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# MIXED LOGIT MODELLING OF AIRPORT CHOICE IN MULTI-AIRPORT REGIONS 

Stephane Hess<br>(corresponding author)<br>Centre for Transport Studies, Imperial College London, Exhibition Road, London SW7 2AZ, stephane.hess@imperial.ac.uk<br>John W. Polak<br>Centre for Transport Studies, Imperial College London, Exhibition Road, London SW7 2AZ, j.polak@imperial.ac.uk


#### Abstract

This paper presents an analysis of the choice of airport by air-travellers departing from the San Francisco Bay area. The analysis uses the mixed multinomial logit model, which allows for a random distribution of tastes across decision-makers. To our knowledge, this is the first application using this model form in the analysis of airport choice. The results indicate that there is significant heterogeneity in tastes, especially with respect to the sensitivity to access-time, characterised by deterministic variations between groups of travellers (business/leisure, residents/visitors) as well as random variations within groups of travellers. The analysis reinforces earlier findings showing that business travellers are far less sensitive to fare increases than leisure travellers, and are willing to pay a higher price for decreases in access-time (and generally also increases in frequency) than is the case for leisure travellers. Finally, the results show that the random variation between business travellers in terms of sensitivity to accesstime is more pronounced than that between leisure travellers, as is the case for visitors when compared to residents.


## 1. INTRODUCTION

During the last decade of the twentieth century, the demand for air travel grew at an average rate of 5\% per annum (International Air Transport Association, 2002), and despite the impacts of the global economic downturn and the events of September $11^{\text {th }}$ 2001, annual growth levels of $5.1 \%$ (passenger-kilometres flown) are forecast for the next 20 years (Boeing, 2003). While the growth in traffic has been accompanied by a comparable increase in the available seat-kilometres, there has been a lack of increases in runway and terminal capacity. As a consequence, pressure exists to expand capacity at many of the world's busiest airports (UK Department for Transport, 2003; Regional

Airport Planning Committee, 2000). These capacity expansion decisions are complicated, not least because of the fact that many of the concerned airports are part of a network of airports serving a multi-airport region. The case for capacity expansion in such regions depends not only on the total level of air traffic growth, but also on its distribution across alternative airports.

To a large degree, the decision-making process in airport expansion schemes in such multi-airport regions depends on the projected levels of passenger demand at the different airports, such that the modelling of travellers' choice of airport is a key component of such studies. Although this area of research has attracted increased activity in recent years (Veldhuis et al., 1999, Pels et al., 2001, 2003; Basar and Bhat, 2004), the development of a systematic understanding of airport choice is still at a relatively early stage. In particular, compared to other dimensions of travel choice, little is known about the variation in tastes across different market segments or within individual market segments.

Here we investigate specifically the prevalence of taste heterogeneity in the context of airport choice in the San Francisco Bay (SF-Bay) area. To do this, we consider only the choice of airport, independently of related choice dimensions such as those of main mode, access-mode and airline. In common with most existing studies, we also concentrate only on departing passengers and exclude passengers using the airports for connecting flights. Moreover, travellers on indirect flights are similarly excluded from the analysis.

## 2. LITERATURE REVIEW

One of the first studies of airport choice was by Skinner (1976), who used a multinomial logit (MNL) model for airport choice in the Baltimore-Washington DC area (3 airports). The results reveal significant effects of flight frequency and ground
accessibility, with travellers being more sensitive to the latter. In a more recent study of airport choice in this area, Windle and Dresner (1995) use an MNL model that shows significant effects associated with flight frequency and airport access-time, and also reveals that the more often a traveller uses a certain airport in a year, the more likely this traveller is to choose the same airport again.

A large number of studies on airport choice have been undertaken in the SF-Bay area, mainly because of the availability of very good data. Harvey (1987) uses an MNL model for airport choice, and finds that airport access-time and flight frequency are significant for both leisure and business travellers, with lower valuations of time for leisure travellers. More recently, Pels et al. (2001) have used a nested logit (NL) model for airport and airline choice in the SF-Bay area. The results indicate that, ceteris paribus, travellers are more likely to switch between airlines than between airports. Pels et al. (2003) analyse the joint choice of airport and access mode by using an NL model (airport choice above access mode choice), showing high sensitivity to access-time, especially for business travellers. Basar and Bhat (2004) take a different approach by explicitly incorporating choice-set formation in the model, thus acknowledging that not all airports are considered by every travellers. The results show that flight frequency is the most important aspect in choice set composition, surprisingly dominating the also significant access-time factor, while, in terms of the actual choice of airport, access-time is the most important factor. In a predecessor to the analysis in this paper, Hess and Polak (2004a) show that there exist differences in choice-behaviour between population groups as well as within population groups, most notably in the sensitivity to accesstime increases. Finally, in an analysis of the joint choice of airport, airline and accessmode, Hess and Polak (2004b) found differences across population groups in the
correlation structure in place in the choice-set of alternatives, and that, in general, the highest level of correlation exists between alternatives sharing the same access-mode.

