Airport choice in a multiple airport region: an empirical analysis for the San Francisco Bay Area.

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1 INTRODUCTION

Airports are nodal centers in an air transport network. They are a sine qua non for the aviation sector. But the size and configuration of mutually linked airports is a complicated research issue which deserves due attention, as the structure and development of airports is decisively influenced by both market forces and regulatory regimes. In a deregulated air transport market, airports have to justify their existence by attracting and accommodating enough passengers to, at least, break even. In a multiple airport region, airports will compete for origin (destination) passengers. Moreover, airports may compete with other (not necessarily close-by) airports for transfer passengers. In a previous paper (Pels et al., 1997), it was found -on the basis of a theoretical model- that airport pricing policies do not influence the airline's network choice as much as the level of demand. This result needs of course further empirical underpinning and testing.

In this paper we address the question which variables influence the level of demand in a multiple airport region and how airports can use these insights in their efforts to attract more passengers. In a multiple airport region, passengers have to decide on both which airport and which airline to use. Competition between (origin) airports for passengers cannot be analyzed without taking into account the airlines' reactions to the airports' policies; see e.g. Pels et al. (1998). Consumer choices are thus critical in this context, and, therefore, we will analyze passenger preferences concerning airports in relation to their preferences concerning airlines. The nested logit model is an appropriate tool for this analysis. This model is widely used in the literature on airport (and airline) choice; hence we can compare our findings to previous findings using similar models. Moreover, on the basis of a nested logit demand function it is possible to develop a competition model in which airlines compete on the basis of both fares and frequencies and airports compete on the bases of airport taxes (see Pels et al., 1998).

Seen from this perspective, the purpose of the present paper is to determine: (i) which variables are the most important (significant) determinants of the passengers' airport choice, (ii) the preferred specification of the statistical model and; (iii) how these results (and the statistically preferred model) can be used to analyze airport competition in a multi-airport context.

The paper is organized as follows. In Section 2 a concise review of the literature on passenger preferences concerning airports and airport choice is given. Next, Section 3 presents some theoretical considerations on discrete choice models. Section 4 presents a description of the data used, while also the choice and competition models developed in the paper are tested. Section 5 offers some conclusions.

2 LITERATURE REVIEW ON DICSCRETE CHOICE MODELS

As mentioned above, passengers (or an agent on their behalf) have to decide on both the preferred airport and the preferred airline. These choices can be based on frequency of service, the airfare (the airlines' policy variables) and airport tax and accessibility (airport policy variables and characteristics). A common method to model these choices is the multinomial logit model (MNL), which is easy to apply and has clear interpretations. All subsequent in this section references use the MNL.

Ashford and Benchemam (1987) model the passengers' choice of airport in central England in the period 1975-1978. Travel time to the airport, fare and frequency of service were taken as the explanatory variables. It was found that for business travelers, travel time was the dominant determinant of airport choice; the frequency of service was the second most important variable. Fare was found to be the dominant factor for leisure and domestic travelers. Thompson and Caves (1993) model the passengers’ choice of airport in the North of England in 1983. For leisure travelers, the access time to the airport, the airfare and the maximum number of seats available were found to be significant variables for the airport choice. For business travelers, the access time, frequency of service and the number of seats were found to be significant. However, in the “business model”, the seats variable had a negative sign while the authors expected a positive sign (which was found in the “leisure model”). Caves et al. (1991) analyze the passengers' choice between selected British airports and identify access time, frequency, and fare as significant variables. Moreover, they conclude that "the hypothesis that frequency is an airport specific variable when considering the competition between an emerging and a mature airport cannot be rejected".

Hansen (1990) estimates market shares of airlines in origin-destination markets. The estimated market share is then used as input for an airline competition model. For direct services, the explanatory variables are the airfare and the (log of) frequency of service. For connecting services, explanatory variables are airfare, frequency of service on the minimum and maximum frequency link and the circuity of service (as a measure of the extra distance associated with the indirect connection). All variables are significant. Harvey (1987) concludes that an MNL with access time and frequency of service as explanatory variables provided a good approximation of airport choice in the San Francisco Bay Area. Both access time and frequency of service are included in a non-linear fashion to capture the diminishing marginal utility (disutility) of frequency (access time). Fares are omitted in the analysis, because (i) no information is available on the fare actually paid by each separate traveler and (ii) there appears to be more variation among fare classes on a given flight to a particular destination than among different flights to that destination or airport.

The MNL is indifferent between any similarity or dissimilarity between (in this case) airports; all are treated as equal. As a consequence, if one airport were added to the system, it will gain its share by a proportional reduction of the shares of the existing airports. No (existing) airport suffers more due to the new entrant than any other airport in the system. This IIA (independence of irrelevant alternatives) property may lead to unacceptable results, and can be overcome by specifying a nested multinomial logit model (NMNL). Ndoh et al. (1990), using UK data, find that a nested multinomial logit model is statistically preferred to an MNL. Bondzio (1996) analyzes the passengers' choice of airport and access mode, and finds that for business travelers an NMNL (with access mode as nest) and for leisure travelers MNL models are the most preferred.

