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Impact of aircraft size and seat availability on airlines' demand and market share in duopoly markets

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Abstract

We build a nested logit model to study the roles of aircraft size, together with service frequency, seat availability and fare, in airlines' market share and total demand in non-stop duopoly markets. We find that airlines can obtain higher returns in market share from increasing service frequency than from increasing aircraft size, and our study confirms an *S*-curve effect of service frequency on airlines' market share. We find that the available capacity per flight—net of capacity absorbed by connecting passengers—affects market share in the same manner whether it is derived from a larger proportion of a smaller aircraft or smaller proportion of a larger one.

Keywords: Aircraft size; Seat availability; Airline demand; Market share; Duopoly market

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1. Introduction

In the late 20th century, when most major airports in the United States were congested and the flight delays were a major concern to both passengers and carriers, the airlines often demanded airport capacity enhancement through building new runways or installing more sophisticated traffic control systems, both of which were very expensive. In the meantime, the airport managers, government policy makers and aircraft manufacturers have been asking the questions of whether the airlines would increase the size of aircraft in their fleet, rather than the number of flights, to accommodate increasing travel demand, and how airlines' choice of aircraft size would influence demand, market share and profit.

The tragedy of September 11 and the slowdown of the economy in both domestic and international markets in the new millennium have significantly changed the airline business. Travel demand has diminished due to security concerns and economy downturn; low cost carriers are competing more aggressively and penetrating in more markets; passengers are unwilling to pay for a premium price due to more transparent prices available on the Internet. To account for these factors, most network carriers, such as American Airlines and United Airlines, are in the process of reconstructing their business models. Simplifying and reconstructing aircraft fleet is a critical component in these reorganization plans, which would result in only the most profitable aircraft type(s) being retained in the fleet. Thus the same question posed by the old environment is equally salient in the new one: what are the market share and profit implications of varying flight frequency and aircraft size to provide a given level of air transport capacity?

The recognition and study of the impact of aircraft size and frequency on airline demand started with the introduction of the concept of "schedule delay", first introduced by Douglas and Miller (1974), and subsequently applied by Viton (1986). "Schedule delay" has two components. The first is frequency delay, which represents the elapsed time between an individual traveler's preferred time and the time of a scheduled flight. The second component is stochastic delay, which represents the additional elapsed time when preferred flights are fully booked. Douglas and Miller estimated empirical frequency and stochastic delay functions by using regression and simulation methods. Frequency delay decreases with frequency, while stochastic delay decreases with frequency and aircraft size, and increases with demand in the market. For the same service frequency provided by the airlines, the larger the aircraft, the higher the probability that a passenger can get a seat on a preferred flight and therefore enjoy a more convenient service. The concept of "schedule delay" was used in a linear regression model by Abrahams (1983) to estimate total air travel demand in a single market. In order to specify "schedule delay," Abrahams used the frequency delay function introduced by Eriksen (1977), and the stochastic delay function introduced by Swan (1979). These two functions have the same form as those proposed by Douglas and Miller (1974), but the parameter values are different. Thus these models capture effects of both frequency and aircraft size.

Instead of using the negative term "schedule delay", Eriksen (1977) and Russon and Hollingshead (1989) used the terms "level of service" or "quality of service"—which are functions of service frequency and aircraft size in a format similar to "schedule delay"—in their models of air passenger travel demand.

Other researchers focused on "service frequency" or "frequency delay" to study the influence of airlines' service on travel demand. Hansen (1990) used service frequency, fare and flight distance to specify a passenger's utility function, and built a logit model for demand analysis. Norman and Strandens (1990) directly related service frequency to the waiting time and cost of passengers, and built a probabilistic air travel demand model under the assumption of uniform distribution for desired departure times over a time interval. Nikulainen (1992) built a similar model based on the assumption that passenger demand at any time is a function of the distribution of all flight departure times. But aircraft size was not explicitly taken into consideration in these models, which emphasized the role of service frequency in air travel demand.