There have also been a number of studies of airport choice in the UK. Ashford and Bencheman (1987) use an MNL model for airport choice at five airports in England (Heathrow, Manchester, Birmingham, East Midlands and Luton), and find that accesstime and flight frequency are significant factors for all types of passengers, while fare is significant for all passengers except international business travellers. Ndoh et al. (1990) compare MNL and NL models for passenger route choice in central England and find the NL model to be superior. Thompson and Caves (1993) use an MNL model to forecast the market share for a new airport in North England; access-time, flight frequency and the number of seats on the aircraft (reflecting size/comfort) are found to be significant, with access-time being most important for travellers living close to the airport and frequency being more important for travellers living further afield.

Outside the US and the UK, Ozoka and Ashford (1989) use an MNL model to predict the effect of building a third airport in a multi-airport region in Nigeria and find access-time to be significant, suggesting that the choice of location plays an important role in the success of an airport, along with the provision of good ground-access facilities. Innes and Doucet (1990) use a binary logit model to predict choice between airports in Canada, and find that travellers prefer jet services to turboprop services. Furuichi and Koppelman (1994) use an NL model for departure and destination airport choice in Japan, and find significant effects of access-time, access journey cost and flight-frequency. Finally, Veldhuis et al. (1999) produce the comprehensive Integrated Airport Competition Model for Amsterdam's Schiphol airport, using a sequential NL choice process that models the choice of main mode, followed by the combined choice of airport and air-route, and finally the choice of access-mode at the chosen airport.

## 3. DATA

The SF-Bay area is served by three major airports; San Francisco International (SFO), San Jose Municipal (SJC) and Oakland International (OAK). SFO is the largest of the three, with, in 1995, some 15 million emplaned passengers ( $\sim 55.8 \%$ ), compared to around 4.2 million passengers at SJC ( $\sim 15.6 \%$ ), and 7.7 million passengers at OAK ( $\sim 28.6 \%$ ). Forecasts by the Metropolitan Transport Commission (2000) predict significant increases in traffic; these will inevitably lead to problems with capacity, and different expansion schemes are already under consideration (Regional Airport Planning Committee, 2000).

Data on individual travellers' choices were obtained from the 1995 Airline Passenger Survey conducted by the MTC, containing information on over 21,000 departing air-travellers (Metropolitan Transport Commission, 1995). The sample of passengers interviewed at the three main airports is not entirely representative of the real-world traffic at the airports; indeed, SJC is over-sampled, while OAK is undersampled. This sampling needs to be taken into account in the modelling in order to avoid any risk of biased results. In the present analysis, we account for the sampling effects by using the weighted exogenous sampling maximum likelihood (WESML) approach, in which each observation is assigned a weight in the likelihood function that represents the relative real-world market share of the chosen alternative compared to its market-share in the sample used in the analysis. Appropriate weights were calculated separately for each of the sub-samples used in the various models.

It was decided to use only destinations that could be reached by direct flight from all three of the modelled airports, on every day of the week. Overall, this approach led to the use of 14 destinations, and an initial sample of 9,924 respondents. After removing observations for individuals who stated that they could not have flown out of a different
airport (c.f. Hess and Polak, 2004a, 2004b), and some further data-cleaning (removal of incomplete records), a final sample of 5,097 individuals was obtained, divided into 1,268 resident business travellers, 1,500 resident leisure travellers, 1,269 visiting business travellers, and 1,060 visiting leisure travellers. The data used are summarised in Table 1, which illustrates the oversampling of SJC, when compared to the actual passenger numbers given above. The specific choice of destinations had little or no effect on the distribution of flights across other dimensions, such as journey purposes and household income. Clearly, the sampling has an effect on the market shares for the different airlines; as this study does not explicitly look at the choice of airline, this is however of little importance.

