| Sydney                    | 14.75      | 14.61      | -0.96      | 14.75      | 15.26      | +3.40      | 14.75      | 14.65      | -0.7       |

| Destination region       | Scenario 4 | Scenario 5 |
|--------------------------|------------|------------|
|                           | Pre (%)    | Post (%)   | Change (%) | Pre (%)    | Post (%)   | Change (%) |
| Canberra                  | 3.58       | 3.58       | 0          | 3.58       | 3.41       | -4.8       |
| Goldfields of Victoria    | 8.43       | 8.43       | 0          | 8.43       | 8.56       | +1.5       |
| Great Ocean Road          | 24.56      | 24.56      | 0          | 24.56      | 24.83      | +1.1       |
| Mornington Peninsula      | 21.81      | 21.81      | 0          | 21.81      | 22.10      | +1.3       |
| Phillip Island/Gippsland  | 26.87      | 26.87      | 0          | 26.87      | 27.23      | +1.3       |
| Sydney                    | 14.75      | 14.75      | 0          | 14.75      | 13.89      | -5.9       |

*Shares rounded to two decimal points.
third simulation scenario in Table 8 shows that Canberra’s market share would increase by nearly 24% if prospective tourists were to consider a comparison between a springtime short-break in Canberra and a summer break elsewhere. This might warrant a further investigation by Canberra’s destination promotion agency to evaluate the costs and the potential benefits of a promotion campaign to attract visitors to Canberra in spring.

The fourth scenario shows the estimated effect of the organisation of an event at Great Ocean Road accompanied by an increase in expenditure of $119. As this rise in expenditure is equal to the implicit price for an event at Great Ocean Road reported above, the effect on market shares is zero. Hence, if expected expenditure levels during an event at Great Ocean Road are higher than $119, its market share would decline.

The final scenario concerns a variable other than a destination attribute. In this case, an increase in the proportion of Melbourne tourists using their own vehicle for holiday purposes to 75% is simulated. The results in Table 8 show that Canberra and Sydney would experience declining market shares. This would be expected because these are the two interstate destinations that most Melbourne tourists visit by plane.

The above simulation results are stated in terms of percentage changes in market shares. To extend those results to the estimated change in the number of holiday trips made by Melbourne residents, it has to be assumed that the choice set incorporated in the survey is representative of all destination regions relevant to Melbourne tourists. An additional assumption is that the total number of trips made by Melbourne holiday makers is constant. For illustration purposes, using Table 1, the results of the final simulation scenario suggest that the number of short-break trips to Canberra and Sydney would fall by approximately 5600 and 28,000, respectively.

SUMMARY AND CONCLUSIONS

Despite the strong focus on international tourism growth, domestic tourism remains the major component of tourism activity in many countries. In Australia, as in other countries, there is reason to expect — at least in the short term — a substitution trend from international to domestic tourism. In order to attract domestic tourists, the agencies charged with the development and promotion of their destination need to acquire or enhance their understanding of the holiday preferences of prospective visitors. This requirement is enforced by the level of competition between destinations for the patronage of domestic tourists.

The stated discrete choice modelling method can be applied to provide an analysis of the determinants underlying holiday destination choices. In this study, the application of discrete choice modelling to short-break holiday destination decisions by prospective Melbourne tourists is presented. The findings reported in this paper demonstrate how the importance of various destination and trip attributes as well as respondent characteristics can be identified.

The destination choice analysis is conducted using a choice experiment consisting of six Victorian and interstate short-break destinations. The nested logit model specification shows the relative importance of the various choice determinants in terms of the destinations’ utilities. Consistent with theoretical expectations, the amount of trip expenditure is negatively related to destination utility and, hence, to the probability of choice. Other results highlight the importance of the quality of amenities and the level of crowdedness at the destination to the utility of nearly all destinations. For the majority of the destinations included in the study, the staging of an event or festival positively affects destination utility, and the same applies to the timing of short-break holidays during the summer period. On the other hand, the environmental setting of the main holiday activities and the length of travel time do not appear to be major discriminating decision factors for short-break tourists from Melbourne.

The findings reveal that Melbourne tourists’ ages and incomes are important choice determinants — to varying degrees for the different destinations. Further, if those tourists consider a destination as their home base and/or if they have visited the destination before, that destination’s utility is enhanced. Finally, the utility
of the interstate capital city destinations is reduced for holidaymakers who use their own vehicle as their mode of transport.

The paper reports the results of a number of model simulations to estimate the market share effects of changes in destinations' attributes and respondent characteristics. They illustrate how the choice modelling tools can be used by destination development organisations as input into their policy considerations regarding the composition of their destination products. Overall, this paper demonstrates the conceptual and practical suitability of the stated discrete choice modelling method in its application to tourism destination choices.

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