More recently, Coldren et al. (2003) built an itinerary level market share model using aggregate multinomial logit methodology. Aircraft size and type, together with such variables as fares, time of day, carrier market presence, itinerary level-of-service (non-stop, direct, single-connect, or double-connect) and connecting quality, are taken as independent variables in the model to measure various itinerary characteristics. Proussaloglou and Koppelman (1995) and Nako (1992) both applied the logit model to study airlines' demand using the survey data from individual passenger. They both investigated the effectiveness of the frequent flyer programs, but did not take aircraft size or type as a factor influencing passengers' choice of airlines.

In practice, some commercial carriers in the US apply the Quality of Service Index (QSI) method to forecast each carrier's weekly market share based on the schedules of all airlines serving in the market. Each service is given a QSI score, which is a weighted metric determined by the schedule "quality" or attributes, including aircraft type used for the flight, whether it is non-stop, one-stop or two-stop connecting service, the carrier's historical dominance in the market, day of the week of this service, its proximity to the "best" non-stop service, and so on. Each carrier's market share is determined by the total QSI scores of the services provided by this carrier in relative to the total QSI scores of all the services available in the market. Surprisingly, the weights assigned for each schedule attribute to calculate QSI for each service are always judgmentally, if not arbitrarily, determined rather than statistically calibrated. There is a commercial software package that takes the QSI score as the "utility" in the discrete choice framework, and thus calibrates the weights for QSI in a logit model for all services in all markets. But this software does not deal properly with some basic statistical issues in the calibration process, such as endogenity and collinearity.

In this paper, we focus on the analysis of the role of aircraft size on airlines' demand and market share in a duopoly competitive environment at the market level, with one major airport in origin and one major airport in destination. Our studies will not only update previous estimates for the role of aircraft size in airlines' demand, but also obtain new estimation results for the specific case of duopoly market based on the data from the homogenous duopoly markets, where exactly two airlines compete with each other. We will study the roles of aircraft size both in an individual airline's market share and in total air travel demand in the market. While all previous studies assume that all the seats in an aircraft are available to local passengers, which is rare in reality, this research takes into account the situation in which some of the seats are taken by connecting passengers. Therefore, not only aircraft size but also the proportion of aircraft capacity available to local passengers will be taken into consideration in our research.

Our research subject is jet aircraft, and does not include small regional aircraft normally with fewer than 60 seats. The seat capacity for current generation jet aircraft ranges from 100 seats to a little more than 400 seats (Airbus 380 is not included in this study). Since different airlines may have different seat configurations for the same type of aircraft, we use the actual number of seats available in the aircraft as aircraft seat capacity to characterize the size of the aircraft operated by each airline in the market.

The rest of this paper is arranged as follows: Section 2 describes in detail an air travelers' choice model; Section 3 applies statistical methods to estimate the coefficients in the model, and discusses the implication and application of the developed model; and Section 4 is a summary of this paper.

2. Air travelers' choice model

We want to understand how aircraft size, together with other service attributes such as fare and frequency, influence both the overall volume of air travel and each airline's share in an individual city-pair market. Since our ultimate aim is to model airlines' competitive behavior in a duopolistic setting, we will focus on markets where service is essentially provided by two airlines. Moreover, to further focus and simplify our analysis, we will examine cases in which the vast majority of traffic consists of direct flights as opposed to flights with one or more stops at an intermediate point.

