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Capturing the Impact of Fuel Price on Jet Aircraft Operating Costs with Engineering and Econometric Models

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***Abstract*— Challenges in forecasting fleet development and deployment are in part due to fuel price uncertainty. To address this issue, a recent study developed an aircraft-specific Leontief technology operating cost model (LM) to compare aircraft costs under fuel price uncertainty. This model considers individual aircraft types to be Leontief technologies, such that the key drivers of cost must be used in fixed quantities. While asserted in the literature that models in this form can more accurately predict operating costs, the Leontief specification precludes a precise examination of how aircraft size will change due to economic forces. To this end, an econometric operating cost model (EM) is developed. The translog functional form is used to capture the effect of the key drivers of cost on jet operating costs and also allow for substitution between inputs. A comparison of the LM and EM shows that the Leontief technology assumption limits the LM to capturing operating costs in only a snapshot in time, while the EM captures the input substitution that occurs with factor price changes. The conclusion that the EM has strong predictive potential encourages a strengthening of the model towards capturing costs related to passenger preferences. This study takes a total logistics cost approach (TLC) and considers passenger value of frequency along with operating cost to be the total cost per operation. The cost-minimizing seat size is smaller and more reflective of existing conditions under TLC compared with operating cost alone, yet the difference diminishes as fuel price increases. This study highlights the predictive potential of econometric cost models and also the importance of considering passenger preferences in predicting future aircraft economics.**

Keywords*—Jet Aircraft; Operating Cost; Aircraft Size; Logistics Cost; Fuel Price; Leontief Technology; Econometric Model

I. INTRODUCTION

Challenges in forecasting fleet development and deployment are in part due to fuel price uncertainty. Fuel price uncertainty is due to fuel and energy price fluctuations and a growing awareness of the environmental externalities related to transportation activities, particularly as they relate to climate change [1]. The impact of fuel price uncertainty is evident in conflicting future fleet forecasts. The Boeing Current Market Outlook predicts the percent of regional jets in service will drop by 10 percent in 2028. This prediction is mainly due to predicted surges in the price of fuel as regional jets have lower fuel economy per seat than larger jets [2]. An increase in single and twin aisle aircraft is predicted over the largest jets because of their ability to balance operating costs with passenger preferences. In contrast, a fleet forecast performed by MITRE predicts a large increase in the percent of regional jets, in part due to surging passenger demand, and an increase in the largest aircraft due to cost savings potential [3]. The conflicting forecasts showcase the challenge of predicting how future fuel prices will affect fleet in the aviation system and also the importance of considering passenger demand and preferences in the forecasts. As airlines are considering new fleets and manufacturers are looking to meet future demands, research on the relationship between aircraft size and fuel price and the influence of passenger preferences on aircraft comparative costs can assist both parties in determining the aircraft type to best meet future cost pressures.

This study will 1. Investigate the potential of two operating cost models to capture the effect of fuel prices on aircraft economics and 2. Develop a Total Logistics Cost model by incorporating passenger preference cost and operating cost. The first cost model presented is an econometric operating cost model (hereafter, EM), in that it uses econometric methods to model operating costs based on airline-aircraft operating cost data. This model allows for detailed analysis on the interactions between the key drivers of cost and also allows for operating cost predictions over a range of fuel prices. However, such a process is data intensive, and the resulting model is cumbersome due to a long variable list. To this end, the EM developed in this study is compared with operating cost models which consider aircraft to be Leontief technologies (hereafter, LM) recently developed by Smirti and Hansen [4] to study aircraft comparative costs under fuel price uncertainty. The LM sums the key drivers of cost and allows for operating cost calculation and prediction with limited input needs. It is

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asserted in [5] that models developed in this manner, termed engineering models, can lead to a more accurate cost functions; this study will explore this assertion by highlighting the unique contributions of econometric models and examining the relationship between the LM and EM estimates.

The comparison sheds light on the ability of EM to capture input substitution and therefore more accurately reflect operating costs and minimum-cost aircraft size under fuel price uncertainty. Therefore, this study also looks to strengthen the predictive power of EM by considering a total logistics cost function which sums operating and passenger costs related to service frequency. Passenger costs are captured through a passenger schedule delay function. The seat capacity which minimizes operating cost alone and the total logistics cost is determined for a range of fuel prices and distances traveled, to identify the aircraft types which provide the lowest costs for a range of future fuel and passenger preference scenarios.

