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Modeling the competition among air-travel itinerary shares: GEV model development

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Abstract

This study reports the results of aggregate air-travel itinerary share models estimated using data from all East West markets in the United States and Canada. These models predict airline ridership at the itinerary level and aid carriers in long and intermediate term decision-making. Official and comprehensive schedule and bookings data is used to estimate generalized extreme value models capturing the inter-itinerary competition dynamic along three dimensions: time of day, carrier and level-of-service (nonstop, direct, single-connect, double-connect). Models incorporate one, two or three of these dimensions simultaneously. Model structures considered include multinomial logit and variations of the nested logit model (two-level nested logit, two-level weighted nested logit, three-level nested logit, three-level weighted nested logit and nested weighted nested logit). Independent variables for the models measure various itinerary service characteristics such as level-of-service, connection quality, carrier attributes, aircraft type, and departure time. Additionally, the advanced models yield inverse logsum and/or weight parameter estimates capturing the underlying competitive dynamic among air-travel itineraries. The results are intuitive, and the advanced models outperform the more basic specifications with regard to statistical tests and behavioral interpretations, giving insight into the competitive dynamic of air-carrier itineraries.

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1. Introduction

This paper develops models that forecast air-travel itinerary passenger (market) shares between airport-pairs. These models forecast the number of passengers expected to travel on each itinerary between any airport-pair conditional on the forecasted airport-pair passenger volume. Itinerary share models support air-carrier long and intermediate term decision-making with respect to fleet planning, merger and acquisition scenarios, route planning, equipment assignment scenarios, code share opportunity scenarios, minimum connection time studies, price-elasticity studies, hub location studies, etc. Improvements to a carrier's itinerary share model translate to improvements in revenue management, schedule efficiency and profitability.

An itinerary, as used here, is a leg (flight number) or sequence of legs connecting a given airport-pair (each flight leg may be included in several itineraries linking the airport-pair as well as being included in itineraries linking many different airport-pairs). Itineraries are either nonstop, direct (a connecting itinerary involving no airplane change), single-connect (a connecting itinerary with an airplane change) or double-connect (an itinerary involving two connections). [2] On any given day, an airport-pair may be served by hundreds of itineraries, each of which offers travelers a potential way to travel between the airports. Once an itinerary share model is estimated, these shares (probabilities) can be applied to airport-pair volume forecasts obtained from a separate model, and these itinerary-level forecasts can be assigned to flight legs to obtain carrier market share at the flight-leg, airport-pair, region, system or any other level of aggregation.

Many aviation demand studies have forecasted air-travel volumes for a given level of aggregation such as system (Brown and Watkins, 1968; English and Kernan, 1976; Transportation Research Circular #348, 1989), metropolitan region (Mumayiz and Pulling, 1992), airport (city) pair (Brown and Watkins, 1968; Brown and Watkins, 1971; Verleger, 1972; De Vany and Garges, 1972; Douglas and Miller, 1974; De Vany, 1974; Kanafani and Fan, 1974; De Vany, 1975; Ippolito, 1981; Anderson and Kraus, 1981; Abrahams, 1983; Reiss and Spiller, 1989; Dresner et al., 1996; Corsi et al., 1997) or airport (Skinner, 1976; Augustinus and Demakopoulos, 1978; Harvey, 1987; Ashford and Benchemam, 1987; Furuichi and Koppelman, 1994; Windle and Dresner, 1995; Suzuki et al., 2003; Hess and Polak, in press; Basar and Bhat, 2004).

Other studies have dealt with the allocation of air-travel volumes to air-carriers at a given level of aggregation. These air-carrier allocation studies typically identify a relationship between airline service attributes and the allocation of air-travel volume. Additionally, these studies usually estimate the relative importance of different carrier attributes (e.g. presence, fare-levels, service quality) on demand share and quantify the tradeoffs that passengers make among these in their air-travel purchasing decisions. Air-carrier demand allocation studies have focused on carrier share at the system (Nason, 1981; Morash and Ozment, 1996; Suzuki et al., 2001), airport-pair (Ghobrial and Soliman, 1992; Nako, 1992; Proussaloglou and Koppelman, 1995) or point-

[2] These four classifications are referred to as an itinerary's "level-of-service" in this study.

to-point (nonstop) flight share level (Yoo and Ashford, 1996; Algers and Beser, 1997; Proussaloglou and Koppelman, 1999; Bruning and Rueda, 2000).

All the above-mentioned carrier-allocation studies fall into at least one of the following categories: (1) studies based on data with a high level of geographic aggregation, (2) studies employing surveys with a very limited range of airport-pairs or (3) studies based on stated preference data which may be subject to bias (Morrison, 2000; Murphy et al., in press). Additionally, a major limitation of these studies is their failure to model air-travel demand at the level of individual itineraries, the products that are ultimately purchased by passengers. Accurate planning requires the modeling of air-travel demand to the itinerary level. The focus of this paper is on the problem of allocating airport-pair demand to the different itineraries linking airport-pairs.

Previous work by the authors (Coldren et al., 2003) estimated itinerary share models measuring the impact of various air-carrier service attributes on itinerary shares using aggregate multinomial logit (MNL) models. MNL models are adequate for describing the impact of service attributes on airport-pair itinerary share. However, the across-itinerary independence of the itinerary error terms (inherent in the derivation of the MNL model structure) implies that all itineraries "compete" equally with each other for a given airport-pair. That is, the underlying competition among air-travel itineraries is assumed to be "uniform" when modeled with an MNL function. This is further demonstrated by a well-known property of MNL models, the independence of irrelevant alternatives (IIA), which states that the relative probability of choosing any pair of itineraries is independent of the attributes (or even the presence) of any other itineraries. This can be seen from the ratio of MNL probabilities for two itineraries, i and j

$$\frac{P_i}{P_j} = \frac{\dfrac{\exp(V_i)}{\sum_{k\in K}\exp(V_k)}}{\dfrac{\exp(V_j)}{\sum_{k\in K}\exp(V_k)}} = \frac{\exp(V_i)}{\exp(V_j)} \tag{1}$$

which excludes any information about the attributes or presence of any other itineraries and is only a function of the itineraries i and j. The IIA property of the MNL model is also apparent by examining the cross-elasticity equation for the change in the probability of itinerary j due to changes in an attribute of itinerary i

$$\eta^{P_j}_{X_{ik}} = \frac{\partial P_j}{\partial X_{ik}}\frac{X_{ik}}{P_j} = -P_i X_{ik}\beta_k \tag{2}$$

where X_{ik} is the value of itinerary i's kth attribute, and β_k is attribute k's parameter estimate. Note that the expression on the right-hand side is not a function of j. That is, changing an attribute of itinerary i affects all other itineraries in the same proportion.

The central hypothesis of this paper is that the underlying competition among air-travel itineraries for a given airport-pair is not uniform. Rather, it is asserted that groups of itineraries sharing one or more common attributes will exhibit more competition (as measured by cross-elasticities) amongst themselves than with itineraries not sharing these attributes.

Generalized extreme value (GEV) models allow for the possibility of correlation between error terms for groups of alternatives (McFadden, 1978; Koppelman and Sethi, 2000) and permit the estimation of differential alternative competition measurements simultaneously with the value function parameters. This allows for flexible and complicated inter-alternative competition dynamics to be modeled. Using aggregate GEV (in particular, variations of the nested logit (NL) model) itinerary share models, this paper measures the differential inter-itinerary competition dynamics that are hypothesized to exist among groups of air-travel itineraries.