A simplified framework for air travelers' choice in a duopoly market is shown in Fig. 1. Basically, our air travel demand and market share model is a two-level nested logit model, in which the upper nest is passengers' binary choice of whether or not to make a trip by air between a particular origin and destination, and the lower nest is passengers' choice of an airline for the trip. If we use the traditional notation V_{im} to represent the deterministic travelers' utility of taking a trip through airline i in market m, where V_{im} is a function of airlines' service attributes, then at the lower level, the market share of airline i at market m, S_{im}, is the exponential function of its utility divided by the sum for the two airlines:

$$S_{im} = \frac{\exp(V_{im})}{\sum_j \exp(V_{jm})} \tag{1}$$

At the upper level, in the standard nested logit framework, the total trips made in market m are

$$Q_m = D_m \frac{\left(\sum_j \exp(V_{jm})\right)^{\theta}}{\exp(V_{om}) + \left(\sum_j \exp(V_{jm})\right)^{\theta}} \tag{2}$$

V_{om} is the utility of not making a trip in market m. D_m can be regarded as saturation demand or total "potential" passenger demand in market m, which has been studied through the gravity-like models introduced by Verleger (1972) and Fridstorom and Thune-Larsen (1989), and the four

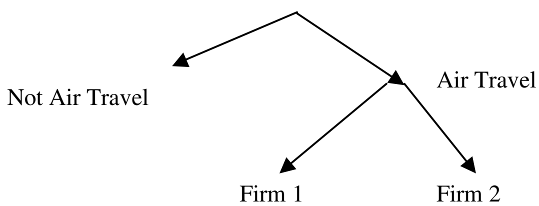

Fig. 1. Air travelers' choice in a duopoly market.

methods summarized by O'Connor (1995). θ, known as the "nesting coefficient", measures the degree of similarity of the elementary alternatives in the lower nest (making a trip in market m by airline 1 or 2) relative to the alternative in the upper nest of not making a trip in market m at all. If $\theta = 1$, then the model reduces to an unnested model, and the alternative of not traveling in market m is treated essentially as another airline. If $\theta = 0$, market demand is totally insensitive to airline service attributes. For $0 < \theta < 1$, the total market demand is sensitive to airline service levels, but to a less degree than in the unnested model.

We assume that because time and money costs of air travel are inherently high, the actual demand in this market is far less than the total saturation demand, which implies that:

$$\left(\sum_j \exp(V_{jm})\right)^{\theta} \ll \exp(V_{om}) \tag{3}$$

Then the formula for the total air travel demand, which is expressed in (2), can be approximated as

$$Q_m \approx \frac{D_m}{\exp(V_{om})}\left(\sum_j \exp(V_{jm})\right)^{\theta} = P_m\left(\sum_j \exp(V_{jm})\right)^{\theta} \tag{4}$$

where P_m, the social economic term capturing the total potential air travel demand in a market, is usually assumed to be a function of the population and income of both the origin and destination areas. It can be expressed as

$$P_m = \exp(K_m)(\mathrm{Incom}_m)^{\rho} \tag{5}$$

where K_m is a characteristic coefficient for market m; Incom_m is the product of total income for all the population in the origin and destination areas; ρ is an exponential coefficient for Incom_m, to be estimated.

We also use the notation Util_m to represent the sum $\sum_j \exp(V_{jm})$, i.e.,

$$\mathrm{Util}_m = \sum_j \exp(V_{jm}) \tag{6}$$

Then, based on (5) and (6), the total air travel demand model in (4) can be expressed as

$$Q_m = \exp(K_m)(\mathrm{Incom}_m)^{\rho}(\mathrm{Util}_m)^{\theta} \tag{7}$$

In order to make the derived market share model (1) and travel demand model (2) operational, we need to specify the deterministic utility function, V_{jm}. We apply the following specification:

$$V_{jm} = \alpha \ln(\mathrm{Freq}_{jm}) + \beta \ln(\mathrm{Size}_{jm}) + \eta \ln(\mathrm{Aval}_{jm}) + \gamma \mathrm{Fare}_{jm} \tag{8}$$

where V_{jm} is passengers' deterministic utility if they take a flight from airline j in market m; Freq_{jm} is the service frequency provided by airline j in market m; Size_{jm} is the average aircraft size (seats per flight) used by airline j in market m; Aval_{jm} represents "seat availability", the percentage of seats, provided by airline j in market m, that are not occupied by connecting passengers; Fare_{jm} is the average fare charged by airline j in market m.