Based on this concise review, we may conclude that an MNL is frequently used in the literature to describe passengers' airport or route choices. Variables of influence appear to be travel time (to the airport), frequency and airfare. It may be, however, that a NMNL is to be statistically preferred.

3 AN ECONOMETRIC MODEL FOR THE JOINT AIRPORT-AIRLINE CHOICE

In this section the discrete choice model is formulated for the joint airport-airline choice.

Suppose a traveler *i* has decided to travel by air to a particular destination. The traveler then has to make two choices; one for the origin airport and one for the airline. These choices are based on the (maximum) (in)direct utility the passenger derives from using a particular (combination of) departure airport *d* and airline *l*.

We distinguish between aggregate alternatives (airlines) and elemental alternatives (seats). The alternative "airline *l*" is made up of a number of flights to a particular destination; call this number f_l for frequency. With an average number of seats per flight s_l, the "size" of airline *l* in a particular market is $S_l = f_l s_l$: airline *l* offers S_l elemental alternatives (seats), each of which results in a utility $U_{l,j} = V_{l,j} + e_{l,j}$; $j=1,\ldots,f_l s_l$. Of all seats available in the market airline *l* offers a fraction $S_l \Big/ \sum_{l'} S_{l'}$. The average systematic utility of an elemental alternative is $\overline{V_l} = \frac{1}{S_l}\sum_j V_{l,j}$. Then, if the utilities of all flights *j* are IID (which implies $\overline{V_l} = V_{l,j}$, $\forall\, j$; the utility of a seat equals the average utility over all seats), it can be shown that the distribution of the utility of the aggregate alternative *l* approaches the Gumbel distribution[1] with a location parameter $h = \overline{V_l} + \frac{1}{a}\ln\left(S_l\right)$. As a result the total utility derived from airline *l* can be written as $U_l = \overline{V_l} + a\ln\left(S_l\right) + e_l = \overline{V_l} + a\ln\left(f_l\right) + a\ln\left(s_l\right) + e_l$ (see Ben-Akiva and Lerman, 1987). The average systematic utility, $\overline{V_l}$, is determined by the airfare p_l and aircraft or flight characteristics, such as the level of comfort and the flight time. Aircraft size can be seen as an indicator of the level of comfort; larger aircraft are more commonly used on long distance routes and have more amenities. Using the average number of seats as a proxy for aircraft size and including it in logarithmic form, multiplied by a parameter *b*, in the utility function to account for decreasing marginal utility (disutility) of comfort (travel time), the systematic utility derived form airline *l* is

$$\begin{aligned} V_l &= a_l + a_p p_l + a \ln\left(f_l\right) + \left(a + b\right)\ln\left(s_l\right) \\ &= a_l + a_p p_l + a_f \ln\left(f_l\right) + a_s \ln\left(s_l\right) \end{aligned} \tag{1}$$

where a_l is an airline-specific constant and p_l is the airfare charged by airline *l;* $a = a_f > 0$, $a_p < 0$. $a_s = a + b$ is assumed to be positive; at a given stage length we assume passengers prefer larger aircraft. The utility of using airport *d* depends on the access time to the airport t_d ($b_t < 0$):

$$V_d = b_d + b_t t_d \tag{2}$$

The airport and airline choices can be made sequentially or simultaneously. In Figure 1 two nested structures for the sequential choice are presented.

Figure 1 about here

In Figure 1a we assume the passenger first chooses an airport and then an airline. In Figure 1b the choice sequence is reversed. Then the probability that a combination (departure airport *d*, airline *l*) is chosen can be expressed as:

$$\mathrm{P}(l,d) = \mathrm{P}(l|d)\mathrm{P}(d) \tag{3}$$

$$P(l,d) = P(d|l)P(l) \tag{3'}$$

where equation (3) corresponds with the choice structure presented in Figure 1a, while equation (3') corresponds with Figure 1b. The conditional and marginal probabilities in equation (3) are:

$$\mathrm{P}(l|d) = \frac{\exp(\frac{\mathrm{V}_l}{m_l})}{\sum_{l'} \exp(\frac{\mathrm{V}_{l'}}{m_l})} \tag{4}$$

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[1] $F(U_l) = \exp(-\exp(-a(U_l - h)))$, where h is a location parameter and a is a positive scale parameter.

$$\mathrm{P}(d) = \frac{\exp(V_d + m_l \ln \sum_l \exp\left(\frac{V_l}{m_l}\right))}{\sum_{d'} \exp(V_{d'} + m_l \ln \sum_l \exp\left(\frac{V_l}{m_l}\right))} \tag{5}$$

The parameter m_l represents the degree of heterogeneity of airlines (flights) within (from) an airport. The closer m_l is to 0, the higher the degree of substitutability between airlines, with $0 < m_l \leq 1$[2]. For $m_l = 1$ the NMNL reduces to the MNL.