Special care is required in the presence of destinations that are themselves located in multi-airport regions. It is in this case important to consider whether passengers' choices of departure airport in the SF-Bay area may have been influenced by their choice of destination airport. After careful consideration, destinations from two such multi-airport regions were included in the present analysis, namely destinations in the wider Los Angeles area, and one of the two main Chicago airports. The decision to include the Los Angeles area airports was motivated primarily by the high representation of these destinations in the survey data, while, in the case of Chicago, the comparatively low frequency of services to the secondary airport at Midway (MDW) meant that the choice of airport in the SF-bay can almost be guaranteed to take precedence. A separate small-scale analysis indicated that the inclusion of these destinations did not lead to any significant bias in the results.

The passenger-survey dataset contains information on the actual choices of a given set of travellers; for a modelling analysis, this needs to be complemented by datasets describing the attributes of the different alternatives contained in the travellers' choice-
sets. To this extent, air-travel level-of-service data were obtained from BACK Aviation Solutions ${ }^{l}$, containing daily information on the different operators serving the selected routes for the time period used in the present analysis (August and October 1995). Besides the frequencies for the different operators, the dataset also contains information on the average fares paid on a given route operated by a given airline. This clearly involves a great deal of aggregation, as no distinction is made between the fares for the different classes of travel. Furthermore, as no information on advance purchase discounts at the time booking was available, it had to be assumed that fares stay constant, and that availability of a specific fare on a given day is the same across all airports offering that route. Unfortunately, such assumption cannot in general be avoided in the area of airport-choice modelling, given the lack of adequate data on fares. A number of other attributes were included in the datasets; these were however not used in the present analysis (Hess and Polak, 2004a; 2004b). As the present study ignores the airline-choice dimension, aggregate air-travel level-of-service data were used, assigning to each passenger the industry-level information on frequencies and fares for flights from each of the three airports to the desired destination on the actual date of travel.

Even though the access-mode choice dimension is not analysed explicitly in the present analysis, information on the access options at the different airports is still a prerequisite for the model-fitting exercise, given that access journeys are known to play an important role in airport choice. The ground-access level-of-service data used in this study were derived from origin-destination level-of-service matrices for a 1099 traffic zone system of the SF-Bay area, assembled by the MTC, containing time and cost information for car travel and public transport. Corresponding data for other modes were calculated separately, based on current prices and the change in the consumer price

[^0]index for California. In the analysis, the travel access-dimension information for a given respondent corresponds to the mode actually chosen by this respondent. This is clearly a significant simplification of the actual situation (as it assumes that the same mode would have been chosen at a different airport), but does at least give some idea of the differences in access journeys to the different airports, in the absence of an explicit treatment of mode-choice. The impacts of this assumption are also weakened by the low elasticity for access-mode changes in the SF-bay area (Hess and Polak, 2004b).

## 4. METHODOLOGY

Discrete choice models have been used extensively in the field of transportation research for over thirty years. Initially, virtually all applications were based on the MNL model and basic NL models; more recently, the use of more flexible model forms, such as advanced generalised extreme value (GEV) models and the MMNL model has increased dramatically (Train, 2003).

The MMNL model (McFadden and Train, 2000) offers significant advantages over the MNL model by allowing for random taste variation across decision-makers, thus acknowledging the differences across agents in their sensitivities to factors such as fare and frequency. The random-coefficients formulation of the MMNL model uses integration of the MNL choice probabilities over the assumed distribution of the taste coefficients, such that the probability of individual $n$ choosing alternative $i$ is:

$$
P_{n i}=\int_{\beta} \frac{e^{\nu\left(\beta, X_{n}\right)}}{\sum_{j=1}^{L} e^{\nu\left(\beta, X_{n j}\right)}} f(\beta \mid \theta) d \beta
$$

where $X_{n i}$ is a vector of explanatory variables for alternative $i$ as faced by decisionmaker $n, \beta$ is a vector of taste coefficients, and the function $V\left(\beta, X_{n i}\right)$ gives the observed utility of alternative $i$ (Train, 2003). In the MMNL model, the vector $\beta$ is distributed randomly across decision-makers, with density $f(\beta \mid \theta)$, where $\theta$ is a vector of parameters
to be estimated that represent, for example, the mean and variance of preferences in the population.

The MMNL model not only allows for random taste variation, but also in principle avoids the unrealistic MNL substitution patterns resulting from the independence from irrelevant alternatives (IIA) assumption, which dictates that the dependency between any two alternatives is the same across alternatives, making the MNL model an inappropriate choice in many scenarios. The MNL model has been used repeatedly in airport choice modelling, and several authors (Ashford and Bencheman, 1987; Thompson and Caves, 1993) have justified the use of the MNL on the basis of tests showing that the IIA assumption is justified, i.e. that the different airports in the system under study are in effect independent entities. This is in general however far from clear, as in some cases, it seems that there is a possibility of varying cross-elasticities across pairs of airports in a multi-airport region (with more than two airports), given the similarities, respectively dissimilarities between some of the airports (e.g. business airport versus no-frills airlines base).