It is hypothesized that the competition among air-travel itineraries is differentiated by proximity in departure time, carrier, level-of-service or a combination of these dimensions. [3] Clearly, itineraries with similar departure times share unobserved characteristics that air-travelers consider in their itinerary selection process. For example, it is likely that air-travelers have desired departure times and consider groups of itineraries with departure times that are close to their desired departure times. That is, if an air-traveler desires to depart in the early morning, he/she will compare/contrast the attributes of different early-morning itineraries more closely than afternoon or evening itineraries. Thus, itineraries within a given time period are likely to compete with each other more than with itineraries in a different time period. Similarly, it is likely that itineraries of a given carrier compete more with each other than with itineraries of different carriers due to loyalty factors such as frequent flyer program affiliations. Finally, it is believed that itineraries with the same level-of-service share many unobserved characteristics that differentiate them from itineraries with different levels-of-service. For example, (by definition) single-connect itineraries involve one stopover with a change of airplane. [4] Therefore, for a given airport-pair, the error terms for itineraries of a given level-of-service are likely to be correlated (resulting in greater substitutability between the itineraries than with itineraries of different levels-of-service).

2. Modeling framework

Itinerary share models can be formulated in a variety of ways. The approach developed in this paper uses an aggregate logit share technique. It is assumed that the air-travel passengers being modeled choose itineraries with the intent of maximizing their utility. Following convention, the utility of itinerary i, U_i, is expressed as the sum of a deterministic component, V_i, and a random component, ε_i

$$U_i = V_i + \varepsilon_i \tag{3}$$

The deterministic component (hereafter referred to as the value) represents the relative desirability of each itinerary connecting an airport-pair. The market share assigned to each itinerary is modeled as a function of the value of itinerary i and the values of all other itineraries serving the airport-pair for a given day of the week. Variables that describe each itinerary, and their corresponding parameter estimates, determine an itinerary's value. For itinerary i, its value, V_i, is assumed to be linear-in-parameters,

$$V_i = \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_n X_{ni} \tag{4}$$

[3] Other itinerary competition dynamics likely exist (e.g. the competition among fare-classes within and across itineraries). However, the data constraints of this study do not permit these relationships to be explored.

[4] From the travelers' perspective, this involves a layover, the inconvenience of switching planes, the possibility of missing his/her connection, etc.

That is, an itinerary's value is a linear function of explanatory variables (attributes, represented by the X_{ki}'s) and their corresponding parameter estimates (represented by the β_k's). The parameter estimates indicate the importance of different attributes on choice. The variables used in our models are service characteristics describing each itinerary including level-of-service indicators, connection quality measurements, [5] carrier attributes, aircraft type, and time of day variables as described in Table 1. The structure of an itinerary share model depends on the assumptions made about the distribution of the error term, ε_i as discussed in later sections of the paper.

The study reported here is based on comprehensive bookings and schedule data obtained from official sources that are linked to support the estimation of itinerary shares for any airport-pair. Bookings data was obtained from a compilation of computer reservation systems (CRS), a data source containing detailed records of individual booked itineraries. The CRS data is believed to include 90% of all bookings. [6] during the study period (May, 2001). However, increasing use of direct carrier bookings (via telephone and Internet) has since reduced the proportion of bookings reported by this source. This is likely to be an ongoing trend due to reduced travel agent commissions and reduced price differentials between "discount" Internet sites and the carriers' own websites. Leg-based air-carrier schedule information was obtained from the Official Airline Guide (OAG Worldwide Limited, 2001). Finally, fare data was obtained from the "Superset" data source (Data Base Products, Inc., 2001). [7]

A major carrier's itinerary building engine was used to generate the set of feasible itineraries between the airport-pairs using the leg-based schedule data. Itineraries are generated for each day of the week keeping in mind the days of the week that each itinerary's flight leg(s) operates. The dependent variables in the models are the number of passengers who booked each itinerary. This was determined by merging the generated itineraries with the CRS booked itineraries. The choice (alternative) sets were modeled as the set of all itineraries between each airport-pair for each day of the week. Using May 2001 data, models were estimated with maximum likelihood techniques using all airport-pairs between the East and West (as determined by time zone) regions of the United States and Canada using the GAUSS modeling software (Aptech Systems, Inc., 2004).

Even though the bookings data employed in this study is based on the choices of individual travelers, it does not include any information on the demographic characteristics of the individual that made the booking, or any trip-related characteristics of the booking (such as income, business vs. leisure, number of days booked in advance of departure, duration of stay). The unavailability of such data can be treated as a measurement error which is likely to introduce some biases

[5] Connection variables could but do not include an indicator that a connection is through one of a carrier's hubs. This variable might provide a small amount of additional information except that the vast majority of connections are, in fact, through carrier hubs.

[6] We are assuming that the small number of bookings not captured by the CRS source have the same characteristics as the bookings contained in CRS. This assumption may be questionable (and hence our results slightly biased) since it is likely that direct carrier bookings contain more leisure bookings than the entire population of bookings.

[7] Fare is obviously an important determinant of itinerary choice (especially for leisure travelers). Detailed fare-class (or even itinerary-level) fare data was not available for this study, however. Rather, average fare by carrier (across itineraries) for each airport-pair is employed as an independent variable in the presented itinerary share models. This is the best fare data currently available for a revealed preference air-carrier demand allocation study.

Table 1
Description of explanatory variables

Variable	Description
Level-of-service	Dummy variables representing the level-of-service of the itinerary (nonstop, direct, single-connect, double-connect) with respect to the best level-of-service available in the airport-pair
Second-best connection	For connection itineraries sharing a common leg, a dummy variable indicating that the itinerary is not the best connection (with respect to ground time) for the given incoming or outgoing leg at a transfer station
Second-best connection time difference	If the second-best connection indicator equals one, this variable measures the ground time difference between the itinerary and the best connection itinerary
Distance ratio	Itinerary distance divided by the shortest itinerary distance for the airport-pair multiplied by 100
Best connection time difference	Elapsed time difference between an itinerary involving a stop or connection and the fastest itinerary involving a stop or connection for each airport-pair independent of transfer airport
Fare ratio	Carrier average fare divided by the industry average fare for the airport-pair multiplied by 100
Carrier	Dummy variables representing each major US domestic carrier All other carriers are combined together in a single category
Code share	Dummy variable indicating whether any leg of the itinerary was booked as a code share
Regional jet	Dummy variable indicating whether the smallest aircraft on any part of the itinerary is a regional jet
Propeller aircraft	Dummy variable indicating whether the smallest aircraft on any part of the itinerary is a propeller aircraft
Departure time	Dummy variables for each hour of the day (based on the local departure time of the first leg of the itinerary)

in the results but much less than the direct use of aggregate data. Thus, since no individual data is available to identify differences among travelers, it may not be appropriate to count the full weight of the individual observations in calculating the statistics for our models. The most extreme adjustment can be accomplished by dividing the log-likelihood values for the models by the ratio of the number of booked passengers to the number of airport-pair, day-of-the-week combinations (469,078/14,893 = 31.50); and the parameter estimate t-statistics by the square root of this ratio (5.61). [8] Intermediate adjustments that take account of the fact that individual choice behavior is observed can be justified, as well. Statistics discussed in the following sections and presented in Tables 2 and 3 refer to the unadjusted values as well as the values obtained after adjusting (according to the ratio described above) due to the aggregate nature of our data.

We begin this paper with a "base" MNL model, which was developed through extensive estimation and validation testing and demonstrated to provide substantially improved itinerary share prediction than models previously used by a major air-carrier (Coldren et al., 2003). Due to the

[8] This procedure is equivalent to the result that would be obtained if each airport-pair, day-of-the-week combination was counted as a single observation, with the itinerary bookings represented as shares and the observations weighted in proportion to the total number or bookings for the observation divided by the total number of bookings for the estimation dataset, with the sum of weights equal to the number of airport-pair, day-of-the-week combinations.