Adjustment of equations (4) and (5) to fit equation (3') rather than equation (3) is straightforward. In the following section both specifications will be tested against the MNL. Using equations (1) - (5) it is possible to set up a theoretical model to derive equilibrium airfares, frequencies and airport taxes (see e.g. Pels et al., 1998). In this paper our aim is to test such models empirically.

4 APPLICATION TO THE SAN FRANCISCO BAY AREA

In this section the model as presented formally and theoretically in section 3 will be estimated using data for the San Francisco Bay Area. The estimation results will be presented in Subsection 4.2; first however, in Subsection 4.1, some general characteristics of the data set will be presented.

4.1 The 1995 MTC Airline Passenger Survey

Passenger characteristic data used in this analysis were obtained from the 1995 Airline Passenger Survey conducted by the Metropolitan Transportation Commission (MTC), Oakland, CA. The survey was held in two waves, from August 25 to August 31 and from October 19 to October 27 1995, for the San Francisco (SFO), Oakland (OAK) and San Jose (SJC) airports. At Sonoma County Airport (STS) the survey was held on

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[2] In theory, in a NMNL there are two scale parameters, where the scale parameter for the upper level (equation (5), the airport choice) is larger than the scale parameter for the lower level (equation (4), the airline choice). For econometric purposes, 1 parameter is scaled to one, in this case the parameter for the upper level. As then the exponents in equation (5) are devided by 1, this parameter is not reported.

September 6 and 7 and October 31. In Table 1 the number of (accurate) responses along with the total number of enplanements at each airport in 1995 is given for each airport. The relatively (too) large number of interviews at SJC was conducted at the request of the airport authority (MTC, 1995). We account for this in the estimation procedure; see subsection 4.2. A vital variable in the analysis is the access time to the airport. The access time is calculated on the basis of the latitude and longitude of the location the passenger left from and the airports using GIS-data on the Bay Area road system available from the Bureau of Transport Statistics[3].

Table 1 Respondents and total enplaned passengers (1995)

Airport	San Francisco	San Jose	Oakland	Sonoma County	Total
Respondents	10,685	7,069	3,630	57	21,459
Passengers	15,013,265	4,267,071	7,750,857	<500,000	
Rank[1]	5	35	31	>50	

1) by total enplaned passengers, 1995. Source: (Bureau of Transportation Statistics, 1997).

In Table 2 the percentage of travelers according to destination is given. It is clear that the North American market (US and Canada) is by far the largest market. SFO and STS have some international traffic, while at SJC and OAK international traffic is marginal.

Table 2 Distribution of (origin-destination) passengers according to destination (%)

Airport	San Francisco	San Jose	Oakland	Sonoma County
US	89.6	96.7	98.6	90.7
Europe	3.9	0.6	0.1	4.7
Far East	1.0	0.7	0.2	-
Australia/Oceania	0.6	0.4	0.3	2.3
Mexico/Caribbean/ Middle America	1.8	0.6	0.3	2.3
Canada	2.7	0.7	0.3	-
Other[a]	0.4	0.3	0.1	-
Total	100	100	100	100

a South America, Middle East, Africa

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[3] These can be downloaded from: www.bts.gov.

In Table 3 the trip purpose is given for the respondents at each airport. At STS the majority of respondents is on a business trip. Also at SJC the majority of travelers is on a business trip, though the difference between the number of leisure travelers and business travelers is less pronounced. At the two other airports leisure travelers form the largest group.

Table 3 Distribution of (origin-destination) passengers according to trip purpose (%)

Airport	San Francisco	San Jose	Oakland	Sonoma County
business	39	52	35	69
leisure	54	40	54	26
other	7	8	11	5

Information on frequencies and average numbers of seats offered by airlines were obtained from OAG Market Analysis, Reed Elsevier Group. Data on fares was only available for flights originating from SFO.

4.2 ESTIMATION RESULTS

In this subsection the estimation results of the joint airport-airline choice model are presented. The purpose is to test the specification in equation (3) against the specification in (3') and the MNL-specification. To be able to estimate airport choice models, only those passengers were selected that had two or more airports to choose from. The Bay Area choice sets for October (for the nested specifications (3) and (3')) are depicted in Figure 2[4].

Figure 2 about here

Note in Figure 2a there is one degenerate case (within the "nest" STS there is only one possible alternative), while in Figure 2a there are more degenerate cases. In the empirical exercise, separate models are estimated for business and non-business travelers.

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[4] The choice sets for August are almost the same; in the August choice set Tower Air (operating from SFO) is included, Air Canada (SFO), Northwest (OAK) and Asiana Airways (SFO) are missing.

