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A Model of World Aircraft Demand

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Abstract

The paper develops an econometric model for predicting aircraft demand by the major world airlines. This model is based on economic theory where firm behavior is assumed to rest on cost minimization and profit maximization. Demand for factors of production, here aircraft, emanate from such behavioral underpinnings. In contrast, we also forecast aircraft demand based on time series methods. These methods are atheoretical in nature and postulate that demand is based on past values and disturbance terms.

1 Introduction

The nature of international trade has changed dramatically over the last decade. Where once the world was a place of nations seeking their own interests individually, it is today a collection of large trading blocks. In one high profile instance of such integration, the European Union (EU) has embarked on an ambitious effort to remove economic barriers among the twelve member states and to establish an integrated market system. The 1992 EU integration effort in fact presages the momentum of global changes in international trading arrangements which place special demands on the global economic community. Arguably, the passage of the North American Free Trade Agreement was a direct outcome of these European initiatives.

This changing environment means that those governments and industries that have enjoyed success in some international and/or domestic markets will find that the terms of trade have changed. Continuation of current subsidies and "business as usual" may prove difficult. On the other hand, economic entities which may have been unable to successfully compete in some markets may find

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new business opportunities and avenues for profitable exploitation. As countries around the world have developed within this new environment, so has the pattern of air traffic. For example, the share of international traffic generated over and near the Pacific Ocean has been increasing at a rate of more than 10% per year, far above the 6.6% annual growth rate for the rest of the world. Projections indicate that by the end of the century over one-third of all international flights will emanate from the Pacific. No doubt another important factor behind this growth in air travel has been the emergence of strong industrial economies in the region, including those of Hong Kong, Indonesia, Singapore, Japan, Korea and Taiwan. China, in fact, represents the world's largest unexploited market. As these newly industrialized economies grow, so too do their demands for air travel and their ability to produce it. In fact, it can be argued that these countries already possess comparative advantage because of low labor costs, an ability to increasingly exploit the advantages of large equipment size, and recent improvements in their productive efficiency. Moreover, the $8 billion loss in the U.S. industry over the last three years and the open-sky policy of the U.S. in its bilateral negotiations point to strong forces for change in government policies toward shared equity stakes, interlining, and integration of networks among international airlines.

In this paper, we estimate the demand for both passenger and cargo services provided by each major international carrier's network. We link the carrier-specific demand schedules with a cost analysis of the carriers in terms of the prices of the firm's factors of production - labor, fuel, materials, and flight equipment.

Our cost model is used to generate derived demand schedules for the factors of production, in particular flying capital. The demand schedules will be functions of the price of the factor of production, prices of other factors, characteristics of the aircraft used by the airline system, and the level of passenger and cargo service.

Our joint model of supply and demand for commercial air service (along with the inferences about the demand for airplanes which are imbedded in that model) allows us to simulate the effects of emerging technologies in engine design capabilities and in airframe capacities in terms of modifications in the hedonic characteristics of the planes in service. We can also simulate the growth in total system demand for service and, thus, for such inputs as planes. We can examine the impacts of emerging technologies that focus on engine fuel efficiencies and noise abatement characteristics (since the former will reduce fuel requirements and since fuel is one of the factors of production).

In addition, we develop forecasts for aircraft demand using time series forecasting. The atheoretical approach assumes that all relevant information of a single series, here the size of each carrier's aircraft fleet, is contained in the history of the data.

We describe the data in section 2. Section 3 specifies the demand functions which we estimate using the world data set. The cost function is explained in section 4. Discussion of the predictions made, based on the above functions, is presented in section 5. Section 6 provides an overview of the methodology of time series forecasting. The results of this approach are presented in section 7 and a brief comparison of the two methods is made in section 8. Finally, section 9 provides concluding comments.

2 Data

Our airline data set consists of a panel of the largest air carriers from Asia, Europe and North America. These carriers supply approximately 85% of the scheduled passenger traffic in the world. The primary sources for our data include the Digest of Statistics for Commercial Air Carriers from the International Civil Aviation Organization (ICAO) and the Penn World Table (Summers and Heston, 1994). There are frequent instances where this source was not complete. Consequently, these data were supplemented with those obtained from the International Air Transport Association's World Air Transport Statistics and Federal Express Aviation Service's Commercial Jet Fleets. Using these sources, we constructed a set of four airline inputs: Labor, Energy, Materials, and Aircraft Fleet. In addition we constructed several aggregate airline output, along with characteristics of these outputs.

Inconsistencies in the definition of labor categories, differences in aggregation, and missing data demanded that our labor index be constructed from a single sub-component. Our labor index uses the number of employees at mid-year as the measure of quantity. Prices are calculated by dividing expenditures by this quantity.