This specification incorporates several effects. First, the Fare_{jm} variable captures the price effect. Second, because the total number of seats available to local passengers is the product, $\text{Freq}_{jm}*\text{Size}_{jm}*\text{Aval}_{jm}$, it captures an overall capacity effect. Third, schedule convenience is captured through Freq_{jm} variable. Fourth, the direct effects of aircraft size on service utility are incorporated through the Size_{jm} variable; such effects may include greater perceived safety and higher amenity levels of larger planes, as well as their slightly higher cruise speeds. Fifth, because the net number of seats per flight available to local passengers is equal to the product, $\text{Size}_{jm}*\text{Aval}_{jm}$, it captures the likelihood that passengers can actually get seats on their preferred flights. Therefore, the schedule delay effect, captured by the variables of Freq_{jm}, Size_{jm} and Aval_{jm}, captures the ability of passengers to find a seat on a flight convenient for their schedules as well as to obtain a seat at all.

Allowing different coefficients for Aval_{jm} and Size_{jm} will reveal whether utility varies with different combinations of these two variables when they yield the same number of seats per flight. For example, we ask whether the attractiveness of a 200-seat aircraft with half its capacity available is the same as a 100-seat aircraft with all seats available to the local market. If there is no significant (statistically) difference between the coefficients of these two variables, then we will replace these two variables with a new variable, Seat_{jm}, the net number of seats per flight available to local passengers from airline j in market m, which is simply the product of Aval_{jm} and Size_{jm}.

All these capacity terms, Freq_{jm}, Size_{jm} and Aval_{jm}, take the logarithm form, while the last term, Fare_{jm}, does not. There are two reasons for this specification: first, we expect diminishing returns with respect to utility from increasing number of flights or seats; second, travelers' choice of an airline can be conceived as aggregation of more specific alternatives, including specific flights and seats. Ben-Akiva and Lerman (1985) demonstrated that the logarithm form is the most appropriate for such attributes.

Based on the specified utility functions, the roles of aircraft size and other service attributes in market share and total air travel demand are demonstrated in the four coefficients in Eq. (8) and the three coefficients in Eq. (7). The estimation for these coefficients and implications of the findings are discussed in Section 3.

3. Model estimation and implications

Based on the utility function proposed in (8) and the derived market share function in (1), the ratio of market size—which is also the ratio of market share—between the two airlines can be expressed as follows:

$$\begin{aligned}\frac{S_{im}}{S_{jm}} &= \frac{\exp(\alpha\ln(\text{Freq}_{im}) + \beta\ln(\text{Size}_{im}) + \eta\ln(\text{Aval}_{im}) + \gamma\text{Fare}_{im})}{\exp(\alpha\ln(\text{Freq}_{jm}) + \beta\ln(\text{Size}_{jm}) + \eta\ln(\text{Aval}_{jm}) + \gamma\text{Fare}_{jm})} \\ &= \frac{(\text{Freq}_{im})^{\alpha}(\text{Size}_{im})^{\beta}(\text{Aval}_{im})^{\eta}(\exp(\text{Fare}_{im}))^{\gamma}}{(\text{Freq}_{jm})^{\alpha}(\text{Size}_{jm})^{\beta}(\text{Aval}_{jm})^{\eta}(\exp(\text{Fare}_{jm}))^{\gamma}}\end{aligned} \tag{9}$$

If we take logarithmic operation on both sides of the Eq. (9), then we get a log-linear format of market share model. We can use statistical techniques to estimate the parameters in the market share model specified as follows:

$$\ln\left(\frac{S_{im}}{S_{jm}}\right)=\alpha\ln\left(\frac{\text{Freq}_{im}}{\text{Freq}_{jm}}\right)+\beta\ln\left(\frac{\text{Size}_{im}}{\text{Size}_{jm}}\right)+\eta\ln\left(\frac{\text{Aval}_{im}}{\text{Aval}_{jm}}\right)+\gamma(\text{Fare}_{im}-\text{Fare}_{jm})+\varepsilon \tag{10}$$

ε is a stochastic error term composed of three major parts. The first two parts derive from unobserved attributes of the alternatives that affect passengers' utility in a systematic way (across all passengers considering a particular airline for travel in a particular market). For example, a given service may have poor on-time performance or a particularly convenient flight schedule. A portion of this error may be constant over time, and the variable part may also be auto-correlated. The third part is sampling error.