The engineering model developed in [4] follows a long line of established aircraft engineering cost model literature [6-8]. Reference [4], however, departs from the literature in that it takes a total logistic cost approach and develops cost models for three representative aircraft using US DOT Form 41 data: a narrow body Boeing 737-400, an Embraer 145 regional jet, and an ATR 72-200 turboprop. Fleets of each vehicle category are compared for operating cost alone and total logistics cost over a range of fuel prices and distances, and the minimum cost fleet mix is determined. A limitation is the consideration of aircraft size as inelastic; as there are currently a wide range of aircraft sizes on the market, it is possible to consider aircraft size to be elastic.[1] In an attempt to generalize engineering aircraft cost models that are not specific to an aircraft type, Swan and Adler [5] develop two jet aircraft operating cost models using Boeing and Airbus aircraft data only: one for single aisle aircraft and one for double aisle aircraft. Limiting the data source to the two airframe manufacturers implicitly limits the aircraft types considered to mid-size and large aircraft. Furthermore, as the model is based on aircraft size and distance traveled, the model is not able to capture cost changes due to economic forces such as fuel price fluctuations. Additional studies considering cost economics of aircraft size related to stage length using engineering cost models prior to 1999 are well discussed in Wei and Hansen [10].

Reference [10] develops an econometric operating cost model for jet aircraft with elastic aircraft size at the aircraft-airline level in a departure from the literature discussed to this point. The model includes fuel price as a variable in an econometric operating cost model, yet it is not a key variable of interest. Reference [10] find that aircraft economies of scale exist, yet attenuate at longer stage lengths. The variables of interest are restricted to those that help investigate economies of aircraft size – seat size and average stage length – and aircraft types that were commonly used in the study period of 1987-1998. The importance of considering a total logistic cost function with passenger and operating cost rather than individual cost components is demonstrated by comparing [10] and [11]. Using a nested logit model, [11] finds that an airline's market share experiences greater increases from increasing vehicle frequency rather than aircraft size. These findings point to the importance of balancing airline operating cost and passenger preference costs when choosing fleet mix and determining flight schedules. Beyond aviation, total cost studies considering a combination of operating passenger, and infrastructure costs have a long history in urban transportation [12].

The remainder of this paper is organized as follows: The following section reviews the data collected for the development of the EM and the modeling approach. Coefficient estimates are presented and interpreted based on the objective of the study. The EM and LM are then used to calculate operating costs for a range of aircraft types and fuel prices, and the results compared. Based on the strength of the EM, the model is used to predict aircraft operating costs over future fuel prices to determine the seat capacity that minimizes costs. Finally, a generalized cost function that sums operating and passenger value of service frequency is developed and used to perform similar predictions.

II. ECONOMETRIC OPERATING COST MODEL

A. Data Description

There are multiple variables which influence operating cost and over which an airline can assert control. Reference [10] includes aircraft size, labor and fuel factor prices, and average distance traveled as such variables. The model developed in this study extends these variables to others that influence operating cost: average aircraft age, technology age, and utilization. To develop the operating cost model, data from the US Department of Transportation (DOT) Form 41 is collected. Form 41 provides quarterly cost data and operating statistics broken down per airline and per aircraft type. Data was collected for all quarters between the years 1996 to 2006, inclusive. Data from which factor prices are derived and the independent variable, Direct Operating Cost, were collected from Form 41 Schedule P-5.2. This variable is termed Operating Cost per Departure (OCD). Ownership costs related to depreciation and rentals were eliminated from this total to capture operational costs only. The data collected to develop factor prices includes expenditures on Aircraft Fuels and Pilots and Copilots Salaries. Aircraft operating statistics were collected from Form 41 Schedule P05B.[2] These statistics, collected for scheduled and non-scheduled service,

[1] It is important to note that this was not always the case. In a 1986 article, Viton [9] expresses an interest in modeling costs with aircraft size as a continuous variable yet cites the limited aircraft sizes available during the study period as reason to perform an aircraft specific analysis.

[2] It is important to note that aircraft fuels is the actual cost of the fuel, without fuel taxes, any additional costs for the act of fueling the aircraft, or other charges. It is not the total cost related to fuel consumption, but rather the actual cost of fuel. The fuel tax exclusion has little impact as the tax on commercial aviation fuel was constant and minimal through at the study period at $0.044/gallon.

include gallons of fuel used; available seat miles; revenue aircraft miles, departures performed; and block hours, or the sum of hours an aircraft spends from gate to gate. From these prices and statistics, the unit price of fuel (UPF), the unit price of labor (PIL), average stage length (ASL), and aircraft seat capacity (Seat) are derived.

As the variable Seat is a key component of the study, a more detailed description of the derivation is presented. Many airlines operate identical aircraft types with different seat capacities determined by their business models. For example, a legacy carrier looking to lure business passengers may operate an aircraft with fewer seats and more differentiated service classes, while a low cost carrier may use a one-class configuration. To exclude any cost impacts to operating different configurations of the same aircraft, each aircraft type is assigned the weighted average seat size for that aircraft type. The resulting seats range from 49 to 360 seats for twenty three unique aircraft types (Table I).