ICAO complies annual information about jet fuel prices within each of its 12 regions. We use this information as a price measure in cents/liter. Quantities are calculated by dividing fuel expenses by this price.

Our materials index is based on the financial data obtained from ICAO. It uses total operating expenses minus the amounts spent on aircraft rental, depreciation, fuel, and labor.

We use an inventory of aircraft fleet provided by ICAO to determine the number of aircraft in over 80 separate aircraft types. For each aircraft type, we construct a user price, roughly comparable to an annual rental price. Total expenses are then the sum of these user prices, weighted by the number of aircraft in a carrier's fleet in each category. Our valuations of individual aircraft types is based on the average of Avmark's January and July subjective valuations of each type of aircraft for every year. These valuations are based on recent sales and perceptions of changing market conditions for aircraft in half-time condition. Because we value aircraft in half-time condition, we assume that their remaining useful life is 14 years and use a 1.5 declining balance method to calculate economic depreciation. In addition to constructing price and quantity measures, we also generate several characteristics of the capital stock: its size (maximum seats per plane), its technological age (in years), and a classification of the aircraft as turboprop, jet or wide-bodied jet.

Our scheduled passenger output is measured in revenue ton kilometers. This is calculated under the assumption that a passenger, along with checked

baggage, constitutes 200 pounds in weight. Our nonscheduled output measure combines charter, mail, and cargo operations. Charter passenger traffic again assumes 200 pounds per passenger. For scheduled and non-scheduled outputs, both quantity and expense information is available. For incidental output, we use the country's purchasing power parity as a deflator to construct a quantity measure.

Finally, we construct two traditional measures of the carrier's output: stage length and load factor. Load factor provides a measure of service quality and is often used as a proxy for service competition. Stage length provides a measure of the length of individual route segments in the carrier's network.

3 Demand Equation

We develop a specific model of international demand for an airline firm's provision of passenger and cargo services. Demand for a carrier's service is driven by the carrier's price (measured by the average ticket price for flights on carrier i) and the size and economic prosperity of the market measured by population, per capita income, and labor force participation rate. The period under consideration is 1977 to 1992. Demand is defined as

$$\begin{aligned}\log Y_{tk} &= \alpha + \sum_{i=1}^{N-1} \alpha_i CARRIER_i + \beta_Y \log P_{Y,tk} \\ &+ \beta_{POP} \log POP_{tk} + \beta_{PCI} \log PCI_{tk} \\ &+ \beta_{LFP} \log LFP_{tk} + \varepsilon_{tk}\end{aligned} \tag{1}$$

where Y is revenue passenger mile originating at time t for carrier k, $P_{Y,tk}$ is the average ticket price for service originating at time t for carrier k, POP_{tk} is the population at time t of country k, PCI_{tk} is the per capita income at time t of country k, LFP_{tk} is the labor force participation rate at time t for country k. The $CARRIER_i$ represents the conventional treatment for fixed effects.

Equation 1 was estimated using ordinary least squares (OLS)[1]. Estimates for the three world demand equations are shown in Table 1. The estimates from these three equations do not seem to be reasonable, given previous studies. The Europe equation has a price variable which is insignificant and the sign on the population variable is negative, which is not expected. For Asia, we have price having a positive effect on demand. Further, the sign on the labor force participation rate is not what we would expect. For the North American demand estimation, the population variable is quite large. These poor estimates could stem from aggregation of the data and from omitted variable bias in the demand equation. We would expect that less aggregated data that included airport-to-

[1]OLS estimation of a least squares dummy variables (LSDV) model such as (1) allows for correlation between the regressors and the effects.

airport travel would improve the estimates. Also, having a variable for competitors' prices on competing routes could only improve the quality of the estimates.

4 Cost Equation

Cost function estimates for the airline industry are necessary to predict fleet size. We do this under two different sets of assumptions:

i) carriers are cost minimizers, and

ii) carriers are profit maximizers.

Under cost minimization, outputs are taken to be exogenous. With profit maximization, outputs are endogenous variables. These different assumptions will affect how our cost model will be estimated. This will be explained in the sections below. We use a translog functional form for our cost equations.