The source data for the coefficient estimation for our market share and demand model come from the database products Onboard and O&D Plus. The data in Onboard are reported on a monthly basis to the US Department of Transportation (USDOT) by all the US certified carriers for all non-stop domestic US market segments and broken down by equipment type. Onboard has such data as onboard passengers, number of departures, segment distance, available seats, revenue passenger miles, available seat miles, load factor and enplanements. The data in O&D Plus are derived primarily from the USDOTs Origin and Destination Survey, and come from flight coupons that carriers issue to passengers. Airlines report data of every 10th coupon ticket, and therefore the database is a 10% sample, which includes such information as number of passengers, the average number of coupons, coupon passenger miles, and average fare outbound and inbound. The data in O&D Plus are reported in each quarter (Data Base Product, 1995a,b).

Because our model focuses on market share and demand in non-stop duopoly markets, we need to identify such markets among all the US domestic markets. To keep the "non-stop" property, we first filter out the markets where more than 3% passengers of the total traveling passengers have one or more stops at other airports. We are interested in markets where each airline has regular service of at least one flight per day on average (i.e. 90 flights in a quarter). Since our demand model will not be jointly estimated with a supply function, we only include markets in which both origin and destination airports are hub airports for at least one of the duopoly airlines. Since services provided on these segments, especially the type of aircraft and service frequency, are determined to a large extent by network considerations not related to traffic in the non-stop market itself, this reduces the problem of supply endogeneity. Also we exclude those markets where there is more than one large airport in the origin or destination regions, so that the concept of "market" represented by airport-pair in our studies is more consistent with the concept of "market" represented by city-pair or region-pair perceived by both airlines and passengers in practice. After applying these filters, we find 13 markets as listed in Table 1. During the investigated time period, the airlines used the same type of aircraft and provided the same service frequency in both directions for each of the markets listed in the table. Moreover the average fares charged and the number of passengers served by the airlines were almost the same in the two directions. Therefore, we just used one directional pair of airports as one market in our analysis. It is noticed that the stage lengths for most of the selected markets are less than 600 miles, and none of the markets has a stage length over 1000 miles. The airlines operating in these markets include six of the largest 10 airlines—Southwest Airlines (WN), American West Airlines (HP), Delta Airlines (DL), Northwest Airlines (NW), Trans World Airlines (TW), USAir (US), excluding American Airlines (AA), United Airlines (UA), Alaska Airlines (AS) and Continental Airlines (CO).

Table 1
Selected markets for parameter estimation for market share and demand model

No. of market	Origin airport	Destination airport	Flight distance	Airline 1	Airline 2
1	ABQ	PHX	328	WN	HP
2	ATL	CLT	227	DL	US
3	ATL	MEM	332	DL	NW
4	ATL	STL	484	DL	TW
5	CLT	STL	575	TW	US
6	DTW	PIT	201	NW	US
7	IND	STL	229	WN	TW
8	LAS	PHX	256	WN	HP
9	MSP	SLC	991	DL	NW
10	MSP	STL	448	NW	TW
11	ONT	PHX	325	WN	HP
12	PHX	SAN	129	WN	HP
13	PIT	STL	553	TW	US

From the database products, we use time series quarter data for the selected markets from first quarter, 1989 to fourth quarter, 1998 to estimate the parameters. Since we use cross-market cross-time period panel data, we include 13 dummy variables representing 13 markets to capture the market-specific fixed effect in the random components in our model. To account for the possible serial correlation in the data of successive quarters in the same markets, we also estimate the first-order auto-correlation efficient σ in the random component in our model. (We also find that the second and higher auto-correlation is much smaller in our data sample.) The estimation results from conditional least square regression are shown in Table 2.