Table 2
Itinerary share models: MNL, two-level NL's and two-level WNL[a,b]

Explanatory variables	Model			
	MNL	2-Level NL time	2-Level NL carrier	2-Level WNL: time|carrier
Level-of-service				
Nonstop itinerary in nonstop market	0.0000	0.0000	0.0000	0.0000
Direct itinerary in nonstop market[c]	−1.9595	−1.6271	−1.7798	−1.4253
Single-connect itinerary in nonstop market	−2.8371	−2.3540	−2.5695	−2.0624
Double-connect itinerary in nonstop market	−6.6264	−5.4663	−5.7872	−4.6364
Direct itinerary in direct market	0.0000	0.0000	0.0000	0.0000
Single-connect itinerary in direct market	−0.7370	−0.6207	−0.6579	−0.5323
Double-connect itinerary in direct market	−3.9250	−3.2331	−3.4217	−2.7375
Single-connect itinerary in single-connect market	0.0000	0.0000	0.0000	0.0000
Double-connect itinerary in single-connect market	−2.6015	−2.1915	−2.3043	−1.8997
Connection quality				
Second-best connection	−0.4208	−0.3331	−0.3216	−0.2396
Second-best connection time difference	−0.0087	−0.0071	−0.0074	−0.0058
Distance ratio	−0.0135	−0.0109	−0.0131	−0.0103
Best connection time difference	−0.0056	−0.0047	−0.0051	−0.0041
Carrier attributes				
Fare ratio	−0.0060	−0.0052	−0.0039	−0.0033
Carrier constants (proprietary)	–	–	–	–
Code share	−1.8601	−1.5241	−1.6861	−1.3383
Aircraft type				
Mainline jet	0.0000	0.0000	0.0000	0.0000
Regional jet	−0.4560	−0.3856	−0.4225	−0.3464
Propeller aircraft	−0.4201	−0.3496	−0.3658	−0.2919
Departure time				
5–6 AM	−0.2184	−0.1931	−0.2084	−0.1814
6–7 AM	0.0000	0.0000	0.0000	0.0000
7–8 AM	0.1385	0.1118	0.1235	0.0964
8–9 AM	0.2381	0.1907	0.2150	0.1663
9–10 AM	0.2646	0.2135	0.2365	0.1848
10–11 AM	0.2672	0.1873	0.2412	0.1619
11–12 Noon	0.2290	0.1643	0.2168	0.1507
12–1 PM	0.2476	0.1761	0.2293	0.1593
1–2 PM	0.1614	0.1043	0.1507	0.0956
2–3 PM	0.1686	0.1058	0.1599	0.0982
3–4 PM	0.1856	0.1219	0.1709	0.1100
4–5 PM	0.0960	0.0486	0.0934	0.0523
5–6 PM	0.0972	0.0490	0.0840	0.0429
6–7 PM	0.1760	0.1179	0.1535	0.1007
7–8 PM	0.0833	0.0443	0.0857	0.0502
8–9 PM	−0.0803	−0.0807	−0.0563	−0.0541
9–10 PM	−0.2587	−0.2243	−0.2131	−0.1778
10 Midnight	−0.3407	−0.3179	−0.2847	−0.2546

(*continued on next page*)

Table 2 (*continued*)

Explanatory variables	Model			
	MNL	2-Level NL time	2-Level NL carrier	2-Level WNL: time|carrier
Inverse logsum parameter (time)	–	1.2244	–	1.5435
Inverse logsum parameter (carrier)	–	–	1.1768	1.4519
WNL weight parameter (time structure)	–	–	–	0.5364
Log likelihood at zero	−2,173,197	−2,173,197	−2,173,197	−2,173,197
Log likelihood at convergence	−1,558,186	−1,557,443	−1,556,663	−1,555,632
Adjusted log likelihood at convergence	−49,466	−49,443	−49,418	−49,385
Rho-square w.r.t. zero	0.2830	0.2833	0.2837	0.2842

[a] All the value function parameter estimates are significantly different from zero, all the inverse logsum parameter estimates are significantly different from one, and the weight parameter estimate is significantly different from zero and one at the 0.05 level after adjustment.

[b] The total number of airport-pair-day-of-the-week combinations, itineraries and booked passengers for the estimation dataset are 14,893, 629,122 and 469,078, respectively.

[c] "Nonstop Market" means the "best" level-of-service available in the airport-pair is a nonstop itinerary, "Direct Market" means the best level-of-service available in the airport-pair is a direct itinerary, etc.

belief that the competition among itineraries is differentiated by proximity in departure time, carrier or level-of-service, the constraints of the MNL model are then relaxed by estimating two-level nested logit models. These models permit itineraries to be grouped (nested) by departure time, carrier or level-of-service. In addition to the value function parameter estimates, these models also contain an inverse logsum parameter [9] representing the level of inter-itinerary competition within nests. For a given two-level NL model, the estimated value of the inverse logsum parameter (along with the overall model fit) indicates whether it is valid to group the itineraries according to the selected nesting structure (i.e. whether increased competition exists among itineraries in the nests, therefore rejecting the MNL model).

It is likely that the competition among air-travel itineraries is differentiated by proximity along more than one of the above-mentioned dimensions. To address this, a two-level weighted nested logit (WNL) model is formulated and estimated combining the competitive results of different two-level NL models. This model allows the simultaneous consideration of parallel two-level nesting structures (each structure yields an inverse logsum parameter estimate indicating the amount of itinerary competition within the nests of that structure) with a weight parameter indicating the relative importance of each structure. The formulation of this model is similar to the principles of differentiation (PD) models developed by Bresnahan et al. (1997).

Clearly, the two-level WNL model has advantages over the more restrictive two-level NL model structure. However, this model cannot capture the inter-itinerary competition dynamic that may exist among itineraries sharing a common attribute *within* another attribute. For example, it is believed that itineraries sharing a common time period compete more closely with each other than with itineraries of different time periods. However, within these time periods it is likely that itineraries of the same carrier exhibit even more competition amongst themselves. Estimating

[9] The inverse logsum parameter is defined in a later section.

Table 3
Itinerary share models: three-level NL's, three-level WNL and NWNL[a]