TABLE I. AIRCRAFT MODELS USED IN OPERATING COST ANALYSIS

Year of Introduction	Aircraft Model	Seats
1992	Canadair RJ-200/ER/-440	49
2001	Canadair RJ-700	68
2002	Embraer EMB-170	72
1982	BAE-146-200	88
1988	BAE-146-300	91
2004	Embraer EMB-190	100
1997	Boeing B-717-200	111
1990	Boeing B-737-500	113
2003	Airbus A318	114
1996	Airbus A319	123
1998	Boeing B-737-700/700LR	128
1988	Boeing B-737-400	143
1988	Airbus A320-100/200	148
1998	Boeing B-737-800	150
2001	Boeing 737-900	169
1996	Airbus A321	170
1982	Boeing B-767-200/ER	178
1983	Boeing B-757-200	184
1998	Boeing B-757-300	222
1986	Boeing B-767-300/ER	231
1995	Boeing 777-200/20LR/233LR	282
1997	Boeing B-767-400	286
1989	Boeing B-747-400	360

Data on aircraft age and utilization is collected from Form 41, Schedule B-43, which includes the total number of each aircraft model in service per airline and the year the airline began to operate them. The aircraft utilization (UTIL) variable, the block hours per quarter operated for each airline-aircraft pair, was derived from these statistics, as well as the average length of time an airline operates a particular aircraft type (AvgAge). Collected from publicly available sources was the first year of entry in service across domestic airlines for a specific aircraft type; this data was used to calculate the technology age (TechAge) of the aircraft, or years that elapsed in between 2006 and the first year of aircraft service.

To capture the materials price, the Producer Price Index is collected from the Bureau of Labor Statistics; a similar method is employed in the work of [13] as well as [14] to develop airline cost functions. Instead of converting each year of data into constant dollars, this study follows [14] and uses the Producer Price Index as both a proxy for materials cost and also a gauge of changes in the economy and inflation. Similarly, a time trend variable is included to capture changes in operating cost over time.

To determine any data reporting inconsistencies, the data was cleaned with assistance from Database Products, the distributor of Form 41 data. The variables derived from the data sources are presented in Table II.

TABLE II. OPERATING COST MODEL VARIABLE DESCRIPTION

Variable Code	Variable Description (Units)
Dependent Variable	
OCD	Total aircraft operating expenses per departure ($)
Independent Variables	
t	Time trend variable 19961: t=1….20064: t=44
Seat	Average seats per departure (Seats)
Util	Block hours in year-quarter t (Utilization metric) (Hours)
ASL	Average stage length (Miles)
Pil	Pilot salaries per block hour ($)
PPI	Producer price index (Proxy for materials price and service)
UPF	Unit price of fuel ($/Gallon)
AvgAge	Average years of aircraft operation by airline (Years)
TechAge	Aircraft technology age (Years)

The twenty six airlines (legacy, regional, and low cost) present in this study are shown in Table III.

TABLE III. AIRLINES USED IN OPERATING COST ANALYSIS

Airlines	
American	AirTran
Alaska	JetBlue
Continental	Midwest
Delta	Independence Air
Northwest	Trans World
United	Air Wisconsin
USAir	Atlantic Southeast
Southwest	Comair
America West	Horizon
National	Skywest
ATA	Hawaiian
Pinnacle	Aloha
Frontier	Spirit

B. Econometric Operating Cost Model Specification and Estimation Results

The model specification used is a demeaned translog model to estimate the operating cost per departure (OCD) (1). The translog model is widely used in cost modeling (for example, [10, 13, 14]); as a second order Taylor series expansion about the mean, it is able to approximate many different model specifications. The variables in the model are defined by two indices that are the unique identifier of one observation: k indicates a unique airline code and aircraft type combination and q indicates year and quarter.

There are four groups of independent variables in the model. The first, α, is a time-invariant and aircraft airline group-invariant constant. The second, τt, is the time trend variable (t) and the coefficient to be estimated (τ). The third, A_k, are the airline-aircraft fixed effects, which capture the unobserved airline-aircraft effect. The variables X^j_{kq} represent the value of independent variable j for a given (k, q) combination (where j and ℓ are indices representing the N=8 independent variables that vary with a particular k). Independent variables j =1,2,…6 are transformed with the natural logarithm (Seat, Util, ASL, Pil, PPI, UPF) and independent variables j =8, 9 not transformed with the natural logarithm (AvgAge, TechAge). Parameters ω_j and δ_j are to be estimated.