4.1 Cost Minimization

The cost function is given by

$$
\begin{aligned}
\log C = {} & \alpha + \sum_{i=1}^{4}\beta_i \log p_i + \sum_{j>i}^{4}\sum_{i=1}^{3}\delta_{ij}\log p_i \log p_j + \frac{1}{2}\sum_{i=1}^{4}\delta_{ii}\log^2 p_i \\
& + \sum_{i=1}^{2}\gamma_i \log Y_i + \frac{1}{2}\sum_{i-1}^{2}\gamma_{ii}\log^2 Y_i + \gamma_{12}\log Y_1 \log Y_2 \\
& + \delta_A \log p_k \log AA + \delta_S \log p_k \log AS + \delta_J PJ \log p_k \\
& + \delta_W PW \log p_k + \beta_{sl}\log SL + \beta_{lf}\log LF + \sum_{i=1}^{36}\alpha_i AIR_i + \varepsilon_c
\end{aligned} \tag{2}
$$

where p_i is the i^{th} input price, Y_i is one of the two outputs (scheduled output, and non-scheduled and incidental output), AA is the average age of an airframe in months, AS is the average size in seats of the fleet, PJ is the percentage of jet aircraft in the fleet, PWB is the percentage of wide-bodied aircraft in the fleet, SL is stage length, and LF is the load factor.

The $\alpha_i AIR_i$ represents fixed firm effects in the cost equation. These firm effects can be given the reduced form interpretation of omitted variables that are specific to the firm and display little variability over the sample period, or can be given a more structural interpretation as time-invariant technical inefficiencies from a stochastic frontier cost function (Schmidt and Sickles, 1984; Cornwell, Schmidt and Sickles, 1990).

The cost share of capital is given by

$$
\begin{aligned}
S_k = {} & \beta_k + \sum_{i=1}^{4}\delta_{ik}\log p_i + \delta_A \log p_k \log AA + \delta_s \log p_k \log AS \\
& + \delta_J PJ \log p_k + \delta_W PW \log p_k
\end{aligned} \tag{3}
$$

Before we do any estimation, we normalize the data so that all the variables are unity at the data median. We estimate the cost function and all but one of the cost share equations using iterated seemingly unrelated regression (ITSUR). Asymptotically, upon convergence, ITSUR will be equivalent to the maximum likelihood estimates, which are invariant to that cost share equation we leave out of the estimation. The parameter estimates (excluding the fixed effects) are found in Tables 2 and 4.

These equations produced estimates which we consider reasonable. The fitted function is concave in prices at the mean of the data as required. The function is concave at 99.6% of the data points. Also, the fit of the model is quite good, with a system weighted R^2 value of 0.9672.

4.2 Profit Maximization

Under profit maximization, companies optimally choose outputs given a set of input prices. This means that output is no longer exogenous and we must use a different method to estimate the cost function above. The estimation we use is a modification of iterated three-stage least squares (I3SLS). The results are shown in Tables 3 and 4.

The parameter estimates found under the assumption of profit maximization should be questioned. The fitted function meets the requirement that it be concave in prices at the mean of the data, and is concave at 98.8% of the data points. The fit of the model is good, with a system weighted R^2 value of 0.9104.

5 Prediction

To predict the number of aircraft which would be in a particular carrier's fleet over a given period, we do the following:

i) predict the growth of service demand over the period using an estimated demand function;

ii) predict the change in total cost per carrier over the time period using our predicted demand growth and an estimated cost function;

iii) use the capital share equation to predict what the total capital expense will be over the period;

iv) assume the number of planes in a period is equal to the total expenditure on capital divided by the cost per plane.

From our estimates shown in Table 1, this scenario leads to an annual service increase of 3.64% in Asia, 1.98% in Europe, and 8.32% in North America. These numbers do not seem as reasonable as we would have hoped. The 3.64% service increase in Asia is below the observed growth rate of 10% in air travel. The increase in demand in North America is much too high when compared to other studies. Obviously, this will affect the quality of the forecast of the fleet size.

With these demand estimates in hand, we can use our estimated cost function and capital share equation(s) to forecast future aircraft demand. We do this by first forecasting total cost and capital share. Capital expenditure can then be found. Aircraft in a fleet is then just the capital expenditure divided by the capital price.

5.1 Cost Minimization

Using the cost minimization procedure, we predict a 1.58% increase in planes in Europe, a 3.11% increase in Asia, and a 7.65% increase in North America. These results are biased by the demand estimates. The 7.65% increase in fleet size in North America is about two times as large as predicted in previous studies which looked only at the U.S. Also, since the Asia demand growth seems to be too low, growth in fleet size would be biased downward.

5.2 Profit Maximization

In this area, our models did not perform as well as we would have liked. For example, we predict a 2.06% increase in planes in Europe, a 4.37% increase in Asia, and a 12.6% increase in North America. As with the cost minimization, the results rely on questionable demand functions.

The projected average number of total aircraft from cost minimization and profit maximization, by individual carriers, are presented in Table 5 at the end.