Explanatory variables	Model			
	3-Level NL: time, LOS	3-Level NL: time, carrier	3-Level WNL: $T\|C$, $T\|L$	NWNL
Level-of-service				
Nonstop itinerary in nonstop market	0.0000	0.0000	0.0000	0.0000
Direct itinerary in nonstop market	−1.6479	−1.6570	−1.6754	−1.6833
Single-connect itinerary in nonstop market	−2.3401	−2.3802	−2.3703	−2.3655
Double-connect itinerary in nonstop market	−5.5099	−5.2215	−5.2649	−5.2761
Direct itinerary in direct market	0.0000	0.0000	0.0000	0.0000
Single-connect itinerary in direct market	−0.5935	−0.6362	−0.6096	−0.5982
Double-connect itinerary in direct market	−3.2467	−3.1347	−3.1467	−3.1465
Single-connect itinerary in single-connect market	0.0000	0.0000	0.0000	0.0000
Double-connect itinerary in single-connect market	−2.2118	−2.1679	−2.1869	−2.1922
Connection quality				
Second-best connection	−0.3290	−0.2504	−0.2473	−0.2449
Second-best connection time difference	−0.0071	−0.0063	−0.0062	−0.0062
Distance ratio	−0.0108	−0.0112	−0.0111	−0.0110
Best connection time difference	−0.0047	−0.0049	−0.0048	−0.0048
Carrier attributes				
Fare ratio	−0.0051	−0.0036	−0.0036	−0.0035
Carrier constants (proprietary)	–	–	–	–
Code share	−1.5082	−1.5408	−1.5257	−1.5179
Aircraft type				
Mainline jet	0.0000	0.0000	0.0000	0.0000
Regional jet	−0.3827	−0.4019	−0.3985	−0.3961
Propeller aircraft	−0.3459	−0.3294	−0.3258	−0.3233
Departure time				
5–6 AM	−0.1925	−0.2152	−0.2139	−0.2127
6–7 AM	0.0000	0.0000	0.0000	0.0000
7–8 AM	0.1099	0.1163	0.1146	0.1136
8–9 AM	0.1880	0.1944	0.1918	0.1902
9 –10 AM	0.2108	0.2148	0.2125	0.2109
10–11 AM	0.1850	0.1971	0.1950	0.1933
11–12 Noon	0.1625	0.1808	0.1791	0.1777
12–1 PM	0.1740	0.1845	0.1824	0.1810
1–2 PM	0.1029	0.1152	0.1140	0.1132
2–3 PM	0.1045	0.1175	0.1163	0.1155
3–4 PM	0.1199	0.1328	0.1309	0.1299
4–5 PM	0.0455	0.0577	0.0550	0.0535
5–6 PM	0.0457	0.0383	0.0355	0.0340
6–7 PM	0.1139	0.1068	0.1032	0.1013
7–8 PM	0.0416	0.0546	0.0521	0.0507
8–9 PM	−0.0818	−0.0586	−0.0599	−0.0607
9–10 PM	−0.2234	−0.1982	−0.1973	−0.1965
10 Midnight	−0.3161	−0.2821	−0.2807	−0.2802

(*continued on next page*)

Table 3 (*continued*)

Explanatory variables	Model			
	3-Level NL: time, LOS	3-Level NL: time, carrier	3-Level WNL: $T\|C$, $T\|L$	NWNL
Upper-level inverse logsum parameter (time)	1.2124	1.0667	1.0594	1.0584
Lower-level inverse logsum parameter (carrier)	–	1.3568	1.3642	1.3637
Lower-level inverse logsum parameter (LOS)	1.2376	–	*1.5492*	*1.7650*
Weight parameter (time|carrier structure)	–	–	*0.9529*	*0.9490*
Log likelihood at zero	−2,173,197	−2,173,197	−2,173,197	−2,173,197
Log likelihood at convergence	−1,557,435	−1,554,227	−1,554,219	−1,554,210
Adjusted log likelihood at convergence	−49,442	−49,341	−49,340	−49,340
Rho-square w.r.t. zero	0.2833	0.2848	0.2848	0.2848

[a] Parameter estimates in italics not significant at the 0.05 level after adjustment procedure.

three-level nested logit models tests this hypothesis. These models group (nest) itineraries at an upper-level for a given dimension and (within each upper-level nest) group itineraries according to a second dimension (lower-level nest). In addition to the value function parameter estimates, these models yield upper and lower-level inverse logsum parameter estimates indicating the differential amount of itinerary competition within the upper and lower-level nests. The estimated values of these inverse logsum parameters (along with the overall model fit) indicate whether a three-level nesting specification is supported (i.e. the hypothesis that a two-level NL model is adequate to describe the underlying itinerary competition dynamic should be rejected).

Finally, a three-level WNL model and a nested weighted nested logit (NWNL) model are estimated. The three-level WNL model is a direct extension of the two-level WNL model (it simultaneously estimates parallel three-level structures with a weight parameter indicating the relative importance of each structure). The NWNL model combines properties of the three-level nested logit and weighted nested logit models. Both of these models are new to the literature and incorporate all three attribute dimensions (time of day, carrier, level-of-service) of interest.

All of the above mentioned models are members of the generalized extreme value family of models (McFadden, 1978) and are shown to outperform the base MNL model with respect to statistical tests and behavioral interpretations, leading to a clearer understanding of the air-travel inter-itinerary competition dynamic.

3. Multinomial logit model

The base or reference model for this study is the MNL model, where the market share of passengers assigned to each itinerary is:

$$S_i = \frac{\exp(V_i)}{\sum_{j\in J}\exp(V_j)} \tag{5}$$

where S_i is the passenger share assigned to itinerary i, exp( ) is the exponential function, V_i is the value of itinerary i and the summation is over all itineraries for the airport-pair-day-of-the week.

The MNL parameter estimates, reported in Table 2, are very similar to the MNL parameter estimates from our previous study. That study details the interpretation of these value function parameter estimates and interested readers are referred to it (Coldren et al., 2003). For the current study, it is sufficient to state that the value function parameter estimates have the correct sign, are of reasonable magnitude and are statistically significant at the 0.05 level after adjustment.

The value function parameter estimates for the advanced models (presented in Tables 2 and 3) are very similar across the different model specifications. However, in general, the estimates for the advanced models are smaller in magnitude than the corresponding estimates for the MNL model. This represents the lower sensitivity (substitutability) between groups of alternatives not in a common nest. The increased sensitivity between groups of alternatives in common nests is captured by the inverse logsum variables.

4. Two-level nested logit models

Initial two-level nested logit estimations assumed nesting based on each of the three dimensions described above. In these models, itineraries are grouped into nests according to time of day (morning, 5:00 9:59 AM; midday, 10:00 AM 3:59 PM; evening, 4:00 PM, Midnight), carrier (six major US carriers. [10] and a group of "other" carriers) or level-of-service (nonstop, direct, single-connect, double-connect). A visual representation of the two-level carrier NL model is shown in Fig. 1.

For the two-level NL models estimated in this paper, the total variance of the itinerary error terms is set equal to $\frac{\pi^2}{6}$ as is commonly done in GEV models. The error term for each itinerary is decomposed into two components: an independent component specific to the itinerary and a component common to all itineraries in its nest. That is

$$U_i = V_i + \varepsilon_i + \varepsilon_c \tag{6}$$

where the error variance for the independent component is given by $\frac{\pi^2}{6\mu^2}$ (μ is the inverse of the logsum parameter [11]) and the error variance for the common component is given by $\frac{\pi^2}{6}(1 - \frac{1}{\mu^2})$. The inverse logsum parameter must be greater than one to ensure that the independent component variance is smaller than the total variance. Inverse logsum parameter estimates can be interpreted as indicating the amount of "competition" among itineraries sharing a common nest with larger values indicating a higher level of substitution within nests. This is because a larger inverse logsum implies that more of the total error variance is associated with the common error term (that is, itineraries sharing a nest with a large inverse logsum parameter have a high level of correlation). Assuming this alternative error term structure and random utility maximization, it can be shown that with a two-level nested logit specification the share of passengers assigned to each itinerary between an airport-pair for a given day of the week is given by

[10] American Airlines, Continental Airlines, Delta Airlines, Northwest Airlines, United Airlines and US Airways.

[11] In many other studies the error variance for the independent component is given by $\frac{\pi^2\theta^2}{6}$, where the logsum parameter is represented by θ and must be less than one. In our derivation, μ, the inverse logsum, is equal to $\frac{1}{\theta}$, leading to identical results.