The model is demeaned such that the dependent variable and the independent variables which vary across a given k are estimated about their mean values. This enables straightforward interpretations of the results: the average effect of each independent variable j is immediately evident from each parameter estimate ω_j.

$$\boldsymbol{ln\, OCD_{kq} - \overline{ln\, OCD_{kq}} = \alpha + \tau t + A_k + \sum_{j=1}^{N} \omega_j \left[X^j_{kq} - \overline{X^j}\right] + \sum_{j=1}^{N}\sum_{l\geq j}^{N} \delta_{jl}\left[X^j_{kq} - \overline{X^j}\right]\left[X^l_{kq} - \overline{X^l}\right] + \varepsilon_{kq}} \quad (1)$$

This is a panel data set as there are k airline-aircraft groups over a set of year-quarters q. Because the elements of k are not constant across years, the panel is unbalanced. To estimate the model, a fixed effects mean-difference model is used, where the fixed effects are captured by A_k. Each observation in a particular group m (where m ∈ k) is estimated about the mean of group m. This method ensures consistent estimates of ωj and δ_{jl}, however, the method precludes estimation of the time-invariant regressors A_k. As the data is over 44 time periods, the estimation method also corrects for autocorrelation present across airline-aircraft pairs. Finally, an examination of residuals shows heteroskedasticity across groups, and therefore generalized least squares with heteroskedastic-robust standard errors estimation is used ensuring consistent standard errors.

Table IV contains estimation results for the EM. The coefficient estimates generally have the expected signs and most are significant at the five or one percent level. The evaluation of operating cost economies of aircraft size (represented by the variable Seat) and fuel price (represented by the variable UPF) begins with the first order coefficient on aircraft size, .44. This implies operating cost economies of aircraft size; a one percent increase in aircraft size would increase operating cost by .44 percent. The second order term of Seat is positive (.27) and implies that aircraft economies of scale attenuate for aircraft sizes larger than the average size. There are economies of fuel price found, and the second order effects show that as fuel prices deviate positively from the mean these cost economies of fuel price decrease. Finally, the interaction term between fuel price and aircraft size, 0.085, shows that as fuel prices increase, economies of scale due to aircraft size diminish slightly. In sum, economies of scale attenuate at larger aircraft sizes and at higher fuel prices, which confirms the assertion that "increases in fuel efficiency are harder to achieve in a larger plane" [15].

TABLE IV. JET AIRCRAFT EMPIRICAL RESULTS

Variable	Parameter Estimate	Standard Error
Constant	-0.129***	0.025
t	0.002***	0.001
Seat	0.436***	0.062
ASL	0.775***	0.041
Pil	0.346***	0.024
UPF	0.364***	0.026
Util	-0.056***	0.025
PPI	0.036	0.163
AvgAge⁺	0.037***	0.004
TechAge⁺	0.009***	0.002
Seat*Seat	0.273***	0.05
ASL*ASL	0.131***	0.013
Pil*Pil	0.045***	0.003
Util*Util	-0.020***	0.006
UPF*UPF	0.161***	0.026
AvgAge⁺*AvgAge⁺	$5.7*10^{-4}$*	$3.0*10^{-4}$
TechAge⁺*TechAge⁺	$4.5*10^{-4}$***	$2.0*10^{-4}$
Seat*ASL	-0.187***	0.062
Seat*Pil	-0.129***	0.033
Seat*Util	-0.0247	0.0285
Seat *PPI	0.2845	0.2164
Seat*UPF	0.085***	0.037
Seat*AvgAge⁺	-0.027***	0.007
ASL*UPF	-0.005	0.025
ASL*Pil	0.0117	0.0212
ASL*Util	-0.0436***	0.0179
ASL*PPI	0.0356	0.1492
ASL*AvgAge⁺	0.0015	0.0039
Pil*Util	-0.0190	0.0127
Pil*PPI	-0.0215	0.0696
UPF*Pil	-0.103***	0.021
Pil*AvgAge⁺	0.0084***	0.0032
PPI*AvgAge⁺	0.0313*	0.0170
AvgAge⁺*UPF	-0.014***	0.003
UPF*PPI	-0.565***	0.185
Util*UPF	-0.021	0.019
Util*PPI	0.1700***	0.0748
Util *AvgAge⁺	-0.0077***	0.0030
TechAge⁺*Seat	-0.0004	0.0049
TechAge⁺*ASL	-0.0011	0.0037
TechAge⁺*Pil	-0.0011	0.0022
TechAge⁺*UPF	$3.54*10^{-3}$	$2.27*10^{-3}$
TechAge⁺*Util	-0.0057***	0.0021
TechAge⁺*PPI	0.0166	0.0138
TechAge⁺*AvgAge⁺	-0.002***	$4.5*10^{-4}$
N obs	1657	
N groups	66	