6 Time Series Methodology

Forecast for aircraft demand by the major world airlines can also be made using time series data of each firm's aircraft fleet size. The data, used in the econometric models described in the previous sections, cover the period 1976 to 1994 and forecasts are made to the year 2004.

To make these time series forecasts, it is necessary to use some important tools. A major diagnostic tool for fitting probability models to time series is the autocorrelation function. This function helps to describe the evolution of a stochastic process through time. The autocorrelation function (ACF) is given by

$$\rho(k) = \frac{\gamma(k)}{\gamma(0)} = \frac{\text{cov}(x_t, x_{t+k})}{\sqrt{\text{var}(x_t)} * \sqrt{\text{var}(x_{t+k})}} \tag{4}$$

A related concept to the ACF is the partial autocorrelation function (PACF). It measures the partial correlation between x_t and x_{t-k} with intervening $x_{t-1} \ldots x_{t-k+1}$ variables held constant. Like the ACF, the plot of the PACF against k lags is important in identifying the stochastic process underlying a time series. (Johnston, 1997, p.212)

Some useful stochastic processes in time series analysis include a purely random process, a moving average (MA) process, an autoregressive (AR) process and a mixed ARMA process. A purely random process, also called white noise, is one where the time series, x_t, consists of a sequence of independent and identically distributed (iid) random variables $\{z_t\}$. The process has a constant mean, variance and covariance over time. Therefore, it is stationary. A moving average process is where the current time series, x_t, is related to random errors $\{z_t\}$ from the present and previous time periods: these errors have mean of zero and variance equal to σ_z^2. MA processes are important because they describe effects of 'random' events, such as strikes and shortages, on various economic variables. These events will have an immediate effect and can also have some limited impact in several subsequent periods (Chatfield, 1989, p.35). An autoregressive (AR) process is one where the stochastic process underlying the time series exhibits autocorrelation: the current value of the series, x_t, is a linear combination of p most recent past values of itself and an error term.

In general, the following theoretical properties of the ACF and the PACF can be used to identify sample processes.

	AR(p)	MA(q)	ARMA(p,q)
ACF	decreases exponentially (dies out slowly) or decreases in sine wave manner	cuts off to zero after lag q	decreases exponentially (dies out slowly)
PACF	cuts off to zero after lag p	dies out slowly	dies out slowly

A method, known as the Box-Jenkins approach which is used to analyze univariate time series, forms the basis for the time series analysis and forecasting that follows. This method, which relies on the above theoretical processes, involves three phases.

i) The first phase is identification, or model selection, where we determine the type of underlying probabilistic process that governs the behavior of the series.
ii) The second phase is estimation of the model parameters. Least squares or maximum likelihood estimation methods can be used.
iii) The third phase is diagnostic checking where we asses the adequacy of the model parameters. It may be necessary to re-specify the model and reestimate parameters until a well fitting model can be found.

Once an adequate model is selected, forecasting follows. For AR(1) process, $x_t = \alpha_1 x_{t-1} + z_t$, using $\hat{\alpha}_1$ we produce forecast for one period into the future. Specifically, we use $\hat{x}_{t+1} = \hat{\alpha}_1 x_t$ for forecasting. For $\hat{x}_{t+2}$, we use $\hat{x}_{t+2} = \hat{\alpha}_1 \hat{x}_{t+1} = \hat{\alpha}_1(\hat{\alpha}_1 x_t)$. Generally, forecasts L periods into the future use

$\hat{x}_{t+L} = \hat{\alpha}_1^{\,L} x_t$. Since $\mathrm{var}(z_t) = \sigma_z^2$, the variance of z_t is the forecast error variance for one future period of an AR process. For L future periods, forecast error variance becomes $(1+\alpha_1^2+\alpha_1^4+.....+\alpha_1^{2L-2})\sigma_z^2$; the error variance increases as forecasts are made further into the future (ibid).

For MA(1) process, $x_t = \theta_0 + z_t + \beta_1 z_{t-1}$, we produce forecasts for one period into the future using $\hat{x}_{t+1} = \theta_0 + \beta_1 \hat{z}_t$ where $\hat{z}_t = x_t - \theta_0 - \hat{\beta}_1 z_{t-1}$. Forecasts for subsequent periods simply equal to θ_0, the mean, since $\hat{z}_{t+1}, \hat{z}_{t+2} \ldots$ are not known at time t. Thus an MA(q) model has forecast values based on only the mean after period q. Forecast error variance for MA (q) is given by

$$\mathrm{var}(z_t) + \mathrm{var}(z_t)\sum_{i=0}^{q} \beta_i^q = \sigma_z^2 + \sigma_z^2 \sum_{i=1}^{q} \beta_i^2 = \sigma_z^2 \sum_{i=0}^{q} \beta_i^2 \qquad (5)$$