Our first model, Model I, allows different coefficients for Size_{jm} and Aval_{jm} to see whether there is difference to passengers with different combinations of these two variables when they yield the same number of seats per flight, Seat_{jm}. The estimated coefficients are 0.351 and 0.487, respectively. A statistical test reveals that the hypothesis that the coefficients for the two variables Size_{jm} and Aval_{jm} are the same cannot be rejected at the 5% significance level. This result indicates that passengers' utility does not vary with different combinations of total number of seats in the aircraft and the percentage of seats available to local passengers, if the net number of seats available to local passengers is the same. For example, the attractiveness of service with a 100-seat aircraft and no connecting passenger is equivalent to that of a 200-seat aircraft with half of its seats occupied by connecting passengers. Therefore, we re-estimate the coefficients in the market share model, Model II, in which we replace the variables of Aval_{jm} and Size_{jm} with the variable, Seat_{jm}, the net number of seats available to local passengers provided by airline j in market m, simply the product of Aval_{jm} and Size_{jm}.

For Model II, the signs of estimated coefficients for the variables of frequency, net number of aircraft seats, fare, and auto-correlation are expected, and all are significant at the 5% level. The corrected R^2 is 0.9582. The fare coefficient, however, is suspiciously low. Based on the estimated coefficients, we find that, with the same service frequency and same net number of aircraft seats, if an airline charges passengers 1% higher than its competitor who charges passengers \$200 in average, then this airline would lose 0.002% of market share to its competitor. Therefore the airlines' point elasticity at the fare level of \$200 is −0.002. There are two possible explanations for

Table 2
Estimation results for market share model

Variables	Model I		Model II	
	Coefficient estimate	*t*-Statistics	Coefficient estimate	*t*-Statistics
$\ln\left(\frac{\text{Freq}_1}{\text{Freq}_2}\right)$	1.098	15.17	1.093	15.04
$\ln\left(\frac{\text{Size}_1}{\text{Size}_2}\right)$	0.351	2.92	N/A	N/A
$\ln\left(\frac{\text{Aval}_1}{\text{Aval}_2}\right)$	0.487	6.74	N/A	N/A
$\ln\left(\frac{\text{Seat}_1}{\text{Seat}_2}\right)$	N/A	N/A	0.445	7.93
$(\text{Fare}_1-\text{Fare}_2)$	−0.004	−5.15	−0.004	−5.07
σ (Auto-correlation)	0.648	17.07	0.656	17.48
D_1 (Market 1)	0.292	3.10	0.317	3.47
D_2 (Market 2)	0.444	5.82	0.432	5.66
D_3 (Market 3)	0.350	3.30	0.319	3.20
D_4 (Market 4)	0.110	1.50	0.099	1.35
D_5 (Market 5)	−0.099	−1.29	−0.080	−1.07
D_6 (Market 6)	0.061	0.76	0.083	1.09
D_7 (Market 7)	−0.043	−0.58	−0.036	−0.48
D_8 (Market 8)	0.531	6.26	0.568	7.51
D_9 (Market 9)	−0.198	−2.43	−0.209	−2.57
D_{10} (Market 10)	0.251	3.25	0.266	3.49
D_{11} (Market 11)	−0.007	−0.08	−0.003	−0.03
D_{12} (Market 12)	0.098	1.04	0.127	1.40
D_{13} (Market 13)	0.184	2.34	0.194	2.46

this. First, the model does not control for service quality variables (such as cabin class, advance purchase requirements, and refundability) that affect fare. Second, as the result of revenue management practices, flights, and therefore services, with more traffic tend to have higher fares, all else equal. Had we been able to obtain more disaggregate fare data or booking information from airlines, we would have used more complex fare variables which could better capture airlines' pricing and revenue management practice based on the characteristics of passengers and of trips.