***Variables are significant at the 1% level
**Variables are significant at the 5% level
*Variables are significant at the 10% level
⁺Variables are not natural log

The negative sign on the interaction term between distance traveled (represented by the variable ASL) and fuel price confirms that there are more scale economies over longer distances due to fuel consumption. As the cruise phase is the most efficient from a fuel consumption perspective, this is the expected result. This finding is further reinforced by the interaction term between aircraft size (Seat) and distance traveled (ASL), which shows that at longer distances traveled there are strong economies of operating cost due to aircraft size.

While previous studies have excluded the technology age (TechAge) and the average age (AvgAge) variables, the model estimates show that the inclusion of these variables is warranted by their significant effect. The negative interaction term between average age and fuel price is unexpected, and could be explained by airline comfort with aircraft. As an airline learns how to operate an aircraft with experience, it learns the optimal fuel level and optimal flying speeds and altitudes. Such benefits are found by Southwest Airlines and their one aircraft type fleet [16]. The interaction of technology age and fuel price is not statistically significant, yet the sign of the coefficient tells us that as an aircraft ages it is more impacted by fuel prices. The interaction between aircraft size and average aircraft age shows that smaller aircraft show the signs of age more quickly, as a larger aircraft has more cost economies due to size than a smaller aircraft of the same age.

III. Comparison of Operating Cost Model Results Under Fuel Price Uncertainty

This section will use the EM to calculate operating costs for a range of inputs and compare these results with the LM.

A. *Econometric Operating Cost Model Analysis*

Using the coefficient estimation results presented in Table IV and other assumed inputs, operating cost per seat mile over a range of stage lengths for pairs of aircraft sizes and prices of fuel is calculated. The operating cost calculation is done by estimating the cost functions at certain specified values. The results presented will be parametric over fuel price and stage length; combinations of these two variables will be specified inputs. The PPI and time trend variable will be set at the 2006 value, and the values reported will be in 2006 dollars. For labor costs, a simple univariate linear model that relates the dependent variable, the unit price of labor, to the independent variable, seats is developed. The following is the resulting equation, with all coefficients significant at the 5 percent level.

$$Pil = 140.1 + 1.78 * Seat \quad (2)$$

For the remaining variables, the average factor prices and aircraft operating statistics for Delta Airlines will be used.

Fig. 1 presents the results.[3] There is a unique minimum operating cost per seat mile for each aircraft size, dependent on the average stage length flown and the fuel price. For constant fuel price, as the distance flown increases, the aircraft size which minimizes operating cost per seat mile increases. This finding is consistent with the negative interaction term between seats and average stage length. For a constant distance flown, as fuel price increases, the aircraft size which minimizes operating cost per seat mile increases; while the interaction term between seats and fuel price is positive, the interaction between labor and fuel price is negative.

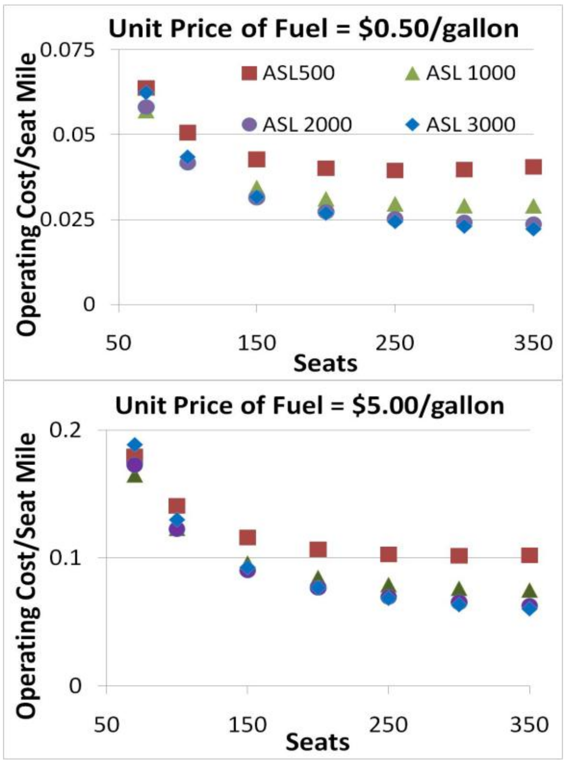

Figure 1. Operating cost per seat mile vs. seats for representative fuel prices.