For ARMA(1,1) model, $x_t = \alpha_1 x_{t-1} + \theta_0 + z_t + \beta_1 z_{t-1}$, $\hat{x}_{t+1} = \hat{\alpha}_1 x_t + \theta_0 + \beta_1 \hat{z}_t$, and $\hat{x}_{t+2} = \hat{\alpha}_1^2 x_t + \theta_0$. Generally, for ARMA(p,q) forecasts L periods into the future are based on (Cryer, 1986, pp.168-169)

$$\begin{aligned} \hat{x}_{t+L} &= \alpha_1^{\,L} x_{t+L-1} + \ldots \hat{\alpha}_p^{\,L} x_{t+L-p} + \theta_0 + \beta_1^1 \hat{z}_t + \ldots \beta_q \hat{z}_{t+l-q} && \textit{for } L = 1......q \\ \hat{x}_{t+L} &= \alpha_1^{\,L} x_{t+L-1} + ... + \hat{\alpha}_p^{\,L} x_{t+L-p} + \theta_0 && \textit{for } L > q \end{aligned} \qquad (6)$$

7 Results

Tables that give forecasts for each airlines using both the econometric and Box-Jenkins approaches appear at the end of the paper; they extend from 1997 to 2004 for each airlines.

The identification phase revealed that nine out of the thirty-three series followed a random process: any autoregressive or moving average processes were absent. As a result, forecasting was based on the mean level of the data. Out of the nine, one series was stationary and exhibited a random process without any differencing. For this case, forecast L periods into the future rested on $\hat{x}_{t+L} = \theta_0$, *where* θ_0 is the mean. For the rest of the random processes, for which stationarity was induced by differencing, forecast L periods into the future used $\hat{x}_{t+L} = \theta_0 + \hat{x}_{t+L-1}$.

The majority of the remaining 24 series exhibited autoregressive processes of varying degrees: specifically, 22 had damped exponential or damped sine wave ACF plots which suggested autoregressive processes. Closer examination revealed spikes at lag one of the PACF plots for 11; spikes at the first two lags for 5; spikes at the first three lags for 2; and spikes at lags four, at lags one and five, and at lags two, three, and five for the remaining 4. Diagnostic checking, involving the examination of the residuals based on initial estimation, the goodness-of-fit of several initially fitted models, and parameter significance provided support for the above findings.

Two series exhibited a moving average process of order 1; their PACF plots tailed off in sine wave manner while their ACF plots cut off to zero after lag 1. Again diagnostic checking supported fitting such a model to the data.

For those following a random process, the one alternative available for forecasting is the use of the mean. It seems that in these cases, such forecasts are highly tentative: in any future period L, the variable being forecasted is random and could take on any value other than the mean. Perhaps, the use of the econometric approach is far better for such instances.

Since the forecast error variance increases overtime, for the rest of the models, predictions only for few periods into the future are sensible. Moving average models are fit for series that were beset by some random shock which persisted into q subsequent periods. AR models are fit for data whose present values depend on p past values of the series. It is surprising that only two series appear to exhibit MA processes since it seems reasonable to expect more airlines to be subjected to shocks, such as a recession, which would affect consequent values of aircraft demand. The predominance of AR processes might suggest that airlines respond to previous periods circumstances more than to a one time shock when acquiring aircraft.

8 Comparing the Two Approaches

I) In general, the forecasts made using the Box-Jenkins approach tend to be under those made using the econometric models.

II) One of the reasons that might have contributed to this outcome is the presence of many missing data points.

III) Another reason has been the shortness of the series. The longest series consisted of only 19 data points. Some analysts believe that ARMA models while very useful, are particularly good for series that have more than 50 observations. In general, the longer the series the better the fit of such models. Therefore, the relatively short series in this study might not have resulted in well fitting models.

IV) Finally, the highly subjective nature of the interpretation of the ACF and PACF in the identification phase can be problematic in that high level of accuracy requires considerable experience.

9 Concluding Remarks

In this paper, we described methods for forecasting fleet size in the international airline industry. The econometric model uses a demand model for air travel and links this to a cost model for air travel production. From derived demand equations for the factors of production, we can predict fleet size given any number of possible scenarios. Our method allows for the endogenity of outputs.

While our cost model seems to be effective, our demand data are somewhat lacking. Our estimates of demand growth seem unreasonable. We will need to get world data on demand that is less aggregated. Ticket prices from particular airports, competitors ticket prices, and unemployment data would substantially improve the estimates. With airport-specific data, we could include city dummies to capture "tourism effects." There are problems, however. Except for OECD countries, unemployment data are difficult to find. While it may be difficult to get better data on air travel demand, this will be of the greatest benefit for our model, and we will be able to better predict world aircraft demand.

