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RICE UNIVERSITY

Essays on Domestic and International Airline Economics with Some Bootstrap Applications

by

Anthony Kenneth Postert

A THESIS SUBMITTED
IN PARTIAL FULFILLMENT OF THE
REQUIREMENTS FOR THE DEGREE

Doctor of Philosophy

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Abstract

Essays on Domestic and International Airline Economics with Some Bootstrap Applications

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We present several essays on topics in airline economics. The first essay presents a model of U.S. aircraft demand. This joint model of demand for and supply of commercial air service allow us to simulate the effects of emerging technologies in engine design capabilities and in aircraft capacities on airline fleet sizes.

The second essay examines the possibility that relatively high prices in the European airline industry are due to market power. We examine the market conduct of firms in the European airline industry and find little evidence that competitive pricing is violated on average.

In the third essay, we present an integrated model of world aircraft demand. We estimate the demand for both passenger and cargo services and tie this demand to cost analysis of the carriers. Our cost model is used to generate derived demand schedules for the factors of production, in particular flying capital.

We take a brief look at bootstrap techniques in the forth essay. Bootstrapping has become a powerful technique for estimating sampling distributions of statistics since its introduction by Efron (1979). We discuss the bootstrapping procedure and present some small sample evidence of its effectiveness through Monte Carlo experiments.

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The fifth essay applies the bootstrap to a model of U.S. aircraft demand. We bootstrap confidence intervals for Allen-Uzawa partial elasticities of substitution and price elasticities. We find prediction intervals for forecasts of airline's fleet size using the bootstrap.

The sixth essay suggests an application of leapfrogging measures to the airline industry. A detailed look at Hultberg and Postert (1998) is presented. Three rank mobility measures are presented and used to determine the amount of leapfrogging in the data. A human capital augmented Solow-Swan model is fit to the data and we use bootstrapping to calibrate the model.

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Chapter 1

Introduction

The domestic industrial policy of the United States has undergone changes that have spread world wide. A major turning point in policy was the Airline Deregulation Act of 1978. The Act influenced moves toward deregulation in trucking and rail, as well as deregulation in non-transport sectors such as banking and telecommunications. It is doubtful that these latter movements toward deregulation would have proceeded so quickly had the early experience with airline deregulation been less positive. Domestic deregulation of the U.S. airlines also has been influential in the policies of other countries. Since 1978, there has been deregulation of the domestic air transportation sectors in Canada and Australia.

Until recently, the European airline industry has been sheltered from competition. Bilateral treaties were used to set fares and flight frequencies and flag carriers were heavily subsidized. With the ongoing liberalization of the industry, these carriers have been exposed to competitive pressures of the sorts that U.S. firms felt in the late 1970s and on.

The traditional superiority of the U.S. has not been limited solely to its airlines. The U.S. has long been the world's leader in aviation technology for civil and military aircraft. During the past several decades, U.S. firms have transformed this position of technological leadership into a thriving industry with large domestic and international sales of aircraft and related products. In 1992, sales of civil aircraft peaked at $39.9 billion, with exports of $24.3 billion. This leadership has contributed significantly towards reducing the current U.S. trade imbalance.

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Dispite its historic record of success, there has been concern about whether the U.S. aeronautics industry will maintain its worldwide leadership position. Increased competition, both technological and financial, from European and other non-U.S. aircraft manufactures has reduced the global market share of U.S. airframe manufacturers to only two. Despite gains made in the recent GATT negotiations that limit subsidies to Airbus, substantial competition is expected to continue. Forthcoming noise abatement requirements and environmental concerns create additional challenges faced by U.S. producers and purchasers of aircraft.

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, this has been replaced by large trading blocks. The European Community has embarked on an ambitious effort to remove economic barriers among the twelve member states and to establish an integrated market system. 1992 EC integration presages the momentum of global changes in international trading arrangements that place special demands on the global economic community. It is hard to argue that these developments in Europe have not been pivotal factors in the passage of the North American Free Trade Agreement.