The biggest drawback of the MMNL model is the fact that the integrals representing the choice probabilities do not have a closed-form expression and need to be approximated through simulation (Train, 2003; Hess et al., 2004a). A second issue with the MMNL model is the choice of distribution to be used for the random taste coefficients, especially in the case where an a priori assumption exists about the sign of a given coefficient (Hensher and Greene,2001; Hess and Polak, 2004c; Hess et al., 2004b).

## 5. ANALYSIS

In this section, we describe the final estimated models used, and report the results produced. The more basic MNL and MMNL models estimated in the early stages of the
research are not described in detail in the present paper; more in depth descriptions and results for these models are available from the first author on request (Hess and Polak, 2004a). In each model, the influence of a number of attributes was explored. These attributes included fare, frequency, access-journey time, access-journey cost, flight time, the number of operators serving a route, the size of aircraft used, and the on-time performance at the different airports. Only fare, frequency and access journey time were found to have a consistently significant effect. The lack of effects by other variables could be due to the use of airport-specific data, and different results can be expected with the use of airline-specific data (Hess and Polak, 2004b). Finally, no effect of travellers' allegiances to given airlines could be included in the models, due to the lack of information on frequent traveller programmes.

At this point, it seems worthwhile noting that the frequency coefficient is of special interest. Indeed, as it is not presently feasible to model the distribution of available departure times and individual travellers' preferred departure times (due to data limitations), this coefficient can be seen as giving an estimate of the effect of changes in the time difference (schedule delay) between a desired departure time and the next best available departure time, making the (considerable) assumption of a relatively even spread of flights across the day. In this context, higher frequency means more reliability, and a lower risk of not arriving at the destination on time. Finally, the frequency coefficient also captures a visibility effect, in that, ceteris paribus, options with a higher frequency of service have a higher chance of being selected, due to higher representation in the choice set.

Due to limitations in model specification, but also in the quality of the data available, it is never possible to capture all information that affects the choice of a given decision-maker. As such, the utility of a given alternative is not fully observed, and an
error term, or unobserved part of utility, remains. By adding alternative specific constants (ASC) to the utility of alternatives, the mean of this randomly distributed error term is added into the observed utility function, such that the remaining error term has a mean of zero. These ASCs thus capture the mean effect of all unobserved variables attributes, including general attitude towards an alternative, while the remaining error term captures the variation in this effect. For identification reasons, one of the ASCs needs to be normalised. In the present analysis, the ASC of OAK was set to zero; in the MNL models, the normalisation is arbitrary, while in the MMNL models, this normalisation was acceptable due to the lack of random variation in this constant across agents (Hensher and Greene, 2001).

Another important issue is the choice of distribution for randomly distributed coefficients. A Normal distribution can safely be used for ASCs, thus allowing for positive as well as negative impacts of unmeasured variables across decision-makers. However, in the case of coefficients with an a priori sign assumption, the use of the Normal distribution should be avoided, as it leads to a positive probability of wrongly signed coefficients (Hess et al., 2004b). To this extent, a lognormal distribution was used for such coefficients in the analysis, producing positive draws only, such that, in the case of an undesirable attribute, the sign of the attribute needs to be reversed. Besides being more intuitively appealing, the use of the lognormal distribution in this case also universally led to better model fit. Models using a lognormal distribution yield estimates of the parameters of the underlying Normal distribution $\boldsymbol{c}$ and $\boldsymbol{s}$; corresponding values for the actual mean and standard deviation of the Lognormal distribution, $\boldsymbol{\mu}$ and $\boldsymbol{\sigma}$, can be found using a simple transformation (Hess and Polak, 2004c). This transformation is used in the presentation in the tables below, along with a sign change, where appropriate.