The airline industry is notorious for ordering equipment at points of peak demand, but getting delivery at a point when demand is slow. If one were to take common approaches and assume that carriers have myopic and naive expectations about future demands for air travel, the negative correlation between the level of new traffic and the number of aircraft deliveries would imply irrational behavior on the part of airline managers. Our experience with these short run models is that they do not work well and also typically imply negative shadow values of increased capital. There are several avenues that we might employ to improve these traditional models and obtain more sensible results. First, we might directly incorporate the lead time necessary to acquire new aircraft. This may prove difficult since there are different kinds of markets for new equipment and since varying constraints are imposed by institutional arrangements and changes in tax law. For example, a carrier has considerable flexibility in the disposition of owned equipment than in that of equipment acquired through an operating or a capitalized lease. This is somewhat complicated by the fact that lead time is a function of the overall demand for equipment of that particular size/fuel efficiency configuration.

Second we might more realistically capture the nature of expectations in our models. Firms use more than a single period of information in developing their expectations about future demands. The modeling strategy thus would be to identify a lag structure of past traffic demands in the construction of expectations regarding future demands. This approach is conceptually easier to describe than to implement. Even fairly stylized and parsimonious lag structures complicate the firm's optimal control problem greatly and may necessitate the use of numerical (instead of analytic) solutions to construct equipment demands.

A final necessary requirement for our modeling approach is that it be able to address a wide range of characteristics of the fleet, including a behavioral model which explains why some of these characteristics have been adopted and others passed over. Not the least of these considerations is that some innovations have not been available (such as the use of 800 passenger jet equipment). Further, it is clear that equipment is chosen to serve a particular route structure. We have begun to address these issues in some of our previous work (Good, Nadiri, Sickles, 1992). However, further work is necessary, particularly with respect to the characterization of the distribution of route types, as against merely averaging their characteristics.

Table 1: Demand Equation Parameter Estimates

Variable	Parameter Estimates for Europe	Parameter Estimates for North America	Parameter Estimates for Asia
LNPRICE	-0.120821 (-1.423)	-0.682482 (-2.963)	0.289537 (3.715)
LNPOP	-2.645656 (-13.173)	6.511079 (3.320)	1.397896 (5.112)
LNPCI	2.720793 (13.154)	1.045872 (1.241)	1.578938 (10.840)
LNLFP	0.013678 (5.533)	0.010168 (1.736)	-0.007008 (-2.115)
R^2 values	0.9813	0.8534	0.9735

Table 2: Fitted Shares under the cost minimization assumption.

Labor Share	0.286
Materials Share	0.429
Energy Share	0.202
Capital Share	0.066

Table 3: Fitted Shares under the profit maximization assumption.

Labor Share	0.287
Materials Share	0.426
Energy Share	0.204
Capital Share	0.068

Table 4: Cost equation parameter estimates under the cost minimization and profit maximization assumptions.

Variable	Parameter Est. under cost minimization	T-Value	Parameter Est. Under profit maximization	T-Value
LNLP	0.286218	.	0.286993	.
LNLPEP	-0.010434	-2.369	-0.024074	-4.440
LNLPKP	-0.005140	-1.386	-0.010554	-2.574
LNEP2	0.037455	7.804	0.038768	8.313
LNEPKP	-0.020244	-6.728	-0.018627	-6.301
LNMP2	0.010030	1.058	-0.45730	-3.768
LNKP	0.082510	.	0.082350	.
LNSQ	0.908328	33.028	0.883560	19.494
LNNQ	0.016033	2.542	-0.008594	-0.771
LNSQNQ	-0.031847	-3.033	-0.024780	-1.143
LNLF	-0.533125	-4.765	-0.464192	-2.353
XWB	-0.012174	-2.465	-0.009137	-1.849
XASZE	0.004371	0.866	0.003030	0.590
LNLP2	0.008244	1.117	-0.017905	-1.589
LNLPMP	0.007330	1.089	0.052533	5.312
LNEP	0.201809	.	0.204270	.
LNEPMP	-0.006777	-1.187	0.003933	0.659
LNMP	0.429463	.	0.426388	.
LNMPKP	-0.010583	-3.166	-0.010736	-3.081
LNKP2	0.035966	11.848	0.039917	13.154
LNSQ2	0.062263	1.504	0.406918	9.634
LNNQ2	0.010609	2.333	0.011143	2.846
LNSL	0.137056	3.061	0.014141	0.182
XPJ	-0.013768	-6.075	-0.013088	-5.856
XAA	0.021570	4.605	0.019196	4.022