Based on our estimation results in Table 2, we find that the coefficient for frequency is 1.093, which means that, in a duopoly market, the carrier with higher frequency share will have an even higher market share, all else equal. Also the frequency coefficient is much higher than aircraft seat coefficient, 0.445. Therefore we expect that airlines can obtain higher returns in market share from increasing frequency than from increasing seats per flight. These findings are demonstrated graphically in Fig. 2, which shows how airlines' market share ratio changes with their capacity share ratio in two circumstances: (1) when two airlines have the same number of aircraft seats and operate with different service frequencies; (2) when two airlines operate with the same service frequency but have different number of aircraft seats. The chart shows clearly that market share ratio increases much faster with the increase of capacity share ratio resulting from fixed number of aircraft seats and varying frequency than from fixed frequency and varying number of aircraft seats.

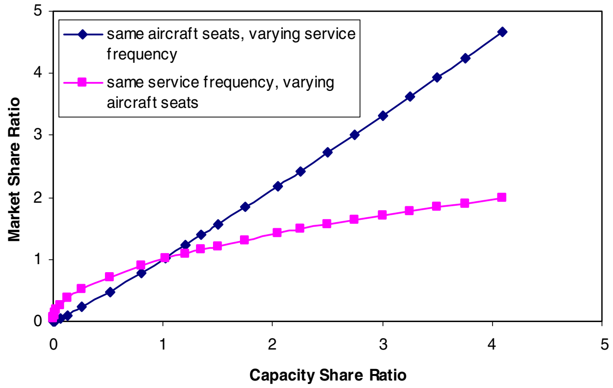

Fig. 2. Changes of market share ratio with capacity share ratio based on increase of service frequency vs. increase of aircraft size.

After we estimate the coefficients for the market share model, we can subsequently estimate the coefficients for the total travel demand model in (7). By taking logarithmic operation on both sides of this equation, we can get a log-linear format of the total demand model, and use statistic techniques to calibrate the model as follows:

$$\ln Q_m = K_m + \rho \ln \mathrm{Incom}_m + \theta \ln \mathrm{Util}_m + \mu \tag{11}$$

All the dependent and independent variables are defined as in (5)–(8). Incom_m is obtained based on the data of income and population in the origin and destination regions. The "log-sum" utility for each market, Util_m, is calculated according to (6) and based on the estimated coefficients above in the utility function. The market characteristic coefficient for market m, K_m, is assumed to be a constant in the whole time period, and thus taken as a dummy variable in the estimating process. The same source data used in the coefficient estimation for market share model are used to estimate the coefficients for the total demand model. Similar to estimations for market share model, we take into account the possible serial correlation in the data of successive quarters in the same markets, and estimate the first-order auto-correlation efficient, ψ, in the random component, μ, for the total demand model. The estimation results from the conditional least square regression are shown in Table 3.

It is noticed that all the estimates are statistically significant, and the corrected R^2 is 0.9999. This high value is not surprising in light of the fixed effects contained in the model. The parameter for the variable Util_m, also known as "nesting coefficient" in nested logit model, is estimated to be 0.584. This implies that, while the utilities of the nested airline alternatives are indeed correlated (since the nesting coefficient is well below 1), market demand is also sensitive to service supply. Besides the income index, Incom_m, which plays as significant a role in total air travel demand as conventionally believed, the variation in estimates for market fixed effects shows that market specific features, such as distance, economic base of the origin and destination regions, historical affinities, and demographic features also play important roles.