While the MMNL model has the power to explain variations in tastes with the use of statistical distributions, for interpretation (as well as estimation) reasons, attempts should always be made to explain as much of this variation as possible in a deterministic fashion. This generally comes in the form of separate models for different population groups, or separate coefficients for different groups within the same model. In the present analysis, three dimensions of segmentation were used; purpose, residency status and income. A further segmentation by ticket type (e.g., business versus economy) was not possible, for data reasons. Four separate models were estimated, dividing resident and visiting travellers each into a business and a leisure group. Results by Hess and Polak (2004a) show this approach to be preferable to the use of separate coefficients for the different groups in a common model. The effect of income was accommodated by dividing the sample population into three roughly equally sized income groups (less than $\$ 21,000$, between $\$ 21,000$ and $\$ 44,000$ and above $\$ 44,000$ per annum). An alternative approach would have been to explicitly model the continuous relationship between income and the sensitivity to factors such as fare and access-time; this is however beyond the scope of the present analysis. Initial results showed that no further gains could be made by estimating separate models for the three different income groups, such that (where necessary) separate coefficients for the three income groups would be used inside the four different models estimated. Finally, for each of the four subgroups, a random sub-sample of roughly $10 \%$ was removed and retained for later validation of the models on data not used in the estimation.

Another important point that warrants further discussion is the way in which explanatory variables enter the utility function. Generally, a linear specification is used in discrete choice models, such that changes in a given attribute lead to linear changes in utility; this is thus not appropriate in the case of attributes for which decreasing
marginal returns in utility would be expected. In the case of airport choice modelling, the most prominent example of such an attribute is flight frequency, where increases at a lower base frequency are relatively more valuable to travellers than increases at already high base frequencies. A non-linear specification of frequency can be accommodated in the models by replacing the absolute frequency levels by a formula that gives a decreasing marginal return. In the present analysis, the natural logarithm transform was used for the frequency attribute; this has been used previously by Veldhuis et al (1999) and Pels et al. (2003) amongst others, and Hess and Polak (2004a) suggest this approach to be superior to that of other non-linear transforms, at least in the present context. The same transformation was used for the past-experience attribute, where decreasing marginal returns should also be expected. Attempts were also made to use a non-linear specification for the remaining coefficients of fare and access-time; this did however not lead to any significant gains in model fit.

## 6. MODELLING RESULTS

The results of the estimation process are summarised in Table 2. In each one of the four models, there was sufficient variation in the sensitivity to access-time to use a random coefficient that follows a Lognormal distribution. In addition, significant variation to enable the use of a normally distributed ASC for SFO was identified in each model except the model for business trips by visitors. It was not possible to identify significant random heterogeneity in the sensitivities to fare and frequency changes; this lack of additional variation can again be partly explained by the use of airport-specific data, and ongoing work has revealed the existence of additional levels of heterogeneity when looking at the related choice dimensions of airline and access-mode.

In each case, the use of the MMNL specification led to statistically significant gains in model fit over the corresponding MNL structure, with the most significant gain being
obtained by the model for visiting business travellers, despite the fact that this model has only one randomly distributed coefficient. Significant effects of income could only be found in the model for resident business travellers, where a significant effect of fare was only identified for the low-income group, and the model for visiting leisure travellers, where a separate frequency coefficient was used for the high-income group, with a common coefficient for the low and medium-income groups. It was not possible to identify a significant fare-effect in the model for business trips by visitors; this comes in addition to the inability to estimate such an effect for the medium and high-income groups for resident business travellers. The failure to estimate a significant fare-effect could reflect the comparatively low sensitivity to fare for business travellers, but could also be partly due to the use of highly aggregate fare information; other authors have encountered similar problems with estimating significant fare coefficients (Pels et al., 2003). Finally, the differences in the estimates of the ASCs across models are largely an effect of the use of the WESML approach, and of the differences in the sampling in different models.

Given that it was not possible to identify a significant effect for access-cost in any of the models, it was similarly impossible to give a proper estimate of the value of accesstime savings. An indication of the monetary value of access-time changes can be given by looking at the ratio between the access-time coefficient and the air-fare coefficient. The estimate of this ratio can however be expected to be higher than the actual value of access-time, given the significant differences in scale between the associated attributes. As such, a lower marginal utility would be associated with a change in air-fare by one dollar than a change in access-cost by the same amount. Additionally, trade-offs were calculated between the frequency and access-time coefficients, and between the frequency and fare coefficients. It should be noted that, due to the lack of significant
fare-coefficients in some of the models, the calculation of trade-offs involving this coefficient was not possible for all population segments. Also, due to the use of the logarithmic transform for frequency, the two trade-offs involving this coefficient need to be adjusted through multiplication by the difference between the logarithm of the new frequency and the logarithm of the old frequency (defined as $\boldsymbol{K}$ ) to obtain a real measure for the trade-off. Finally, for the trade-offs involving randomly distributed coefficients, it is of interest not just to calculate the mean values of access-time, but to incorporate the full distribution of this coefficient in the calculation. This not only gives an account of the variation in these trade-offs across the population, but also avoids a major risk of biased estimates (Hensher and Greene, 2001; Hess and Polak, 2004c). The distributional characteristics of such randomly distributed trade-offs were found analytically in the case of the trade-off between the access-time and flight frequency coefficients, and through simulation in the case of the trade-off between the flight frequency and access-time coefficients (where the random variable forms the denominator of the ratio). The resulting values are shown in Table 3. To give a meaning to the calculated trade-offs involving the frequency coefficient, the table also gives values for an increase by one flight at a base frequency of 5 flights per day, where $\boldsymbol{K}$ is equal to 0.182 . The corresponding value of $\boldsymbol{K}$ at a base frequency of 10 flights is 0.095 , showing the decreasing marginal returns with this specification.