Table 5: Forecasts for Aircraft Demand

Air Canada	1997	1998	1999	2000	2001	2002	2003	2004
average number with cost minimization and profit maximization	136.3	146.7	158.1	170.6	184.3	199.4	216.0	234.2
number using time series forecasting	118.2	119.3	119.2	118.5	117.5	116.8	116.4	116.4

Air France	1997	1998	1999	2000	2001	2002	2003	2004
average number with cost minimization and profit maximization	156.4	159.1	161.9	164.8	167.7	170.7	173.8	176.9
number using time series forecasting	172.7	176.4	179.7	182.7	185.4	188.1	190.7	193.2

Air India	1997	1998	1999	2000	2001	2002	2003	2004
average number with cost minimization and profit maximization	25.8	26.6	27.5	28.4	29.4	30.4	31.4	32.5
number using time series forecasting	19.5	19.5	19.5	19.5	19.5	19.5	19.5	19.5

Air New Zeland	1997	1998	1999	2000	2001	2002	2003	2004
average number with cost minimization and profit maximization	49.2	51.0	52.9	54.9	57.0	59.1	61.4	63.7
number using time series forecasting	28.8	30.0	31.2	32.4	33.6	34.8	36.0	37.2

Air Pakistan	1997	1998	1999	2000	2001	2002	2003	2004
average number with cost minimization and profit maximization	49.9	51.6	53.4	55.4	57.3	59.4	61.6	63.9
number using time series forecasting	42.5	41.5	40.4	39.5	38.6	37.9	37.3	36.7

Alitalia	1997	1998	1999	2000	2001	2002	2003	2004
average number with cost minimization and profit maximization	102.8	104.6	108.0	108.4	111.1	112.3	114.3	116.3
number using time series forecasting	112.9	114.7	115.9	116.8	117.5	118.0	118.3	118.6

American	1997	1998	1999	2000	2001	2002	2003	2004
average number with cost minimization and profit maximization	876.1	963.4	1061	1170	1293	1432	1588	1765
number using time series forecasting	723.4	747.8	772.5	797	822	847	872.4	897

British Air	1997	1998	1999	2000	2001	2002	2003	2004
average number with cost minimization and profit maximization	229.5	233.6	237.8	242.1	246.5	251.0	255.6	260.3
number using time series forecasting	219.6	221.9	224.2	226.5	228.8	231.2	233.5	235.8

Continental	1997	1998	1999	2000	2001	2002	2003	2004
average number with cost minimization and profit maximization	405.3	446.2	492.0	543.7	601.9	667.6	742.2	826.9
number using time series forecasting	337.5	350.8	364.1	377.4	390.6	403.9	417.2	430.4

Delta	1997	1998	1999	2000	2001	2002	2003	2004
average number with cost minimization and profit maximization	741.7	814.1	895.0	985.7	1087	1201	1330.7	1476
number using time series forecasting	631.7	653.5	675.4	697.3	719.2	741.1	762.9	784.8

Finnair	1997	1998	1999	2000	2001	2002	2003	2004
average number with cost minimization and profit maximization	46.5	47.4	48.3	49.2	50.1	51.1	52.1	53.1
number using time series forecasting	46.2	47.0	48.0	49.0	49.0	49.6	50.1	50.7

Garuda	1997	1998	1999	2000	2001	2002	2003	2004
average number with cost minimization and profit maximization	70.3	72.9	75.7	78.6	81.7	84.9	88.3	91.8
number using time series forecasting	61.6	80.4	81.7	89.1	77.7	76.0	63.7	68.1

Iberia	1997	1998	1999	2000	2001	2002	2003	2004
average number with cost minimization and profit maximization	126.8	129.1	131.5	133.9	136.4	139.0	141.6	144.3
number using time series forecasting	126.4	128.4	130.4	132.4	134.4	136.4	138.4	140.4

Indiana Airlines	1997	1998	1999	2000	2001	2002	2003	2004
average number with cost minimization and profit maximization	59.9	61.9	64.1	66.3	68.6	71.0	73.5	76.2
number using time series forecasting	55.7	55.2	56.4	56.7	57.1	57.8	58.5	58.2

JAL	1997	1998	1999	2000	2001	2002	2003	2004
average number with cost minimization and profit maximization	97.1	102.1	105.8	110.0	113.5	117.7	122.0	126.5
number using time series forecasting	91.2	91.8	92.3	92.9	93.5	94.1	94.7	95.3