This changing environment means that governments and industries that have enjoyed success in some international and/or domestic markets will find that terms of trade are altered. Continuation of current subsidies and business as usual may prove infeasible. On the other hand, economic entities that may have been unable to successfully compete in some markets may find new business opportunities and avenues for their profitable exploitation. As countries around the world have developed under this new environment, so has the patterns of air traffic. For example, before the start of the "Asian Crisis," 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

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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.

Often in applied econometrics, one sees point estimates for various elasticities and other estimates. These are almost never presented with standard errors or confidence intervals. However, no one would think to report parameter estimates of a regression without reporting either t-statistics or p-values. A possible reason that many econometricians do not report standard errors on elasticities is that the distribution theory for these values is intractible. Bootstraps can be of some help in this regard. By boostrapping parameter estimates, distributions for elasticities can be built, no matter how non-linear the elasticity as a function of the parameters.

One of the most important tasks of the applied econometrician is to produce forecasts of some type. However, forecasts are always steaped in some uncertainty. The econometrician will never exactly predict the value of interest. This does not mean that the forecasts are of no use, but the degree of confidence in the forecast should be expressed. By expressing forecasts as both point estimates and prediction intervals, the forecast user is given the information that allows for sound judgement. The values at the edge of the prediction intervals can be used in "what if" analysis.

Typically, there are two sources of error in forecasts. One is the sampling error in the parameter estimates of the model being used. The other is random error term in the model. While the parameter estimates may be very precise, forecasting the error term is, by definition, impossible. Bootstrapping allows us to find prediction intervals in a straighforeward fashion.

In this dissertation, we explore some applied economic issues as they relate to the airline industry, both U.S. and international. In Chapter 2, we develope a model of aircraft demand for the U.S. We explore the competitiveness of European airline

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industry in Chapter 3. In Chapter 4, we outline a procedure for forecasting the world-wide size of airline fleets. In Chapter 5, bootstrapping and Heterogeneous and Autocorrelation Consistent (HAC) Covariance Estimators, which are used to calculate confidence and prediction intervals in the analyses carried out in Chapters 6 and 7. We apply the bootstrap to calculate confidence intervals for elasticity estimates and to produce prediction intervals for forecasts of airline fleet growth in Chapter 6. We examine the application of recent work in the growth literature to the convergence in production of carriers in the international airline industry in Chapter 7. We also utilize bootstrapping procedures to test for rank movements in such measures in Chapter 7. Chapter 8 concludes.

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Chapter 2

A Model of U.S. Aircraft Demand

2.1 Introduction

The airline industry has grown considerably since 1978 when the industry was deregulated, and continues to grow (Morrison and Winston, 1995). Consumers have benefited greatly due to airline deregulation. Caves, et al. (1987) state that deregulation has increased passenger-mile productivity growth between 1.3 and 1.6 percent per year. Morrison and Winston (1995) show that deregulation has lead to fares that are, on average, 22 percent lower than if regulation was still in place.

In addition to lower prices, other benefits have occurred. With the increase in hub-and-spoke systems due to the elimination of restrictions on routing, Morrison and Winston (1995) find a $10.3 billion a year benefit from the increased flight frequency offered by the hub-and-spoke system. While it is true that passengers often must take less direct routes to their destinations, the number of passgers changing planes has not increased dramatically since deregulation (Morrison and Winston, 1995). Additionally, the passengers changing planes rarely have to change airlines. This constitutes an improvement in service as most passengers perfer on-line conections (Morrison and Winston, 1995).

The benefit of hub-and-spoke systems is reduced due to longer travel time, both in-flight and waiting for flights. Ground time has increased by five minutes regardless of distance traveled. However, the cost of the increase in travel time ($2.8 billion per year) is more than offset by the benefit of hub-and-spoke systems (Morrison and Winston, 1995).

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While consumers have gained a great deal through deregulation, there are other possible innovations that will benefit not only consumers, but airlines and airframe manufactures as well. In this essay, we examine airframe and engine innovations and the benefits of those innovations that accrue to equipment manufacturers, airlines and passengers.

The primary role of the National Aeronautics and Space Administration (NASA), in supporting civil aviation, is to develop technologies that improve the overall performance of the integrated air transportation system, making air travel safer and more efficient, while contributing to the economic welfare of the United States. NASA conducts much of the basic and early applied research that creates the advanced technology introduced into the air transportation system. Through its technology research program, NASA aims to maintain and improve the leadership role in aviation technology and air transportation held by the United States for the past half century.