The results indicate a greater willingness to accept higher flight fares in return for access-time decreases for resident business travellers than for resident leisure travellers, especially when taking into account that the fare coefficient estimated for resident business travellers is for the low income group only. The results further indicate that, while the mean willingness to pay is very similar for resident and visiting leisure travellers, the within-group variation is more important for visiting leisure travellers.

The implied willingness to accept higher flight-fares in return for shorter access-times can be expected to be even greater for visiting business travellers, given that it was not possible to identify a significant fare effect for this group of travellers. Although, as mentioned before, the calculated trade-offs should not be seen as an estimate of the value of access-time reductions, given the use of the flight-fare rather than the access cost coefficients, the estimated values are still very high. This is a direct result of the low air-fare coefficient, which is at least partly due to the relatively poor quality of the fare information used. However, the size of the ratio is clearly also a result of the high access-time coefficient, which could possibly indicate that travellers associate increases in access-time with increases in the risk of missing a flight. This explanation is supported by the high values of access-time reported in studies where an access-cost coefficient could be identified. For example, Pels et al (2003) report values of $\$ 2.90$ /min for business travellers in August and $\$ 1.97 /$ min for business travellers in October, using the same data as the present analysis. Lower values were reported in older studies; for example, Harvey (1986) gives a value of $\$ 0.69 / \mathrm{min}$, while Furuichi and Koppelman (1994) give a value of $\$ 1.21 / \mathrm{min}$.

In terms of the willingness to accept access-time increases in return for frequency increases, the results indicate a higher mean willingness for visiting business travellers than for resident business travellers ( $20.99 \boldsymbol{K}$ vs $15.64 \boldsymbol{K}$ ), despite the fact that the simple ratio between the coefficient mean values would suggest the opposite ( $8.73 \boldsymbol{K}$ vs $9.93 \boldsymbol{K}$ ). This is caused by the much larger standard deviation in the coefficient for visitors than for residents, and illustrates the importance of incorporating the full distribution of the coefficients in the calculation of trade-offs, especially in the case of asymmetrical distributions (special care was taken in the simulation to reduce the impact of outliers on the calculation). The use of the simple ratio of means approach thus not only
underestimates the trade-offs, but also incorrectly predicts a higher willingness to accept access-time increases for residents than for visitors, potentially leading to wrong policy implications. A similar problem occurs when using the MNL model.

Finally, the models show a higher relative desire for frequency increases for visiting leisure travellers than for resident leisure travellers, with increasing willingness to accept access-time increases for travellers in higher income classes. The results also suggest that in both income groups for visiting leisure travellers, this trade-off is larger than the common trade-off for resident business travellers. The observations for the willingness to pay for frequency increases are very similar, with the exception that only the willingness to pay of high-income visiting leisure travellers is above the common willingness of resident business travellers. In terms of the actual real-world values of one additional daily flight with a base frequency of five flights, the implied trade-offs between frequency and access-time increases seem a bit low, but should be put into context by noting that the average access-time in the data used was just below 30 minutes. Finally, the monetary values of one additional flight seem realistic, though possibly also at the low end of the real values.

## 7. MODEL VALIDATION AND PREDICTION PERFORMANCE

The first part of the model validation process was concerned with applying the four models to the respective estimation samples, and calculating the average choice probabilities assigned by the models to the actual chosen alternatives. This approach produces correct prediction probabilities of $64.3 \%$ for resident business travellers, 68.0\% for resident leisure travellers, $66.5 \%$ for visiting business travellers and 65.9\% for visiting leisure travellers. These values are lower than those reported recently by Basar and Bhat (2004), who obtained an average correct prediction rate of $74.9 \%$. However, when taking into account the use of a simplistic utility function, the use of
airport rather than airline-specific level-of-service information, and the fact that choiceset formation was excluded from the analysis, the performance of the models is actually very good, and reflects the relative explanatory power of the three variables used in the models.