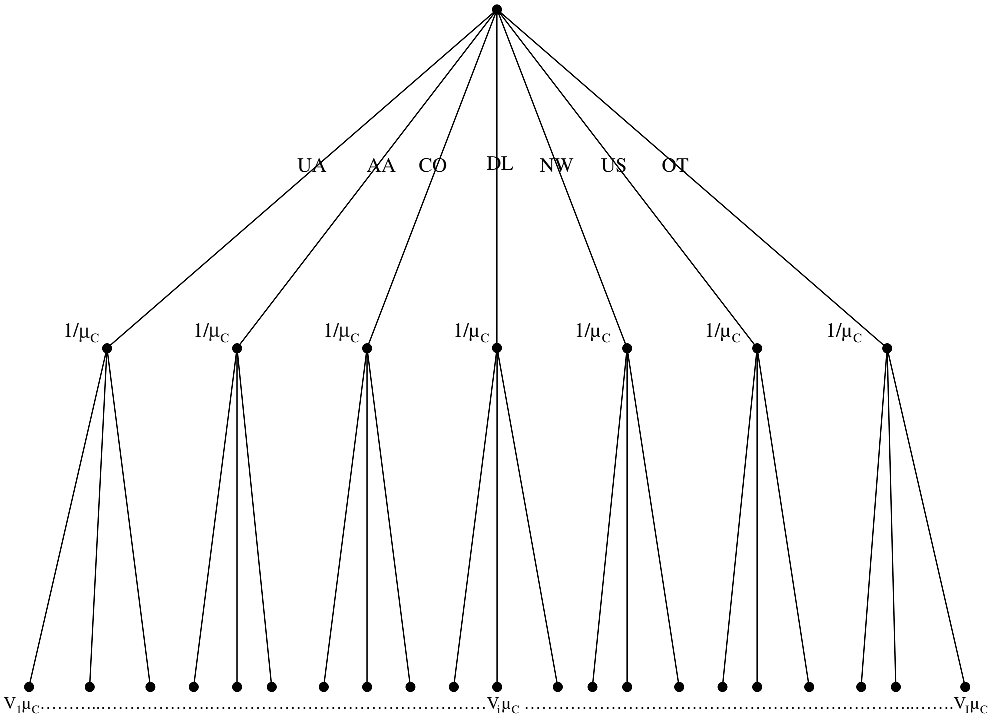

Fig. 1. Two-level NL carrier model structure.

$$S_i = S_n \times S_{i|n} = \frac{\exp\left(\frac{1}{\mu}\Gamma_n\right)}{\sum_{n'\in N}\exp\left(\frac{1}{\mu}\Gamma_{n'}\right)} \times \frac{\exp(\mu V_i)}{\sum_{i'\in n}\exp(\mu V_{i'})} \tag{7}$$

where S_i is the passenger share assigned to itinerary i; S_n is the passenger share assigned to nest n; $S_{i|n}$ is the passenger share assigned to itinerary i given nest n; μ is the inverse logsum parameter associated with the nests; [12] $\Gamma_n = \ln(\sum_{i'\in N_n}\exp(\mu V_{i'}))$ and V_i is the value of itinerary i.

The increased competition among itineraries sharing a common nest can be seen from cross-elasticity formulas gotten from the two-level NL model. The cross-elasticity equation for the change in the probability of alternative j due to changes in the kth attribute of alternative i (where i and j belong to the same nest) is given by:

$$\eta^{P_j}_{X_{ik}} = \frac{\partial P_j}{\partial X_{ik}}\frac{X_{ik}}{P_j} = -\{P_i + P(i|n)[\mu_n - 1]\}\beta_k X_{ik} \tag{8}$$

where P_i is the probability of itinerary i, $P(i|n)$ is the probability of itinerary i given nest n and μ_n is the inverse logsum parameter for nest n. Alternatives not sharing a common nest have cross-elas-

[12] Early experimental estimations yielded similar parameter estimates for the inverse logsum variables across nests in each nesting dimension. Given this result and a desire for consistency across nests of the same type, the inverse logsum parameter is constrained in each case to be equal across all common nests.

ticities of the same form as the MNL model (Eq. (2)); however, there are likely to be differences in the magnitude of the value function parameters between the MNL and NL model so that the cross-elasticities for nonnested alternatives will be smaller than the MNL cross-elasticities. More importantly, the cross-elasticities for alternatives sharing a common nest in the two-level NL model are larger in magnitude than the cross-elasticities for alternatives that do not share a common nest. This is apparent from the comparison of Eqs. (2) and (8) since μ must be greater than or equal to one. The higher the value of μ, the more sensitive itineraries are to attribute changes in other itineraries sharing a common nest.

The estimation results for two-level NL models with itineraries nested by time of day and carrier are reported in Table 2 showing that itineraries within a common time period and itineraries flown by the same carrier have common attributes that passengers consider in their itinerary selection process. These models reject the hypothesis that the MNL model is the true model at the 0.001 level after adjustment. On the other hand, grouping itineraries by level-of-service did not yield theoretically acceptable results (the inverse logsum parameter was estimated to be less than one, which is inconsistent with utility theory). This was surprising since it seems likely that an itinerary within a given level-of-service nest would share many characteristics with the other itineraries within the same nest and thus should have higher cross-elasticities among themselves than with itineraries of different levels-of-service.

5. Two-level weighted nested logit model

The two-level weighted nested logit model simultaneously estimates parallel two-level nesting structures (each structure is equivalent to a two-level NL model) with a weight parameter indicating the relative importance of each structure. Each itinerary in each alternative set appears twice in the model, once in each of the parallel structures. The WNL model can be shown to be a special case of the generalized nested logit (GNL) model (Wen and Koppelman, 2001).

Due to the strong empirical results from the two-level time and carrier NL models, a two-level WNL model was estimated with a time structure and a carrier structure (see Fig. 2). The share of passengers assigned to each itinerary between an airport-pair for a given day of the week is

$$\begin{aligned} S_i &= w_t \times S_t \times S_{i|t} + w_c \times S_c \times S_{i|c} \\ &= w_t \times \frac{\exp\left(\frac{1}{\mu_t}\Gamma_t\right)}{\sum_{t'\in N}\exp\left(\frac{1}{\mu_t}\Gamma_{t'}\right)} \times \frac{\exp(\mu_t V_i)}{\sum_{i'\in t}\exp(\mu_t V_{i'})} + w_c \times \frac{\exp\left(\frac{1}{\mu_c}\Gamma_t\right)}{\sum_{c'\in N}\exp\left(\frac{1}{\mu_c}\Gamma_{c'}\right)} \times \frac{\exp(\mu_c V_i)}{\sum_{i'\in c}\exp(\mu_c V_{i'})} \end{aligned} \tag{9}$$

where c represents the carrier nests; t represents the time nests; w_c is the weight given to the carrier structure and $w_t = 1 - w_c$ is the weight given to the time structure.

Estimation results for this model are reported in Table 2. The inverse logsum parameters for both the time and carrier nests are significantly greater than one (at all levels of significance after adjustment), indicating increased itinerary competition among itineraries sharing a common time