To meet its objective of assisting the U.S. aviation industry with the technological challenges of the future, NASA must identify research areas that have the greatest potential for improving the operation of the air transportation system. By thoroughly understanding the economic impact of advanced technologies and by evaluating how those new technologies would be used within the integrated aviation system, NASA can balance its research program and help speed the introduction of high-leverage technologies.

The chapter is organized as follows. First, we discuss the model of aircraft demand in Section 2.2. This includes models of air travel demand and air travel supply. The specifics of how we use the estimated parameters from our travel demand and travel supply models to project aircraft demand are explained in Section 2.3. In Section 2.4, we define a baseline scenario and three alternative scenarios for changes in the supply

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and demand variables. From these changes, we project travel demand changes, air fleet sizes and operating margins for the period 1995–2005. Section 2.5 concludes.

2.2 The Aircraft Demand Model

In creating this model, we had some specific goals in mind. A primary objective was to generate high-level estimates from broad industry-wide supply and demand factors. We envisioned being able to forecast the demand for air travel under a variety of scenarios. From these air travel demand forecasts, we then could then estimate the derived demand for the factors of production, most importantly, the number of aircraft in the fleets of U.S. passenger air carriers.

To create the model, we first identified 85 key U.S. airports from which flights originate and then developed airport-level demand models for passenger service provided by major air carriers. Furthermore, we linked the air carrier-specific demand schedules to an analysis of the carrier's technologies via their cost functions expressed in terms of the prices of the major inputs—labor, fuel, materials, and flight equipment. Flight equipment was modeled in an especially detailed way by incorporating some key operating characteristics of aircraft.

From the cost functions, we generated derived demand schedules for the factors of production, particularly aircraft fleets. The derived demand schedules are functions of the price of the factor of production, prices of the other factors, parameters that describe the both the aircraft and network used by the carrier, and the level of passenger service supplied.

The aircraft demand model starts with the factors affecting the demand for air passenger travel at the airline and airport levels. It then examines the determinants of airline cost functions and the resulting industry supply curves. The objective of both analyses is to obtain parametric estimates for the air travel demand and airline

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cost functions. These parametric estimates can then be combined with user-specified values of key supply and demand variables to generate industry-level forecasts of revenue passenger-miles (RPMs) flown and the number of aircraft in the fleets of U.S. passenger air carriers.

2.2.1 Air Travel Demand

Our first analytical task was to develop a model of demand for an airline's passenger service. From a particular airport at origin i, carrier j will generate a certain level of passenger traffic. The U.S. Department of Transportation's (DOT's) Origin and Destination data records a one in ten sample of all tickets; from these, the RPM service origination at a particular airport for a particular carrier is constructed. Demand for a carrier's service is driven by the carrier's passenger fare yield (measured by the average ticket price for flights originating at airport i divided by the average number of RPMs flown), its competitors' yields, and the size and economic prosperity of the market. We modeled the economic characteristics of the Standard metropolitan Statistical Area (SMSA) surrounding the 85 airports in the study in terms of the area's population, per capita income, and unemployment rate. The period under consideration was from the first calendar quarter of 1979 through the last calendar quarter of 1992.

The demand function, in equation form, is

$$q_{t,i,j} = D_{t,i,j}\left(p_{t,i,j}, P_{t,i,c}, x_{t,i}\right), \tag{2.1}$$

where $q_{t,i,j}$ is the scheduled demand (in RPMs) originating at time t from airport i for carrier j; $p_{t,i,j}$ is the average yield for service originating at time t from airport i for carrier j; and $p_{t,i,c}$ is the average yield for the other carriers generating traffic at time t from airport i for carrier j. The $x_{t,i}$ are the other demand characteristics at

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time t for airport i. Conventional treatments for firm and airport fixed effects were used. These effects capture those important characteristics of a particular city that are not easily measured, such as tourism effects. We use a log–log specification for (2.1). so that the regression coefficients may be interpreted as elasticities.