The most telling test of model performance is however the ability of the final calibrated models to correctly predict the market shares and choices in data that were not used in the actual model calibration process. For this purpose, the four models were applied to the validation samples retained for this use. The results of this process are shown in Table 4, giving the weighted predicted market shares, along with the average probability of correct prediction. The results show that, except for the model for resident leisure travellers, the correct prediction performance on the validation sample is actually higher than that obtained with the estimation sample, suggesting that the models have not been over-fitted on the estimation data, and are capable of offering good performance on unknown data. In terms of reproducing the weighted market shares for the three airports, the performance is again very good, although the two models for leisure travellers tend to slightly overestimate the market share for OAK and underestimate the market share for SFO (as a reminder, the overall real-world marketshares were $55.8 \%, 15.6 \%$ and $28.6 \%$ for SFO, SJC and OAK respectively).

## 8. CONCLUSIONS

The paper has looked at airport choice in the San Francisco Bay area. In line with previous research, the analysis shows there exist significant influences on airport choice due to access-time, fare, and frequency of service. Moreover, the results indicate that there are significant differences across travellers in their sensitivity to these factors, and that while differences in sensitivity to fare and frequency can be adequately accommodated by deterministic market segmentation, the sensitivity to access-time
additionally varies randomly within these market segments. This shows that the MMNL model can lead to important gains in modelling accuracy and explanatory power in the analysis of air-travel behaviour.

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Table 1: Destinations used in the analysis

|  | Destination airport |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  |  |  | $\begin{aligned} & \text { H.x } \\ & \text { n } \\ & 4 \\ & y \\ & 4 \\ & 0 \\ & 0 \end{aligned}$ | O- | $\begin{aligned} & \text { z } \\ & \text { n } \\ & \text { S } \\ & M \\ & 3 \\ & \mathbb{y} \end{aligned}$ | $\begin{aligned} & \text { n } \\ & \text { y } \\ & \text { y } \\ & 0 \\ & z \\ & 4 \\ & 0 \\ & 0 \\ & 0 \end{aligned}$ | U 0 0 2 2 0 |  | $\begin{aligned} & \text { N } \\ & \text { x } \\ & \underset{y y y}{\mid c} \\ & 0 \\ & 0 \\ & \end{aligned}$ | $\begin{aligned} & \text { n } \\ & 0 \\ & \text { Qu } \\ & 4 \\ & 1 \\ & 0 \\ & 0 \\ & 0 \end{aligned}$ | $\begin{aligned} & \text { z } \\ & 0 \\ & \text { z } \\ & \text { zax } \end{aligned}$ |  |  |  | $$ |
| Departure Airport | SFO | 54 | 97 | 45 | 74 | 65 | 203 | 35 | 38 | 129 | 140 | 1 | 48 | 261 | 220 | 1410 |
|  | SJC | 161 | 71 | 97 | 89 | 158 | 370 | 113 | 246 | 128 | 105 | 147 | 66 | 237 | 157 | 2145 |
|  | OAK | 203 | 6 | 26 | 12 | 67 | 370 | 130 | 168 | 47 | 96 | 35 | 42 | 133 | 207 | 1542 |
| Total |  | 418 | 174 | 168 | 175 | 290 | 943 | 278 | 452 | 304 | 341 | 183 | 156 | 631 | 584 | 5097 |

Table 2: Mixed logit models using segmentation by purpose and division into residents and visitors