The utility functions are specified in equations (1) and (2)[5]. As already mentioned in subsection 4.1, a disproportionally large number of interviews was conducted at SJC: the actual choices were sampled rather than the economic actors (decision makers); sequences of chosen alternatives were stratified and then the individual characteristics of the travelers were observed. To accommodate for these problems, weighted estimations have been carried out. To calculate the weights we need the sample fractions and population fractions for each alternative (airport-airline combination). The latter are unavailable. However, from Table 1 we can determine the airports' population fractions, r_d, for 1995. At each airport, we can determine the relative size $s_{l,d} = S_l \big/ \sum_{l'} S_{l'}$ of each airline operating from that airport. Then the population share for each alternative is approximated as $r_d s_{l,d}$. Six models were estimated, model I (II) is estimated with airport specific constants and fixed (free) inclusive value parameters[6]. Model III (IV) is estimated with fixed (free) inclusive value parameters and without airport specific constants. Model A (B) is a NMNL-estimation with (without) airport specific constants and inclusive value parameters fixed at 1; these models were estimated to test the nested structures.

Results for the business travelers are reported in Table 4. For business travelers, the nested structures with the choice sequence first airline, then airport were rejected. Although the likelihood was higher than for the models with the reversed choice sequence (as was to be expected, the number of (inclusive value) parameters is much higher, see Figure 2), in all cases a_s was smaller than 0 (and in most cases $|a_s| > a_f$, which is unlikely, see section 3). In August model II is the preferred model, while in October model IV is preferred (model II is rejected because the inclusive value parameters are larger than 1). Reestimating model II with the airport specific constants fixed at 0 we reproduce model IV. The LR-test of model IV against model II is 8.226; hence the hypothesis that model IV is a restricted version of model II is not rejected at

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[5] In theory, the airport tax also should be included as an explanatory variable. However, while the airport taxes differ according to the passengers status (national, international, transfer etc.), there were hardly any differences between the airports for a given passenger type in the choice set. The taxes therefore can be treated as a constant. In equation (1) an airline specific constant was specified. This constant was deleted from the analysis as the Hessian matrix with a full set of airline specific constants failed to invert.

[6] Fixed inclusive value parameters mean that each nest has the same inclusive value parameter: the demand parameter for the maximum expected utility of all airlines (airports) in each nest is the same over all airports (airlines). Free inclusive value parameters mean that these parameters are not (necessarily) the same over all nests.

the 95% confidence level. We conclude that for the business travelers a nested model with the airports as nests, without airport specific constants and free inclusive value parameters best explains the joint airport-airline choice. The conclusion also holds for the full sample. However, given the substantial differences between the August- and October estimates, separate estimates are preferred as these reflect there are seasonal influences.

Table 4 Estimation results, business travelers[1,2]

	August		October		full sample	
	II	IV	II	IV	II	IV
a_f	1.382^*	1.469^*	1.077^*	1.280^*	1.19^*	1.365^*
	(0.070)	(0.063)	(0.048)	(0.054)	(0.040)	(0.039)
a_s	1.462^*	1.865^*	1.808^*	3.011^*	1.402^*	2.293^*
	(0.224)	(0.216)	(0.174)	(0.186)	(0.124)	(0.136)
b_{SFO}	reference state		reference state		reference state	
b_{SJC}	-0.026	-	-0.472^*	-	-0.123	-
	(0.226)		(0.141)		(0.105)	
b_{OAK}	0.144	-	1.711^*	-	1.406^*	-
	(0.379)		(0.182)		(0.212)	
b_{STS}	5.021^*	-	13.792^*	-	9.098^*	-
	(1.539)		(1.103)		(0.792)	
b_t	-0.061^*	-0.058^*	-0.034^*	-0.015^*	-0.04^*	-0.03
	(0.006)	(0.005)	(0.003)	(0.001)	(0.002)	(0.002)
m_{SFO}	0.854	0.642	1.691^*	0.862	1.359^*	0.789^*
	(0.101)	(0.029)	(0.026)	(0.011)	(0.072)	(0.010)
m_{SJC}	0.870	0.646	1.770^*	0.887	1.411^*	0.805^*
	(0.107)	(0.031)	(0.099)	(0.011)	(0.077)	(0.011)
m_{OAK}	0.825	0.612	1.700^*	0.862	1.345^*	0.768^*
	(0.102)	(0.031)	(0.095)	(0.011)	(0.073)	(0.011)
m_{STS}	1 (fixed parameter)		1 (fixed parameter)		1 (fixed parameter)	
L	-2666.86	-2670.98	-3642.32	-3743.39	-6491.42	-6548.17
$\chi^2_{A,B}$	88.03	196.72	263.98	164.63	294.12	366.09
χ^2_c	5280.96	5272.74	7762.643	7560.51	13225.15	10488.36
ρ^2(c)	0.50	0.50	0.52	0.50	0.50	0.50
obs.	2129	2129	2887	2887	5016	5016

1) L is the log of likelihood. χ^2_c is the likelihood ratio test of the estimated model against the model with constants only. $\chi^2_{A,B}$ is the likelihood ratio test of the estimated model against model A or B, depending on whether the estimated model has airport specific constants. ρ^2(c) (= 1-L/L(c)) is the likelihood-index. * indicates a parameter is significantly different from 0 (or 1 in case of the *m*'s) at the 95% confidence level. Standard errors between parentheses.