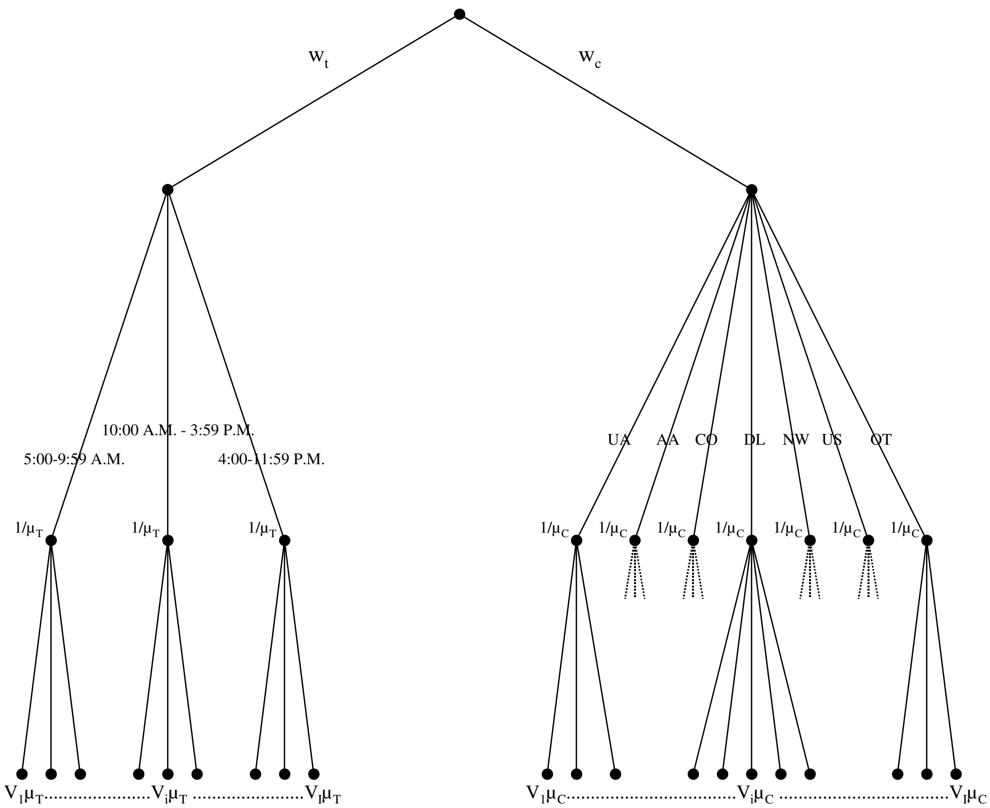

Fig. 2. Two-level WNL time|carrier model structure.

period or carrier. The weight parameter is close to 1/2 and significantly different than zero or one (at all levels of significance after adjustment) indicating that each portion of the structure is important. Finally, this model outperforms both the two-level time and carrier NL models at the 0.001 level after adjustment.

6. Three-level nested logit models

Six three-level nested logit model specifications were estimated representing all possible three-level combinations for the three itinerary dimensions under study (upper-level time and lower-level carrier (time, carrier); carrier, time; time, level-of-service; level-of-service, time; carrier, level-of-service; level-of-service, carrier).

For the three-level NL models, the total variance of the itinerary error terms is decomposed into three components: an independent component specific to the itinerary, a component common to all itineraries in its lower-level nest (nest n) and a component common to all itineraries in its upper-level nest (nest m). That is,

$$U_i = V_i + \varepsilon_i + \varepsilon_n + \varepsilon_m \tag{10}$$

where the error variance for the independent component, ε_i, is given by $\frac{\pi^2}{6\mu_n^2}$ (μn is the inverse logsum parameter for the lower-level nest), the error variance for the random component distinct to the lower-level nest but not including the error component of the independent elemental alternative is given by $\frac{\pi^2}{6\mu_m^2} - \frac{\pi^2}{6\mu_n^2}$ (μ_m is the inverse logsum parameter for the upper-level nest), and finally the error variance for the random component associated with the upper-level nest but excluding the error component of the lower-level nest and the elemental alternative is $\frac{\pi^2}{6} - \frac{\pi^2}{6\mu_m^2}$. Thus, both upper and lower-level inverse logsum parameters must be greater than one, and the lower-level inverse logsum parameter must be greater than the upper-level inverse logsum parameter. The share of passengers assigned to each itinerary between an airport-pair for a given day of the week is given by

$$S_i = S_m \times S_{n|m} \times S_{i|n} = \frac{\exp\left(\frac{1}{\mu_m}\Gamma_m\right)}{\sum_{m' \in M} \exp\left(\frac{1}{\mu_m}\Gamma_{m'}\right)} \times \frac{\exp\left(\frac{\mu_m}{\mu_n}\Gamma_n\right)}{\sum_{n' \in N} \exp\left(\frac{\mu_m}{\mu_n}\Gamma_{n'}\right)} \times \frac{\exp(\mu_n V_i)}{\sum_{i' \in n} \exp(\mu_n V_{i'})} \tag{11}$$

where S_m is the passenger share assigned to upper-level nest m; $S_{n|m}$ is the passenger share assigned to lower-level nest n given upper-level nest m; μ_m is the inverse logsum parameter associated with the upper-level nests; μ_n is the inverse logsum parameter associated with the lower-level nests; $\Gamma_n = \ln(\sum_{i' \in N_j} \exp(\mu_n V_{i'}))$ and $\Gamma_m = \ln(\sum_{n' \in N_m} \exp(\frac{\mu_m}{\mu_n}\Gamma_{n'}))$.

The requirement that the lower-level inverse logsum parameter be greater than the upper-level inverse logsum parameter implies that itineraries within the same lower-level nest (and hence within the same upper-level nest) share the most unobserved attributes and compete more closely with each other than with other itineraries. Itineraries sharing a common upper-level nest (but not a lower-level nest) have less competition amongst themselves than with itineraries that share the same lower-level nest, but a greater level of competition than with itineraries in a different upper-level nest.

Of the six three-level NL models estimated, only two satisfied the inverse logsum conditions described above (before adjustment). These models, reported in Table 3, are for time, level-of-service and time, carrier. A visual representation of the three-level time, carrier NL model is shown in Fig. 3. The time, carrier model rejects both the time and carrier two-level NL models at the 0.001 level after adjustment.

The time, level-of-service model does not reject the two-level time NL model after adjustment. However, it does improve upon the two-level NL time model before adjustment and both its inverse logsum parameters are significant after adjustment (they are significantly different from each other after adjustment as well). Regardless, the marginal significance of this model implies that this three-level nesting specification may not be valid. Variations of this model are revisited in the next two sections.

These three-level NL results indicate that there is moderate itinerary competition among itineraries sharing a common time period and greater competition among itineraries sharing both time period and carrier or (to a lesser extent) time period and level-of-service. This demonstrates the importance of conditioning the within carrier (or level-of-service) competition dynamic by time period. However, note that the three-level time, carrier NL model implies that itineraries of the same carrier, but of different time periods, do not exhibit much competition amongst themselves.