The total demand for an air carrier's passenger service was then constructed by summing the airport-specific demand equations. In terms of (2.1), the total demand for a carrier's service is given by

$$q_{t,j} = \sum_{i=1}^{ap} q_{t,i,j}, \tag{2.2}$$

where ap is the number of airports (85).

Table 2.2.1 shows the demand variables that were incorporated into the model. All the explanatory variables were found to be statistically significant at the 95 percent level of confidence.

2.2.2 Air Travel Supply

The second major component of our econometric study explains total carrier costs in terms of output quantities, factor prices, aircraft attributes, and network traits. The cost analysis was based mainly on observations from the DOT Form 41 data. The cost

Table 2.1 U.S. RPM Demand Variable Estimates

Variable	Parameter Estimate	T-Ratio
Own yield	-1.165	-46.00
Competitors' yield	0.095	1.83
Per capita income	1.334	8.33
Population	1.228	10.64
Unemployment rate	-0.121	-4.63

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data follows 13 U.S. passenger air carriers with quarterly observations between the beginning of 1979 and the end of 1990. These firms are the set of former certificated carriers that existed throughout the study period and account for well over 95 percent of the domestic air traffic. From the Form 41 data, we generated a separate set of demand equations for each of the carrier's factors of production based on standard economic assumptions concerning the cost-minimizing behavior of a carrier. In turn, these demand equations permitted examinations of the impact of factor price and factor productivity changes, fleet and network configurations, and aircraft operation characteristics.

Scheduled RPM traffic for carrier j at time t was constructed as the sum of origination traffic supplied by the carrier for all airports from which it offered flights. This was the first of the two outputs considered in the cost function below. The second was the level of nonscheduled RPM service. The two generic output categories at time t for carrier j are designated $y_{t,j,1}$ and $y_{t,j,2}$ for scheduled and nonscheduled RPM demand, respectively. The factors of production are labor, energy, materials, and capital. Factor prices are labeled w. In the model, capital refers to aircraft fleets only. Capital other than aircraft, such as ground structures and ground equipment, is included in the materials category. Omitting the time and firm subscripts, the transcendental logarithmic (translog) costs function is given by

$$\begin{aligned}\log TC \; = \; & \alpha_0 + \sum_{i=1}^{2} \alpha_i \log y_i + \sum_{i \leq j}^{2} \sum_{j=1}^{2} \alpha_{ij} \log y_i \log y_j + \sum_{i=1}^{4} \beta_i \log w_i \\ & + \sum_{i \leq j}^{4} \sum_{j=1}^{4} \beta_{ij} \log w_i \log w_j \\ & + \sum_{i=1}^{4} \rho_i \text{aircraft attributes}_i \log w_{capital} \\ & + \sum_{i=1}^{2} \gamma_i \text{network traits}_i . \end{aligned} \quad (2.3)$$

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Cost shares for labor, energy and materials are given by

$$M_i = \beta_i + \sum_{j=1}^{4} \beta_{ij} \log w_j. \tag{2.4}$$

The cost share for capital is

$$M_{capital} = \beta_{capital} + \sum_{i=1}^{4} \beta_{capital,j} \log w_j + \sum_{i=1}^{4} \rho_j \log \text{aircraft attributes}_j. \tag{2.5}$$

The translog cost equation can be viewed roughly as a second-order approximation of the cost function dual to a generic production function. The translog is the most widely used of the flexible functional forms (Green, 1993). The translog functional form was introduced by Christensen, et al., (1973) as a production function that did not impose homotheticity or separability. However, we did impose homotheticity in the cost function and imposed symmetry of the cross-price derivatives. Symmetry and linear homogeneity in input prices are imposed by the restriction:

$$\alpha_{ij} = \alpha_j i, \forall i, j; \beta_{ij} = \beta_j i, \forall i, j; \sum_i \beta_i = 1; \sum_j \beta_{ij} = 0; \text{ and } \sum_j \rho_j = 0. \tag{2.6}$$

Summary statistics based on the translog cost equation and its associated share equations are provided by the Allen-Uzawa and Morishima partial elasticities of substitution and by price elasticities. A measure of returns to scale may also be obtained from the parameter estimates.