|  | Resident business |  | Resident leisure |  | Visitor business |  | Visitor leisure |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Parameter <br> Fare (common) Fare (income < \$21,000) | Estimate | t-statistic | Estimate | t- statistic | Estimate | t- statistic | Estimate | t- statistic |
|  |  |  | -0.0475 | -3.8 |  |  | -0.0477 | -3.7 |
|  | -0.0430 | -2.55 |  |  |  |  |  |  |
| Frequency (common) <br> Frequency <br> (income < \$44,000) <br> Frequency <br> (income > \$44,000) | 1.9469 | 5.6 | 1.8333 | 5.7 | 1.8881 | 7.7 |  |  |
|  |  |  |  |  |  |  | 1.9701 | 5.2 |
|  |  |  |  |  |  |  | 3.0328 | 5.2 |
| Access-time c | -1.8571 | -15.5 | -1.8916 | -17.1 | -1.9706 | -20.6 | -1.9669 | -13.0 |
| Access-time s | 0.6742 | 4.3 | 0.5102 | 3.6 | 0.9373 | 5.4 | 0.6934 | 5.5 |
| Access-time $\boldsymbol{\mu}$ | -0.1960 | N/A | -0.1718 | N/A | -0.2163 | N/A | -0.1779 | N/A |
| Access-time $\boldsymbol{\sigma}$ | 0.1487 | N/A | 0.0937 | N/A | 0.2566 | N/A | 0.1398 | N/A |
| ASC SFO mean | 1.1563 | 4.2 | 0.9289 | 3.9 | 0.3632 | 2.5 | 0.5028 | 1.9 |
| ASC SFO std.dev | 2.0260 | 3.6 | 1.3650 | 2.7 |  |  | 1.6019 | 2.2 |
| ASC SJC | -0.1045 | -0.5 | -0.1515 | -0.8 | -0.7767 | -3.7 | 0.7784 | 2.8 |
| Observations | 1,140 |  | 1,347 |  | 1,142 |  | 952 |  |
| LL | -604.03 |  | -659.67 |  | $-573.67$ |  | -514.62 |  |
| LL (MNL) | -615.53 |  | -666.22 |  | -592.05 |  | $-519.92$ |  |

Table 3: Trade-offs [standard deviations in brackets, where applicable]

|  | Resident business | Resident leisure | Visitor business | Visitor leisure |
| :---: | :---: | :---: | :---: | :---: |
| Trade-off between access-time and flight fare coefficient (\$/min) | $\begin{gathered} 4.56 \\ {[3.46]^{\mathrm{b}}} \end{gathered}$ | $\begin{gathered} 3.62 \\ {[1.97]} \end{gathered}$ | N/A | $\begin{gathered} \hline 3.73 \\ {[2.93]} \end{gathered}$ |
| Trade-off between frequency increases and accesstime increases (min/flight) ${ }^{\text {a }}$ | $\begin{aligned} & 15.64 K \\ & {[11.84]} \end{aligned}$ | $\begin{gathered} 13.85 \boldsymbol{K} \\ {[7.55]} \end{gathered}$ | $\begin{aligned} & 20.99 \mathrm{~K} \\ & {[24.62]} \end{aligned}$ | $\begin{gathered} 17.91 \boldsymbol{K} \\ \text { [14.00] }^{\mathrm{c}} \\ 27.57 \boldsymbol{K} \\ {[21.56]^{\mathrm{d}}}^{\text {d }} \end{gathered}$ |
| Willingness to pay for frequency increases (\$) ${ }^{\text {a }}$ | $45.27{ }^{\text {b }}$ | 38.60K | N/A | $\begin{gathered} 41.30 \boldsymbol{K}^{\mathrm{c}} \\ 63.58 \boldsymbol{K}^{\mathrm{d}} \end{gathered}$ |
| Mean willingness to accept access-time increases for one additional flight at a base frequency of 5 flights (min) | 2.85 | 2.53 | 3.83 | $\begin{aligned} & 3.27^{\mathrm{c}} \\ & 5.03^{\mathrm{d}} \end{aligned}$ |
| Willingness to pay for one additional flight at a base frequency of 5 flights (\$) | 8.25 | 7.04 | N/A | $\begin{gathered} 7.53^{\mathrm{c}} \\ 11.59^{\mathrm{d}} \end{gathered}$ |

[^1]Table 4: Prediction performance on validation sample

|  | Resident business | Resident leisure | Visitor business | Visitor leisure |
| :--- | :---: | :---: | :---: | :---: |
| Observations | 128 | 153 | 127 | 108 |
| Share SFO | $56.4 \%$ | $52.4 \%$ | $56.2 \%$ | $52.7 \%$ |
| Share SJC | $15.9 \%$ | $16.0 \%$ | $15.3 \%$ | $15.2 \%$ |
| Share OAK | $27.7 \%$ | $31.6 \%$ | $28.5 \%$ | $32.2 \%$ |
| Correct prediction | $67.6 \%$ | $66.1 \%$ | $67.0 \%$ | $68.3 \%$ |


[^0]:    ${ }^{1}$ Back Aviation Solutions, 6000 Lake Forrest Drive, Suite 580, Atlanta, GA 30328, www.backaviation.com

[^1]:    ${ }^{\mathrm{a}} \boldsymbol{K}=\ln (f+1)-\ln (f) ;{ }^{\mathrm{b}}$ low-income travellers only;
    ${ }^{\text {c }}$ low-income and medium-income travellers only , ${ }^{\text {d }}$ high-income travellers only