Japan Asia Airways	1997	1998	1999	2000	2001	2002	2003	2004
average number with cost minimization and profit maximization	8.9	9.3	9.6	10.0	10.4	10.8	11.2	11.6
number using time series forecasting	7.5	7.4	7.3	7.2	7.1	7.0	7.0	6.9

KAL	1997	1998	1999	2000	2001	2002	2003	2004
average number with cost minimization and profit maximization	98.2	101.9	105.8	109.9	114.1	118.6	123.3	128
number using time series forecasting	109.0	116.0	123.0	130.0	137.0	144.0	151.0	158

KLM	1997	1998	1999	2000	2001	2002	2003	2004
average number with cost minimization and profit maximization	59.4	60.5	61.6	62.7	63.9	65.1	66.3	67.5
number using time series forecasting	53.5	53.8	54.0	54.3	54.5	54.8	55.0	55.3

Lufthansa	1997	1998	1999	2000	2001	2002	2003	2004
average number with cost minimization and profit maximization	238.8	243.1	247.5	252.0	256.6	261.4	266.2	271.2
number using time series forecasting	222.5	222.5	222.5	222.5	222.5	222.5	222.5	222.5

Northwest	1997	1998	1999	2000	2001	2002	2003	2004
average number with cost minimization and profit maximization	484.8	534.1	589.4	651.6	721.6	800.7	890.1	991.6
number using time series forecasting	338.8	331.0	323.7	317.0	310.8	305.0	299.6	294.6

Philippines Airlines	1997	1998	1999	2000	2001	2002	2003	2004
average number with cost minimization and profit maximization	58.0	60.1	62.4	64.8	67.3	69.9	75.6	75.5
number using time series forecasting	54.6	55.5	56.4	57.3	58.1	59.0	59.9	60.8

Quantas	1997	1998	1999	2000	2001	2002	2003	2004
average number with cost minimization and profit maximization	56.8	58.7	60.8	62.9	65.2	67.5	70.0	72.5
number using time series forecasting	63.1	67.3	71.2	70.1	72.4	74.6	77.2	84.2

SAS	1997	1998	1999	2000	2001	2002	2003	2004
average number with cost minimization and profit maximization	178.2	181.5	184.8	188.1	191.6	195.1	198.7	202.4
number using time series forecasting	192.5	203.5	208.6	214.7	224.0	231.6	236.7	242.9

SIA	1997	1998	1999	2000	2001	2002	2003	2004
average number with cost minimization and profit maximization	76.9	79.8	82.8	86.0	89.3	92.8	96.4	100.2
number using time series forecasting	82.7	86.8	90.8	94.8	98.8	102.7	106.6	110.5

Sabena	1997	1998	1999	2000	2001	2002	2003	2004
average number with cost minimization and profit maximization	33.6	34.1	34.7	35.3	35.9	36.5	37.1	37.8
number using time series forecasting	29.9	29.7	29.5	29.3	29.1	28.8	28.6	28.4

Swissair	1997	1998	1999	2000	2001	2002	2003	2004
average number with cost minimization and profit maximization	59.1	55.0	56.0	57.0	57.9	58.9	59.9	61.0
number using time series forecasting	46.4	45.5	44.7	43.8	42.9	42.1	41.2	40.3

TAP	1997	1998	1999	2000	2001	2002	2003	2004
average number with cost minimization and profit maximization	40.0	40.1	41.5	42.2	43.0	43.8	44.6	45.4
number using time series forecasting	37.4	35.1	34.2	35.1	35.6	36.7	38.6	39.9

Thai International	1997	1998	1999	2000	2001	2002	2003	2004
average number with cost minimization and profit maximization	46.5	48.3	50.2	52.2	54.2	56.4	58.7	61.1
number using time series forecasting	56.7	59.7	65.9	69.0	72.0	75.1	78.2	81.3

TWA	1997	1998	1999	2000	2001	2002	2003	2004
average number with cost minimization and profit maximization	236.3	254.2	273.9	295.4	319.0	344.9	373.3	404.6
number using time series forecasting	217.6	219.4	217.6	213.4	208.6	204.3	201.7	200.8

USAir	1997	1998	1999	2000	2001	2002	2003	2004
average number with cost minimization and profit maximization	690.9	767.9	855.2	954.5	1067.7	1197.1	1345.3	1516
number using time series forecasting	605.4	637.5	669.6	701.7	733.8	765.9	798.0	830

United	1997	1998	1999	2000	2001	2002	2003	2004
average number with cost minimization and profit maximization	742.8	816.6	899.0	991	1095	1211	1343	1491
number using time series forecasting	601.5	607.8	615.2	617	624	632	639.5	649

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