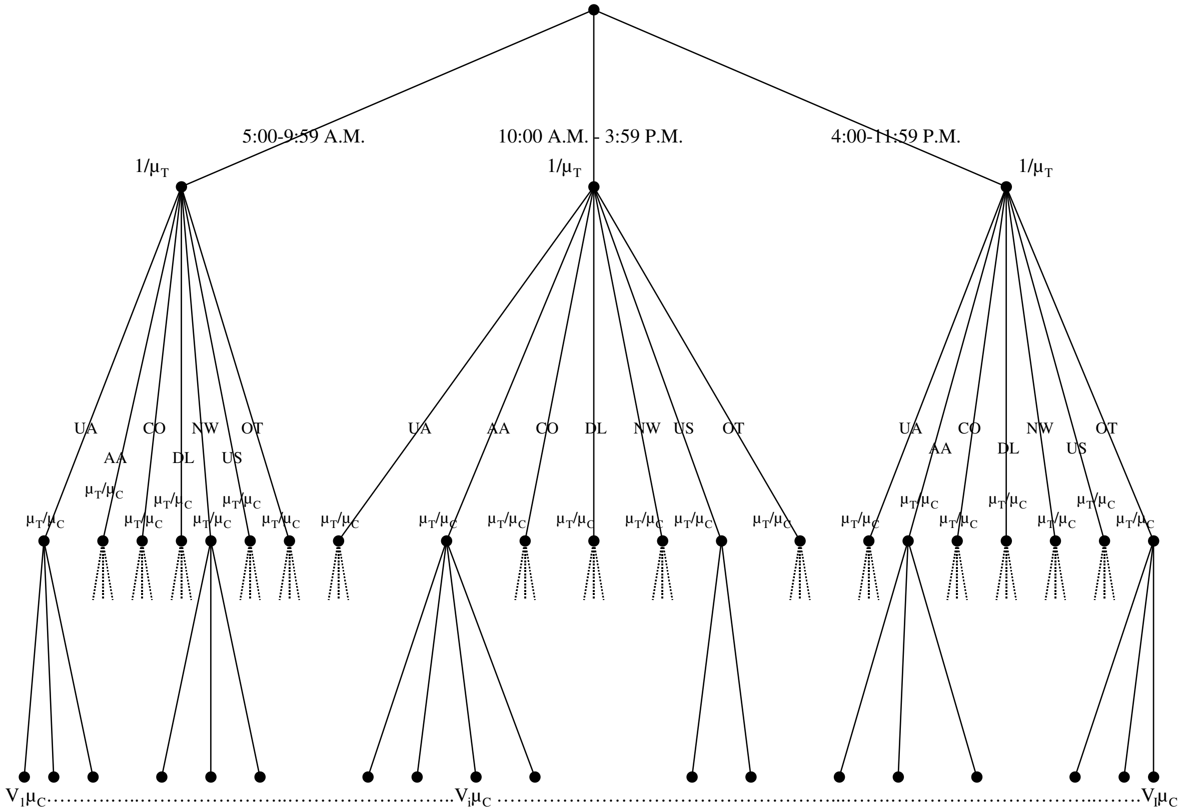

Fig. 3. Three-level NL time, carrier model structure.

7. Three-level weighted nested logit model

The three-level weighted nested logit model is a direct extension of the two-level weighted nested logit model. The mathematical structure of the model is

$$
\begin{aligned}
S_i &= w_{ct} \times S_{ict} + w_{st} \times S_{ist} = w_{ct} \times S_t \times S_{c|t} \times S_{i|ct} + w_{st} \times S_t \times S_{s|t} \times S_{i|st} \\
&= w_{ct} \times \frac{\exp\left(\frac{1}{\mu_T}\Gamma_t\right)}{\sum_{t'\in T}\exp\left(\frac{1}{\mu_T}\Gamma_{t'}\right)} \times \frac{\exp\left(\frac{\mu_T}{\mu_C}\Gamma_c\right)}{\sum_{c'\in C}\exp\left(\frac{\mu_T}{\mu_C}\Gamma_{c'}\right)} \times \frac{\exp(\mu_C V_i)}{\sum_{i'\in c}\exp(\mu_C V_{i'})} \\
&\quad + w_{st} \times \frac{\exp\left(\frac{1}{\mu_T}\Gamma_t\right)}{\sum_{t'\in T}\exp\left(\frac{1}{\mu_T}\Gamma_{t'}\right)} \times \frac{\exp\left(\frac{\mu_T}{\mu_S}\Gamma_s\right)}{\sum_{s'\in S}\exp\left(\frac{\mu_T}{\mu_S}\Gamma_{s'}\right)} \times \frac{\exp(\mu_S V_i)}{\sum_{i'\in s}\exp(\mu_S V_{i'})} \qquad (12)
\end{aligned}
$$

Due to the marginal significance of the three-level time, level-of-service NL model and the significance of the three-level time, carrier NL model, a three-level WNL model was estimated with parallel three-level structures for time, carrier and time, level-of-service. A visual representation of this model is shown in Fig. 4 and its estimation results are presented in Table 3. Both the upper and lower-level inverse logsum parameters for time and carrier, respectively, are significant at the

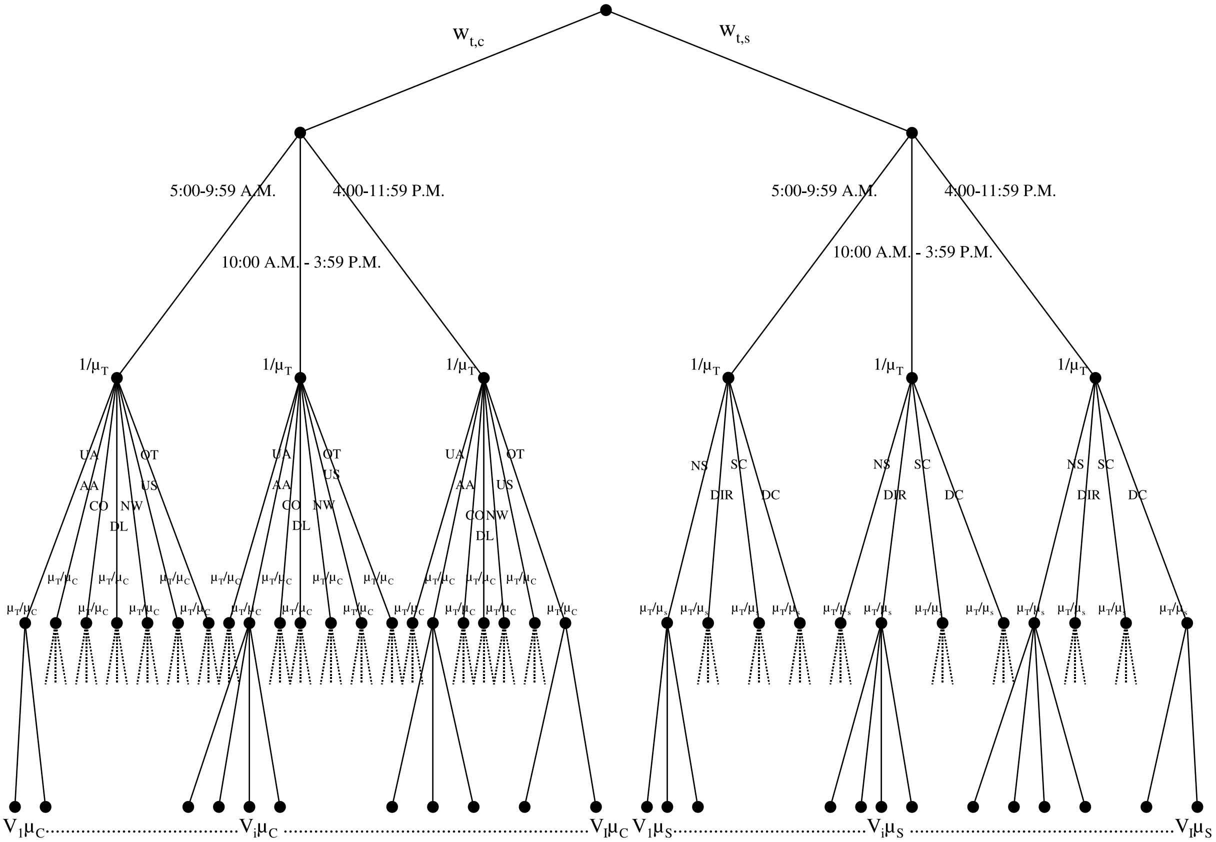

Fig. 4. Three-level WNL time|carrier, time|level-of-service model structure.

0.001 level (after adjustment) indicating a high level of competition among itineraries during the specified time periods and among itineraries flown by the same carrier within these time periods. However, neither the lower-level inverse logsum parameter for level-of-service nor the weight on the time, carrier structure are significantly different from one. These results indicate that the time, carrier side of the model "dominates". Finally, after adjustment, the model is only marginally better than the three-level time, carrier NL model.