2) m_d is the inclusive value parameter for airport *d*.

Based on the parameter estimates presented in Table 4, elasticities of demand can be computed. These are reported in Table 5 (see Appendix 1 for details). From Table 5 it appears that demand at STS (a small airport with only 1 airline available in the choice set) is relatively insensitive compared to the other three airports. The elasticities of frequency (and seats) are smaller than 1 at SFO and higher than 1 at SJC and OAK; a 1 percent change in the frequency (inclusive value) will make SJC and OAK relatively more attractive than SFO. Pels et al. (1998) argued that a necessary condition for an airfare-frequency equilibrium to exist in a multiple airport region is that the frequency elasticity of demand is smaller than 1. This is the case for the Bay Area. At SFO, SJC and OAK, a 1 percent change in the number of available seats will result in a more than 1 percent change in demand (as the "size" of the airport in terms of available seats and the quality have increased). A 1 percent change in the access time will lead to a less than 1 percent change in demand.

Table 5 Demand elasticities, business passengers

		SFO	SJC	OAK	STS	Bay Area
frequency	August	0.86	0.94	1.24	0.00	0.93
	October	0.85	1.05	1.05	0.20	0.95
	Pool	0.84	1.04	1.10	0.04	0.95
seats	August	1.09	1.20	1.57	0.00	1.18
	October	2.01	2.47	2.47	0.47	2.24
	Pool	1.41	1.74	1.85	0.07	1.59
access-time	August	-0.58	-0.21	-1.57	-0.01	-0.55
	October	-0.23	-0.18	-0.32	-0.07	-0.24
	Pool	-0.40	-0.25	-0.73	-0.07	-0.42

Estimation results for leisure travelers are presented in Table 6. The choice sequence is first airport, then airline. The preferred model for August is model II, while model IV (no airport specific constants, airport specific inclusive value parameters) is preferred for October and the full sample. For the reversed choice sequence, models I and III were preferred. The log-likelihoods were higher, but again, so was the number of explanatory variables. As the seats parameter was negative and in absolute value larger than the frequency parameter, the reversed choice sequence (first airline, then airport) was rejected. It appears parameter estimates vary more over time than over passenger types. Based on the literature review we would expect more pronounced differences between passenger types. It should however also be noted that the airfare was not included in any model so far. Various authors have found the airfare to be of influence on both the airport- and route choice; see Section 2.

Table 6 Estimation results, leisure travelers^{1,2}

	August		October		full sample	
	II	IV	II	IV	II	IV
a_f	1.241^*	1.304^*	1.025^*	1.179^*	1.100^*	1.256^*
	(0.051)	(0.047)	(0.041)	(0.049)	(0.031)	(0.033)
a_s	1.523^*	1.810^*	1.709^*	2.756^*	1.278^*	2.035^*
	(0.168)	(0.151)	(0.153)	(0.163)	(0.092)	(0.102)
b_{SFO}	reference state		reference state		reference state	
b_{SJC}	0.463^*	-	0.249	-	0.462^*	-
	(0.179)		(0.141)		(0.097)	
b_{OAK}	0.113	-	2.133^*	-	1.513^*	-
	(0.309)		(0.167)		(0.207)	
b_{STS}	4.216^*	-	14.153^*	-	9.381^*	-
	(1.174)		(1.000)		(0.674)	
b_t	-0.058^*	-0.058^*	-0.036^*	-0.013^*	-0.041^*	-0.032
	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)	(0.001)
m_{SFO}	0.852	0.637	1.834^*	0.874	1.443^*	0.777^*
	(0.083)	(0.023)	(0.092)	(0.012)	(0.067)	(0.010)
m_{SJC}	0.861	0.637	1.908^*	0.894	1.488^*	0.788^*
	(0.087)	(0.024)	(0.099)	(0.012)	(0.071)	(0.011)
m_{OAK}	0.822	0.604	1.835^*	0.867	1.430^*	0.751^*
	(0.084)	(0.024)	(0.094)	(0.013)	(0.068)	(0.011)
m_{STS}	1 (fixed parameter)		1 (fixed parameter)		1 (fixed parameter)	
L	-4181.79	-4189.60	-3950.33	-4082.63	-8324.08	-8413.11
$\chi^2_{A,B}$	102.43	133.39	258.39	134.17	147.29	200.68
χ^2_c	8147.09	8131.47	7793.14	7528.54	16173.86	15995.81
$\rho^2(c)$	0.49	0.49	0.49	0.48	0.49	0.49
obs.	3281	3281	3031	3031	6249	6249

1) L is the log of likelihood. χ^2_c is the likelihood ratio test of the estimated model against the model with constants only. $\chi^2_{A,B}$ is the likelihood ratio test of the estimated model against model A or B, depending on whether the estimated model has airport specific constants. $\rho^2(c)$ (= 1-L/L(c)) is the likelihood-index. * indicates a parameter is significantly different from 0 (or 1 in case of the *m*'s) at the 95% confidence level. Standard errors between parentheses.