B. *Leontief Technology Operating Cost Model Comparison*

This section will investigate the difference in predicted values between the LM and EM developed in section II of this study. The LM was developed by Smirti and Hansen [4] using average values from the same data set used in the current study, but for the year 2007. In [4], three specific aircraft types are chosen for cost calculation, two of which are jet aircraft: an ERJ 145 regional jet (50 seats) and a Boeing 737-400 narrow body (141 seats). The key drivers of cost including fuel costs, labor costs, and maintenance costs are summed based on statistical relationships between fuel burn and distance traveled and travel time and distance traveled.[4] The values presented in [4] are reported in Table V. Using the same methodology as in [4], the cost coefficients for a mid-sized aircraft, the narrow body Boeing 757-200 are determined so the comparison can cover aircraft with ranges up to 3000 miles. The values calculated for the Boeing 757-200 are reported in Table V.

[3] Fig. 1 presents four representative stage lengths for ease of presentation.

[4] It should be noted that [4] also includes airport charges as part of the operating costs; these are eliminated for this analysis because they are not part of the direct operating costs.

To perform the comparison of LM and EM results, three key inputs are necessary: fuel price, distance traveled, and seat size. The seat size input is only necessary in the EM: the three set seat sizes for the aircraft in the LM are used. Three representative fuel prices: \$0.50/gallon, \$3.00/gallon, and \$5.00/gallon are used and stage lengths between 100 and 3000 miles are used as the additional inputs.[5]

TABLE V. OPERATING COST PER DEPARTURE EQUATIONS

Aircraft Category	Coefficient Value				
	Fuel Price (f)	**Distance*Fuel Price (d*f)**	**Distance (d)**	**Fixed**	
B757-200	$5.1*10^2$	2.0	2.5	$9.4*10^2$	
B737-400	$2.7*10^2$	2.1	2.6	$8.8*10^2$	
ERJ 145	$1.9*10^2$	1.9	1.2	$4.8*10^2$	

The LM estimates, developed using the inputs and the values in Table V, are compared with the EM estimates calculated in Section III(A). For comparison, the values are plotted against each other for the three aircraft types in Fig. 2.

Fig. 2 shows a relatively linear relationship along the 45-degree equality line between the LM and EM for the three aircraft at each fuel price. However, there is under prediction by the LM present at low fuel prices and over prediction by the LM for high fuel prices. This is due to the technology assumptions behind the EM and LM. The LM considers aircraft to be a Leontief technology, in that all inputs must be used in fixed proportions. The EM model allows substitution between inputs when factor prices change.

The LM was developed at a time when the operators of a 737-400 were paying an average of \$2.01/gallon; the operators of a 757-200 were paying an average of \$1.99/gallon, and operators of the ERJ 145 were paying an average of \$1.22/gallon. The average fuel price for Delta Airlines in 2006, the year of the projection data for the EM, is \$2.08 per gallon of jet fuel. It therefore follows that when the EM and LM are estimated at fuel prices close to this \$2.00/gallon average, the EM predictions and the LM predictions will be close. For fuel prices above this average, the LM should have higher estimates than the EM. This is because the EM allows for input substitution: as fuel prices increase, airlines will take steps to use fuel more efficiently by leveraging other inputs, a technical infeasibility of the LM. This hypothesis is confirmed in Fig. 2.

IV. OPERATING COST AND TOTAL LOGISTICS COST COMPARISON

The EM proves to be a useful predictor of operating cost, as it is able to capture costs in the current and future environment. To this end, the EM is improved by adding to it a passenger cost component. Schedule delay, or the concept that passengers place a value on the difference between desired arrival time and actual arrival time is well known to airlines and manufactures. This generalized cost model incorporates schedule delay and is termed the Total Logistics Cost (TLC) function. In this section, this model is used to compare the aircraft sizes that optimize operating cost alone and TLC for a range of fuel prices.