The Allen-Uzawa partial elasticities of substitution are given by

$$\begin{aligned} \theta_{ij} &= \frac{\beta_{ij} + S_i S_j}{S_i S_j} \\ \theta_{ii} &= \frac{\beta_{ii} + S_i(S_i - 1)}{S_i^2}. \end{aligned} \tag{2.7}$$

Morishima elasticities are given by

$$\sigma_{ij} = (\theta_{ji} - \theta_{ii}) S_i, i \neq j. \tag{2.8}$$

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The own- and cross-price elasticities are

$$\begin{aligned} \epsilon_{ii} &= \theta_{ii} S_i \\ \epsilon_{ij} &= \theta_{ij} S_j, i \neq j \\ \epsilon_{ji} &= \theta_{ij} S_i, i \neq j. \end{aligned} \tag{2.9}$$

Our menu of flight capital characteristics was modeled with a set of attributes of the aircraft fleet. A major component in productivity growth is measured by the effects of changes in these attributes over time (see Baltagi and Griffin, 1988 for an alternative panel data treatment of technological change). We considered the attributes of the capital stock with the following rationales. We expect newer aircraft types, all other things being equal, to be more productive than older types. Newer wing designs, improved avionics, and more fuel efficient engine technologies make the equipment more productive. Once a design is certified, a large portion of the technological innovation becomes fixed for its productive life. The most significant contribution to productivity growth in the 1960s was the introduction of jet equipment. While this innovation was widely adopted, it was not universal for carriers in our sample.

In an engineering sense, transportation industries tend to be characterized by increasing returns to equipment size. Costs for fuel, pilots, terminal facilities and even landing slots can be spread over more passengers. However, large size is not without potential diseconomies. As equipment size increases, it becomes more difficult to fine tune capacity on a particular route. Also, as capacity is concentrated into fewer departures, quality of service declines (the probability that a flight is offered at the time a passenger demands it decreases). This raises particular difficulties in competitive markets where capacity must be adjusted in response to the behavior of rival carriers. Deregulation has accentuated this liability by virtually eliminating monopolies in domestic high-density markets. On the other hand, through more vigorous fare

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competition, deregulation has increased the total volume of traffic, somewhat attenuating this liability. In any event, the operating economies of increased equipment size must be traded off for this limited flexibility.

Fleet diversity also represents tradeoffs. On one hand, having different sizes of aircraft allows a carrier to obtain a better fit between the demands for capacity on a particular route and the type of equipment used. On the other hand, there has been a major trend toward increased standardization of fleets. Having a single aircraft type minimizes costs associated with crew training, maintenance and the inventory of spare parts.

In addition to our two outputs–revenue passenger and revenue cargo ton mile—we include three variable inputs—labor, fuel and materials (an aggregation of supplies and outside services); one quasi-fixed input—flight and ground equipment; and two attributes of airline networks–the stage length and the load factor. Stage length allows us to account for different ratios of costs due to ground-based resources to costs attributable to the actual flight length. Short flights use a higher proportion of ground-based systems than longer flights for a RPM of output. Also, shorter flights tend to be more circuitously routed by air traffic control and spend a lower fraction of time at an efficient altitude than longer flights. The other output characteristic is load factor. Although this variable also can be viewed as a control for capacity utilization and macroeconomic demand shocks, it has been interpreted in many transportation studies as a proxy for service quality. As load factors increase, the number and length of flight delays increase as do the number of lost bags and ticketed passengers who are bumped. Inflight service also declines since the number of flight attendants is not adjusted upwards as load factor increases.

We estimated (2.3), (2.5) and the labor and energy share equations given in (2.4) using iterated seemingly unrelated regressions. The estimates of the cost function are

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provided in Table 2.2.2. The estimation produced estimates that are reasonable. The return to scale estimate at the data mean is 1.073. Seasonal variations were controlled by the inclusion of three seasonal dummy variables. We control for fixed firm effects by including firm dummy variables in the 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, et al., 1990).

The summary statistics for the various elasticities are shown in Tables 2.2.2, 2.2.2 and 2.2.2.

2.3 Forecasting Aircraft Demand

The joint model of supply and demand for commercial passenger air service specified in this paper and the inferences about the demand for airplanes that are embedded in our econometric results allows us to simulate the effects of emerging airframe and engine technologies by modifying characteristics of the planes in service. We can also simulate the growth in total system demand for passenger service and for factor inputs such as the number of aircraft in the fleet.