2) m_d is the inclusive value parameter for airport *d*.

Based on the parameter estimates presented in Table 6, we can calculate the elasticities presented in Table 7. In most cases, the frequency elasticities appear to be smaller and the access time elasticities appear to be larger for leisure travelers; the difference is more pronounced with the access time elasticities. Note that Ashford and Benchemam (1987) found, using UK data, that both access time and frequency elasticities were higher for business passengers than for leisure travelers. Moreover, for business travelers access time elasticities were higher than frequency elasticities, opposite to our findings presented in Table 5. Caves et al. (1991) found frequency elasticities for business passengers in the UK of about 0.11-0.18. These are significantly smaller than the elasticities presented in Table 5. These differences may be attributed to (i) the different model specification, (ii) the different geographical location and (iii) the different time period. Further research should indicate what is the main cause of the difference. Harvey (1987), using Bay Area data for 1980, included both the relative direct flight frequency and a quadratic frequency term; these parameter estimates are difficult to compare with those in Table 5. Hansen (1990) finally used the log of (direct) frequency as an explanatory variable in a route choice model. The estimated coefficient of 1.29 is not far removed from the estimations presented in Tables 5 and 7.

Table 7 *Demand elasticities, leisure passengers*[1]

		SFO	SJC	OAK	STS	Bay Area
frequency	August	0.85	0.90	1.11	0.00	0.91
	October	0.79	1.01	0.94	0.37	0.88
	Pool	0.84	0.99	1.01	0.08	0.92
seats	August	1.18	1.25	1.54	0.01	1.26
	October	1.84	2.37	2.19	0.87	2.05
	Pool	1.36	1.60	1.64	0.13	1.48
access-time	August	-0.70	-0.35	-1.89	-0.02	-0.76
	October	-0.26	-0.35	-0.38	-0.38	-0.31
	Pool	-0.54	-0.49	-0.94	-0.19	-0.62

1) Elasticities for August calculated on the basis of model IV.

In Tables 4 and 6 no airfare parameters are presented because the necessary data are not available. Only for a limited number of flights originating from the city of San Francisco standard airfares are available. It was not possible to derive any meaningful airfare parameters based on these limited choice sets. However, based on the estimations presented in Tables 4 and 6 and the (not-presented) estimations including the airfares, we do conclude that the parameter estimates presented in Tables 4 and 6 are rather robust.

5 CONCLUSION

In this paper a statistical model for the passengers' sequential choice of airport and airline was formulated. In Section 2 it was concluded that access time to the airport and frequency of service are generally considered to be among the most influential determinants of the choice of airport and airline. Some authors also found the airfare to be significant for the choice made by leisure travelers, while other authors argue that there appears to be more variation among fare classes on a given flight to a particular destination than among different flights to that destination or airport; hence the airfare was omitted from their analysis.

In Section 3 the statistical model was formulated. Based on theoretical arguments, the frequency of service was included in logarithmic form. The particular specification was chosen, as it is the foundation of a previous theoretical paper in which unique airfare - frequency (- airport tax) equilibria are derived (see Pels et al. (1998).

In Section 4 it was found that both business and leisure travelers choose the departure airport and airline sequentially (first airport, then airline). In general, the estimations presented compare to those found in the literature with two distinctions. First, there are little differences between the estimations for business and leisure passengers. Second, passengers choose first the departure airport and then the airline, rather then choosing both simultaneously.

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REFERENCES

Ashford, N. and M. Benchemam (1987), Passengers' Choice of Airport: An Application of the Multinomial Logit Model, *Transportation Research Record 1147*, National Research Council, Washington D.C.

Ben-Akiva, M. and S.R. Lerman (1987), *Discrete Choice Analysis: Theory and Application to Travel Demand*, Cambridge, Mass., MIT Press.

Bondzio, L. (1996), *Modelle fuer den Zugang von Passagieren zu Flughaefen* (Models for the Passengers’ Access to Airports), Ph.D. thesis, Ruhr-University Bochum (in German).

Caves, R.E., N.N. Ndoh and D.E. Pitfield (1991), *Route Choice Modeling applied to the Choice between Mature Airports and Emergent Airports in their Shadow,* Paper presented at the 31st RSA European Congress, Lisbon, Portugal, 27-30 August 1991.

Hansen, M. (1990), Airline Competition in a Hub-Dominated Environment: an Application of Noncooperative Game Theory, *Transportation Research*, **24B**(1), 24-43.