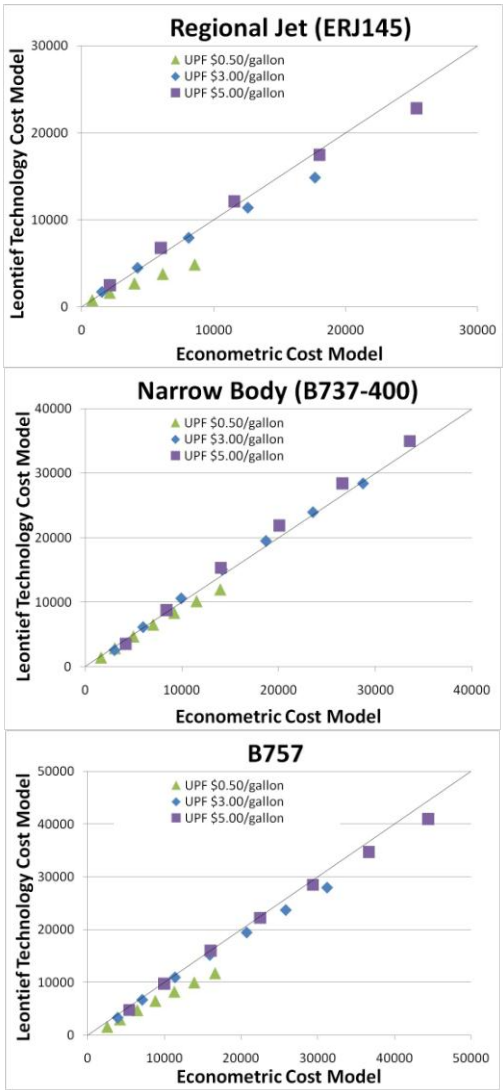

Figure 2. Leontief technology vs. econometric operating cost model results.

A. *Total Logistics Cost Analysis*

As the consideration of operating cost alone does not capture the entire motivation behind fleet adoption and utilization decisions, this study develops a generalized cost function including operating cost and passenger schedule delay cost. To capture schedule delay costs, two relationships must be determined, one between vehicle size and frequency and the other between frequency and schedule delay. Reference [17] develops a relationship for frequency and schedule delay based on flight frequency, which accounts for schedule peaking. Equation (4) shows the schedule delay function $g(f_i)$ in hours based on a frequency function (3). The

[5] As the ERJ 145 has a range of 1,550 miles, the operating cost estimation is not performed for distances further than 2000 miles. The B737-400 has a range of 2,255 miles, and the cost estimation is not performed for distances further than 2,500 miles.

equation for flight frequency (f_i) is determined by the market density, or the passenger flow per day between a given origin and destination per day (q); the aircraft seat capacity (s); and the load factor, or the percent of seats occupied per departure (ℓ). The resulting schedule delay, $g(f_i)$, can be multiplied by the weighted average of schedule penalties for business and non business travelers, λ_{SD} ($15.77/hour [18]). Delays in either direction (early or late) are considered equally onerous.

$$f_i = q / (\ell * s) \tag{3}$$

$$g(f_i) = 5.7 / f_i \tag{4}$$

B. Determining of Minimum Cost Seat Capacity for Operating Cost and Total Logistics Cost

1) Minimum Operating Cost Seat Capacity

To find the seat size which minimizes operating cost per seat mile, the operating cost function (1) is minimized for each stage length and fuel price combination. The results are shown in Table VI. For a constant stage length, the seat size which minimizes operating cost per seat mile increases with fuel price, yet at a decreasing rate. Certainly, as fuel price increases, the cost economies of aircraft size are stronger; while this is evident, the aircraft sizes in Table VI are much larger than those seen today. As noted in the previous subsection, passenger preference for level of service, or schedule frequency, is an important component of airline decision of aircraft deployment.

TABLE VI. SEAT SIZE CORRESPONDING TO THE MINIMUM OPERATING COST PER SEAT MILE FOR A RANGE OF FUEL PRICES AND STAGE LENGTHS

		UPF			
		0.5	1	3	5
ASL	100	143	148	157	161
	500	255	271	297	310
	1000	332	354	393	413
	1500	387	414	464	489
	2000	431	476	526	552
	2500	470	506	572	606
	3000	504	544	617	654

2) Minimum-Total Logistics Cost Seat Capacity

The aircraft seat size that minimizes the generalized cost function, the TLC, over a range of fuel prices and stage lengths is the seat size that minimizes the operating cost function plus $g(f_i) * \lambda_{SD}$. Table VII shows the aircraft seat size that minimizes TLC over a range of fuel prices and stage lengths. Three representative market densities are chosen: a relatively low market density of 250 passengers/day, a medium market density of 750 passengers/day, and a high market density of 3000 passengers/day. The load factor is set to one. The values in the tables on the left side are the solutions to the minimization of the TLC and the values in the table on the right are the percent difference between seat capacities before and after the inclusion of schedule delay.