Before concluding this discussion, we need to address simultaneity issues related to the estimation of the market share and demand models. First of all, the market share model and the total demand model here are estimated sequentially rather than simultaneously, which make the esti-

Table 3
Estimation results for total air travel demand model

Variables	Coefficient estimate	t-Statistics
$\ln \text{Util}$	0.584	11.84
$\ln \text{Incom}_m$	0.287	6.67
ψ (Auto-correlation)	0.517	12.50
K_1 (Market 1)	3.609	7.31
K_2 (Market 2)	2.995	6.49
K_3 (Market 3)	3.264	7.05
K_4 (Market 4)	3.106	6.91
K_5 (Market 5)	2.280	5.44
K_6 (Market 6)	2.558	5.77
K_7 (Market 7)	2.615	5.62
K_8 (Market 8)	3.794	7.34
K_9 (Market 9)	2.587	6.10
K_{10} (Market 10)	2.933	6.46
K_{11} (Market 11)	3.688	7.44
K_{12} (Market 12)	3.878	7.69
K_{13} (Market 13)	2.387	5.59

mation process easier, but may reduce the efficiency of derived estimation results for the total demand model. Given that the estimation results have fairly high t-statistics, this is not a major concern. Secondly, neither the market share model nor the total demand model is jointly estimated with a supply model, in which airlines' service attributes such as service frequency or fare are considered as dependent on perceived air travel demand. Originally we did attempt to use simultaneous estimations of demand and supply functions, as was done by Eriksen (1977), Meyer and Oster (1984), and Abrahams (1983). The results were not satisfactory, however, due to the unavailability of suitable instrument variables on the supply side. Recall, however, that in choosing the sample for estimation, we only included markets with both the origin and destination airports being hubs for one or two operating airlines. Thus it is reasonable to assume that airlines' strategic decisions in these markets, such as the choice of service frequency and aircraft size, depend mainly on demand on the whole hub-and-spoke network rather than on local traffic, so that supply-side decisions can be regarded as exogenous in our models. While this strategy reduces the risk of biased estimates, further research in this area is clearly called for.

4. Summary

In this paper, we build a nested logit model to study the roles of aircraft size, together with service frequency, seat availability and fare, in airlines' market share and total air travel demand in competitive non-stop duopoly markets. We find that airlines can obtain higher returns in market share from increasing service frequency than from increasing aircraft size, and our estimation result confirms previous findings of a S-curve effect of service frequency on airlines' market share, i.e., airline's market share is superproportional to airline frequency share. Therefore, we conclude that airlines have an economic incentive to use aircraft smaller than the least-cost aircraft, since for the same capacity provided in the market, an increase of frequency can attract more passengers.

We also find that, it is the net number of seats available to local passengers, the product of total seat capacity and the proportion of that capacity not used by connecting passengers, that plays the most important role in airlines' market share. With the same net number of seats available to passengers, there is no significant difference in attractiveness to passengers between a smaller aircraft with higher percentage of seat availability and a larger aircraft with lower percentage of seat availability. While passengers may prefer larger aircraft in the market for such reasons as comfort, amenity and security, we did not observe this effect here. Perhaps it is absorbed in the market-specific fixed effect in our estimations.

Based on the derived demand model in this paper and the cost model such as that in Wei and Hansen (2003), which studied the cost economies of aircraft size and explore the influence of aircraft size on airlines' cost, we can analyze airlines' choices of aircraft size in their operations under various circumstances. If we assume that our duopoly demand model also applies in monopoly markets, we can identify a monopoly airline's optimal choice of aircraft size by solving a profit maximization problem. We can also find the optimal combination of size and frequency that provides service of a given utility at least cost. Given the strong effect of frequency on service utility found in this paper, these optima are likely to involve aircraft smaller than those that minimize cost per seat-mile, which are identified in Wei and Hansen (2003). Besides the applications in these two special cases, the derived demand models can be applied with the game-theoretical analysis approach to systematically study airlines' choice of aircraft size in a general competitive environment, where one carrier's market share and revenue depend not only on its own service but also on the services provided by all other airlines in the market. Such analysis is presented in Wei (2001).

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