Harvey, G. (1987), Airport Choice in a Multiple Airport Region, *Transportation Research*, **21A**(6), 439-449.

Metropolitan Transportation Commission (1995), *1995 Metropolitan Transportation Commission Airline Passenger Survey.*

Ndoh, N.N., D.E. Pitfield and R.E. Caves (1990), Air Transportation Passenger Route Choice: A Nested Multinomial Logit Analysis, *Spatial Choices and Processes*, eds Fischer, M.M., P. Nijkamp and Y.Y. Papageorgiou, 349-365, Elsevier Science Publishers, North-Holland.

OAG Market Analysis, Reed Travel Group (1995), *World Airways Guide*.

Pels, E., P. Nijkamp and P. Rietveld (1997), Substitution and Complementarity in Aviation: Airports versus Airlines, *Transportation Research E*, forthcoming.

Pels, E., P. Nijkamp and P. Rietveld (1998), *Equilibrium Airfares, Frequencies and Airport Taxes in a Multiple Airport Region: an Application of the Nested Logit Demand Model*, Free University, mimeo.

Thompson, A. and R. Caves (1993), The Projected Market Share for a New Small Airport in the North of England, *Regional Studies*, **27**(2), 137-147.

Appendix 1 Graphs

Figure 1 Nested Choice Structures

Figure 1a, Choice sequence: first airport, then airline

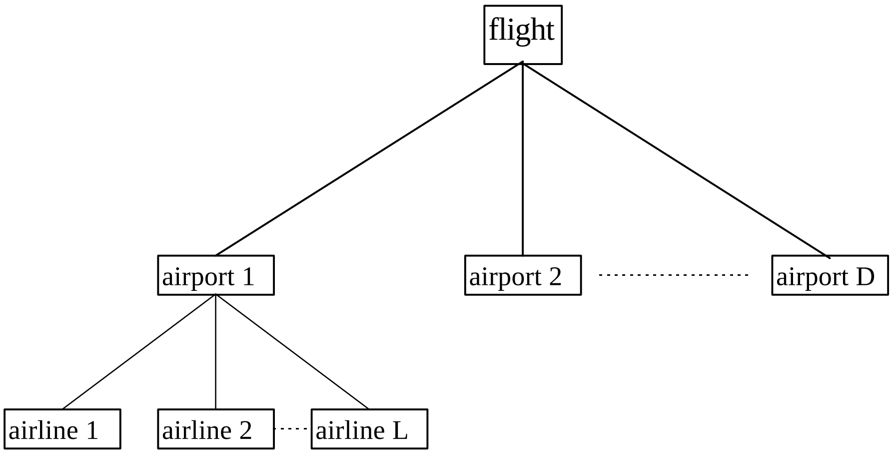


Figure 1b, choice sequence: first airline, the airport

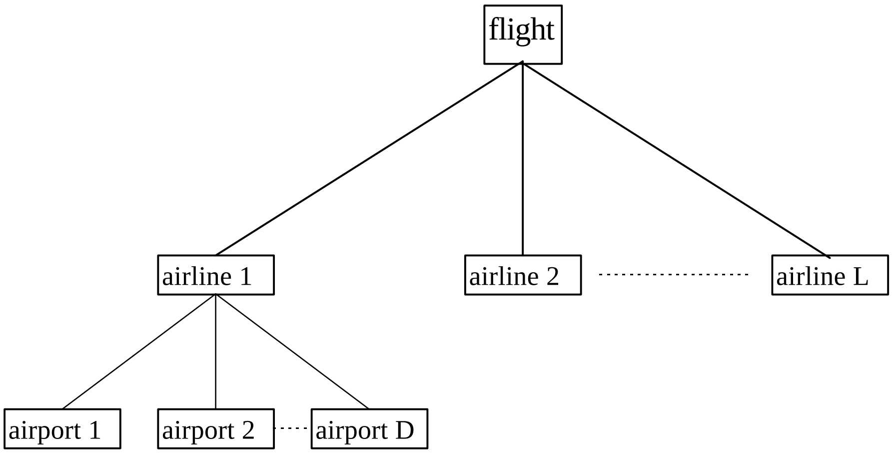


Figure 2 Nested Structures for the airport-airline choice[a,b]