TABLE VII. SEAT SIZE CORRESPONDING TO THE MINIMUM TOTAL LOGISTICS COST COST PER SEAT MILE FOR A RANGE OF FUEL PRICES, STAGE LENGTHS, AND MARKET DENSITIES

Market Density = 250 Passengers per Day										
		UPF					UPF			
		0.5	1	3	5		0.5	1	3	5
ASL	100	40	43	52	59		-72%	-71%	-67%	-63%
	500	69	74	91	105		-73%	-73%	-69%	-66%
	1000	92	99	124	144		-72%	-72%	-68%	-65%
	1500	112	120	152	176		-71%	-71%	-67%	-64%
	2000	129	139	176	205		-70%	-71%	-67%	-63%
	2500	144	157	198	231		-69%	-69%	-65%	-62%
	3000	159	173	219	256		-68%	-68%	-65%	-61%
Market Density = 750 Passengers per Day										
		UPF					UPF			
		0.5	1	3	5		0.5	1	3	5
ASL	100	61	65	78	88		-57%	-56%	-50%	-45%
	500	105	113	140	160		-59%	-58%	-53%	-48%
	1000	141	152	190	218		-58%	-57%	-52%	-47%
	1500	170	184	231	266		-56%	-56%	-50%	-46%
	2000	180	213	267	307		-58%	-55%	-49%	-44%
	2500	228	239	300	345		-51%	-53%	-48%	-43%
	3000	250	263	331	381		-50%	-52%	-46%	-42%
Market Density = 3000 Passengers per Day										
		UPF					UPF			
		0.5	1	3	5		0.5	1	3	5
ASL	100	96	102	117	127		-33%	-31%	-25%	-21%
	500	166	179	214	237		-35%	-34%	-28%	-24%
	1000	180	239	288	320		-46%	-32%	-27%	-23%
	1500	282	287	347	385		-27%	-31%	-25%	-21%
	2000	320	328	397	441		-26%	-31%	-25%	-20%
	2500	354	365	441	490		-25%	-28%	-23%	-19%
	3000	385	398	482	535		-24%	-27%	-22%	-18%

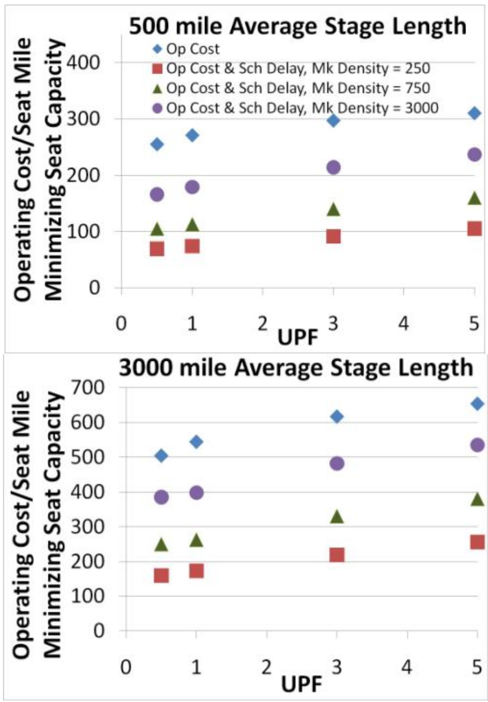

Figure 3. Seat size corresponding to minimum TLC per seat mile for a range of fuel prices, stage lengths, and market densities.

For all three market densities, the seat capacity that minimizes the TLC is reflective existing aircraft fleets. This is clear from Fig. 3, which shows the seat capacity which minimizes four scenarios of cost (operating cost alone, and the TLC function for the three market densities). Holding fuel price and stage length constant, as market density increases, the aircraft size which minimizes TLC increases. Higher demand necessitates larger aircraft sizes (Fig. 3); we would also expect this trend to appear if we were to decrease λ_{SD} (6).

By comparing the upper and lower panels of Fig. 3, it can be seen that an increase in stage length leads to an increase in seat size which minimizes cost per seat mile, holding fuel price and market density constant. Finally, across common market densities and stage lengths, as fuel price increases, the percent difference decreases. This is because in the generalized cost function, the operating cost becomes the dominant cost.

V. CONCLUSIONS

This study helps shed light on airline choice of aircraft size; as airlines are not looking to minimize operating cost alone but rather considering profit and market share, a strong weight is put on passenger preference when considering aircraft deployment. The difference observed in the minimum cost aircraft with the incorporation of passenger costs points to the importance of considering multiple costs when evaluating aircraft types. Results of this study show that the consideration of passenger preferences erodes as fuel price increase and that high fuel prices rationalize the use of larger aircraft in fleet composition despite higher passenger costs. Therefore, if fuel prices were to include other costs such as environmental taxes, the advantage of larger aircraft would be evident to airlines and airframe manufacturers.

This study also highlights the predictive potential of econometric operating cost models. The Leontief technology operating cost model has many strengths: transparency, few inputs, and the ability to provide predictions at a snapshot in time. The econometric model, in comparison, is shown to make predictions at a point in time and also capture how an airline might adapt to changes in factor prices. Both models play an important role in the aviation cost modeling space. However, this study shows the strengths of econometric cost models and their ability to provide consistent estimates and deep insight into current and future aircraft cost economics.

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