8. Nested weighted nested logit model

The nested weighted nested logit model, a "hybrid" version of the NL and WNL models, in the class of GEV models, is new to the literature. The motivation for estimating this model came from the estimation results of the three-level NL and WNL models discussed in the last two sections. Both three-level NL models that yielded significant (or marginally significant) results (time, level-of-service and time, carrier models) had itineraries nested at the upper level by time of day. However, when these models were "combined" into a three-level WNL model, the weight parameter and the lower-level inverse logsum parameter for level-of-service in the time, level-of-service

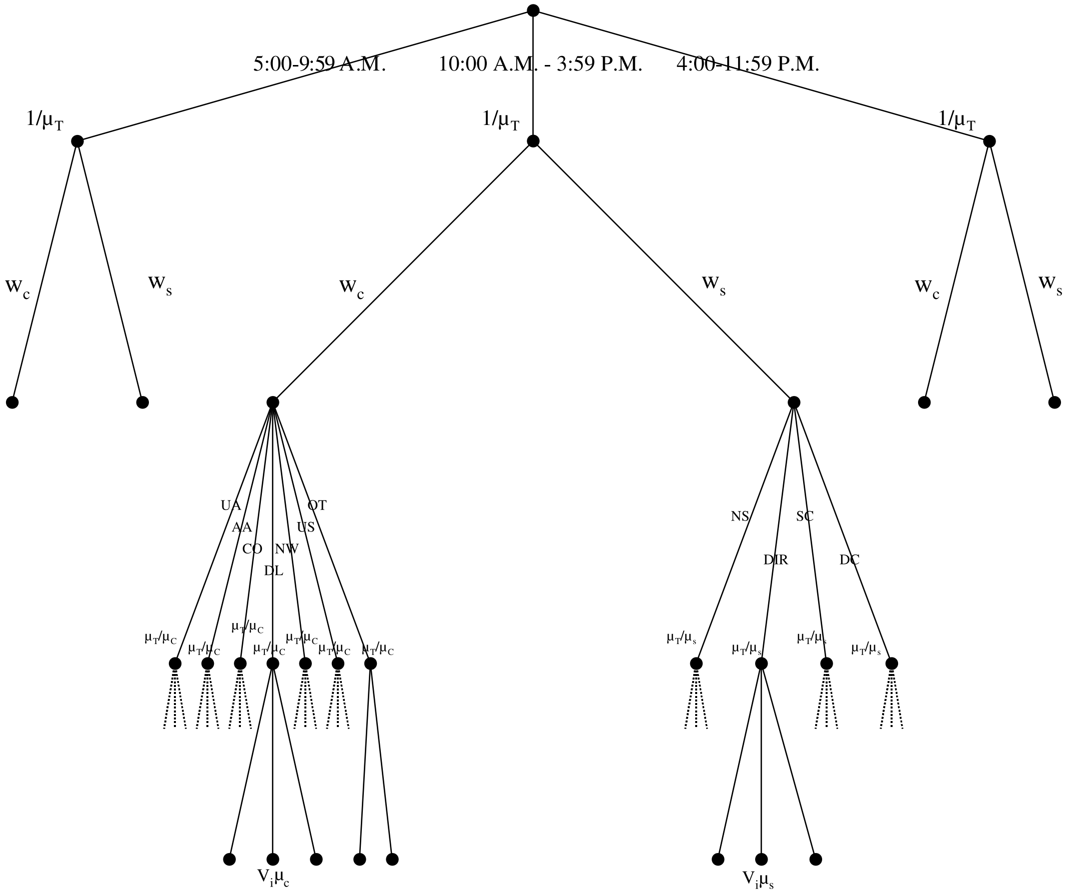

Fig. 5. Nested weighted nested logit model structure.

structure were not significant. To address this, the NWNL was developed. Fig. 5 gives a visual representation of this model. In the structure shown in the figure, itineraries are grouped at the upper level by time-of-day. On the lower level (within a time period) each itinerary is placed into two parallel nesting structures: a carrier structure and a level-of-service structure. A weight parameter indicates the relative importance of each of these structures within the upper-level time-of-day nest. The share of passengers assigned to each itinerary between an airport-pair for a given day of the week is

$$\begin{aligned} S_i &= S_t \times \left[(w_c \times S_{c|t} \times S_{i|ct}) + (w_s \times S_{s|t} \times S_{i|st}) \right] \\ &= \frac{\exp\left(\frac{w_c}{\mu t}\Gamma_{tc} + \frac{w_s}{\mu_t}\Gamma_{ts}\right)}{\sum_{t' \in T} \exp\left(\frac{w_c}{\mu_{t'}}\Gamma_{t'c} + \frac{w_s}{\mu_{t'}}\Gamma_{t's}\right)} \times \left(\left(w_c \times \frac{\exp\left(\frac{\mu_t}{\mu_c}\Gamma_c\right)}{\sum_{c' \in C} \exp\left(\frac{\mu_t}{\mu_{c'}}\Gamma_{c'}\right)} \times \frac{\exp(\mu_c V_i)}{\sum_{i' \in c} \exp(\mu_c V_{i'})} \right) \right. \\ &\quad \left. + \left(w_s \times \frac{\exp\left(\frac{\mu_t}{\mu_s}\Gamma_s\right)}{\sum_{s' \in S} \exp\left(\frac{\mu_t}{\mu_{s'}}\Gamma_{s'}\right)} \times \frac{\exp(\mu_s V_i)}{\sum_{i' \in s} \exp(\mu_s V_{i'})} \right) \right) \end{aligned} \tag{13}$$

The estimation results for this model are presented in Table 3. The results indicate that this model is almost identical to the three-level WNL model discussed earlier. That is, its value function parameter estimates are very similar to the three-level WNL and its lower-level inverse logsum parameter for level-of-service and weight parameter are not significant after adjustment. [13] Finally, even though the NWNL model only marginally improves upon the three-level time, carrier NL model (and the three-level WNL model) and "weighting" carrier and level-of-service structures within a time period does not improve the statistical quality of the model, this model may provide additional insight into the possible importance of inter-itinerary competition among itineraries with a common level-of-service.

9. Summary and conclusions

This study shows that the competition among air-travel itineraries is not "uniform". Thus, itinerary share models employing multinomial logit methodology are not adequate. Two-level nested logit models are estimated showing that itineraries sharing a common time period or carrier (but not level-of-service) exhibit a strong amount of competition among themselves. Using these results, a two-level weighted nested logit model (a new variation in the GEV family of models) with parallel time and carrier nesting structures is estimated. It significantly rejects the standard two-level NL models and has advantages over the more restrictive NL model structure.

Three-level nested logit models are estimated. The results of these models show that itineraries sharing a common time period have a moderate amount of competition amongst themselves, while itineraries sharing both time period and carrier or (to a lesser extent) time period and level-of-service exhibit a strong amount of competition among themselves.

This paper introduces the three-level weighted nested logit and nested weighted nested logit models. These models are new to the literature and are in the GEV family of models. Although these models simultaneously incorporate the three dimensions of time of day, carrier and level-of-service, they only marginally improve upon the three-level NL model with itineraries nested at the upper level by time of day and at the lower level by carrier. However, the improvement in these models (with respect to log-likelihood values) demonstrates the potential to obtain more interesting and, possibly, significant improvements in model goodness of fit through more complex nesting structures.

Finally, while the estimations for models with itineraries nested by level-of-service were generally not significant, it is still reasonable to expect that increased competition exists within level-of-service nests (especially when the level-of-service nests are within upper-level time period nests, as demonstrated by the marginal significance of the time, level-of-service three-level NL model). Regardless, it appears that the underlying competition among air-travel itineraries can almost fully be described by nesting itineraries by the time of day and carrier dimensions.

[13] The weight parameter is not significantly different than one, indicating that (like the three-level WNL model) the carrier structure "dominates" the level-of-service structure.

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