Figure 1a: Choice sequence: first airport, then airline

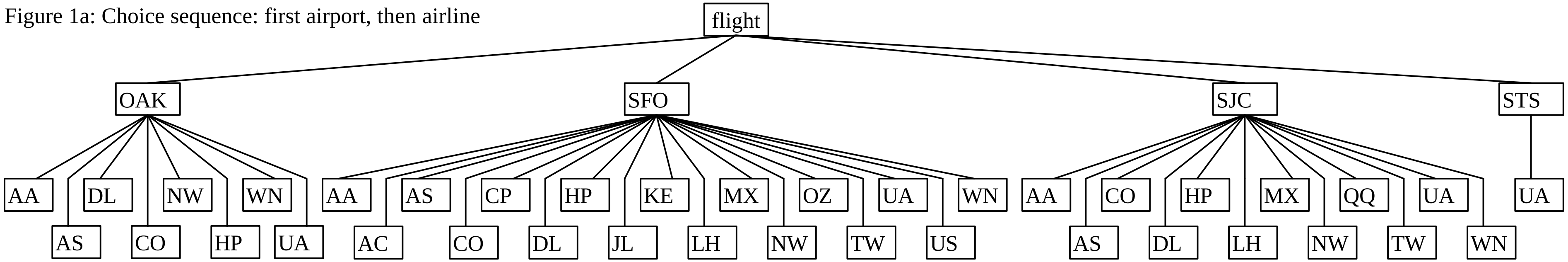
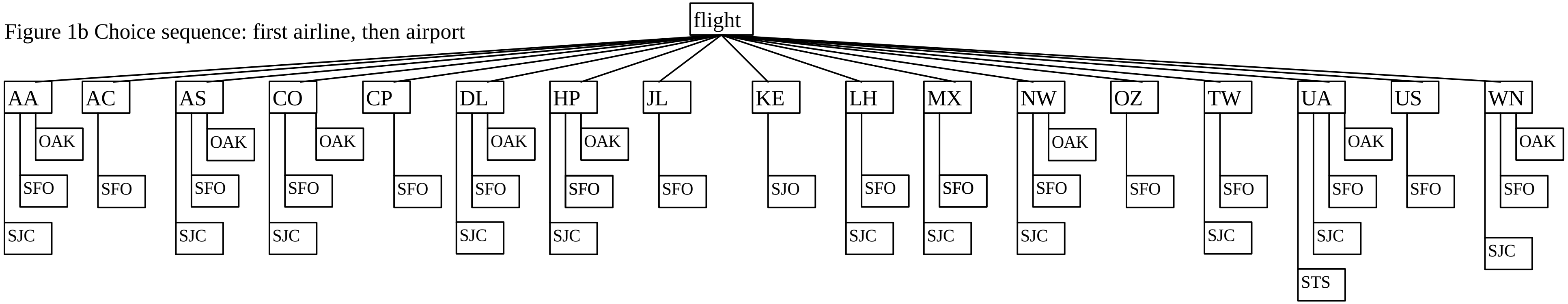


Figure 1b Choice sequence: first airline, then airport



a) These are the full choice sets. Not all alternatives may be available to an individual; the actual alternatives available depend on the destination. The destinations are: Boston MA), Chicago (IL), Dallas-Ft. Worth (TX), Philadelphia (PA), Denver (CO), Boise (ID), Las Vegas (NV), Reno (NV), Salt Lake City (UT), Buffalo (NY), Los Angeles (CA), Ontrio (CA), San Diego (CA), Santa Barbara (CA), San Francisco (CA), Orange County (CA), Spokane (WA), Seattle (WA), Portland (OR), Minneapolis-St. Paul (MN), St. Louis (MO), Tokyo (JP), Guadalajara (MX) and Vancouver (BC).

b) AA: American Airlines, AC: Air Canada, AS: Alaska Airlines, CO: Continental Airlines, CP: Canadian Airlines, DL: Delta Airlines, HP: America West Airline, JL: Japan Airlines, KE: Korean Air, LH: Lufthansa, MX: Mexicana Airlines, NW: Northwest Airlines, OZ: Asiana Airlines, QQ: Reno Air, TW: Trans World Airlines, UA: United Airlines, US: US Air, WN: Southwest Airlines, OAK: Oakland International Airport, SFO: San Francisco International Airport, SJC: San Jose International Airport (CA, USA), STS: Santa Rosa.

Appendix 2 Derivatives

At the individual level, the elasticity of logit is:

$$\varepsilon_{i,x_i}^{P_i(l,d)} = \frac{\partial \ln\left(P_i(l,d)\right)}{\partial \ln\left(x_i\right)} = \frac{\partial \ln\left(P_i(l|d)\right)}{\partial \ln\left(x_i\right)} + \frac{\partial \ln\left(P_i(d)\right)}{\partial \ln\left(x_i\right)} =$$

$$\left(1 - P_i(l|d)\right)\frac{\beta_{ix} x_i}{\mu} + P_i(l|d)\left(1 - P_i(d)\right)\beta_{ix} x_i$$

where the subscript *i* denotes the individual. When x_i appears in logarithmic form in the utility function, $\varepsilon_{i,x_i}^{P_i(l,d)}$ is multiplied by $\frac{1}{x_i}$.

The aggregated elasticity is

$$\varepsilon_x^{\overline{P(l,d)}} = \frac{\sum_i P_i(l,d)\varepsilon_{i,x_i}^{P_i(l,d)}}{\sum_i P_i(l,d)}$$