We follow several general steps when evaluating scenarios:

1. We predict the change in RPMs based upon economic forecasts and demand equation estimates.

2. We estimate airline revenues based upon forecast RPM growth and hypothesized changes in ticket prices.

3. We estimate airline operating costs on the basis of forecasted RPM growth, changes in input prices, and changes in aircraft and network characteristics.

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Table 2.2 U.S. Cost Function Variable Estimates

Variable	Parameter Estimate	T-Ratio
Labor price	0.584	n/a
Labor price squared	-0.020	-2.53
Labor × energy	-0.017	-4.32
Labor × materials	0.032	5.25
Labor × capital	0.005	1.87
Energy price	0.173	n/a
Energy price squared	0.104	40.10
Energy × materials	-0.074	-24.09
Energy × capital	-0.013	-9.20
Materials price	0.164	n/a
Materials price squared	0.089	12.01
Materials × capital	-0.047	-14.80
Capital price	0.079	n/a
Capital price squared	0.055	25.40
Scheduled demand	0.642	25.13
Scheduled demand squared	0.091	1.71
Nonscheduled demand	0.228	10.55
Nonscheduled demand squared	-0.006	-0.11
Scheduled × nonscheduled demand	-0.023	-0.50
Stage length	-0.220	-4.81
Load factor	-0.511	-7.68
Average seats	0.014	4.61
Average age	-0.011	-3.69
Percentage jets	0.003	3.91
Percentage wide-bodied aircraft	-0.060	-6.45

Table 2.3 Allen-Uzawa Partial Elasticities of Substitution at Data Mean

	Labor	Energy	Materials	Capital
Labor	-0.771	×	×	×
Energy	0.832	-1.301	×	×
Materials	1.334	-1.601	-1.789	×
Capital	1.108	-1.268	-2.628	-2.846

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Table 2.4 Morishima Partial Elasticities of Substitution at Data Mean

	Labor	Energy	Materials	Capital
Labor	×	0.936	0.172	1.098
Energy	0.370	×	-0.052	0.006
Materials	0.512	0.030	×	-0.138
Capital	0.312	0.125	0.017	×

Table 2.5 Price Elasticities at the Data Mean

	Labor	Energy	Materials	Capital
Labor	-0.450	0.144	0.219	0.088
Energy	0.486	-0.226	-0.264	-0.100
Materials	0.779	-0.278	-0.293	-0.208
Capital	0.647	-0.219	-0.431	-0.225

4. We predict the aircraft inventory from airline operating costs, the capital share equation, and hypothesized changes in aircraft price and aircraft size.

2.3.1 Forecasting Changes in Travel Demand

To predict changes in travel demand, the model starts with actual airline output for the last two quarters of 1993 and the first two quarters of 1994 and changes it over time based on the estimated demand function coefficients and predicted changes in the explanatory variables. The equation for predicting annual changes in demand is

$$\%\Delta\text{RPM} = \sum_{i=1}^{5} \beta_i \%\Delta X_i, \tag{2.10}$$

where the β_i are the coefficients estimated from the econometric model and the X_i are the explanatory variables. Due to the logarithmic structure of the statistical model, the coefficients are interpreted as elasticities. For example, the coefficient of 1.334 on

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per capita income means that a one percent increase in per capita income raises the demand for air travel by 1.334 percent.

The econometric estimates of the demand function are based on quarterly traffic volume for each airline and airport in the sample. While it is possible to build the demand forecasts up from this highly detailed level, it would be time-consuming and probably add more inaccuracy to the final estimate. Instead, we use the actual scheduled and nonscheduled RPM data for the domestic and international routes of U.S. passenger airlines as the starting point and grow demand at the rate indicated by (2.10). This imposes the constraint that output grows at the same rate for each airline. While this is clearly inaccurate, this is not a significant bias in the model since our goal is to forecast industry-wide demand, costs, and aircraft fleets. For long-run forecasts such as those generated by the model, it is immaterial whether the aggregate demand for air travel is satisfied by a particular carrier such as United Airline or Continental Airlines.

For the purpose of forecasting fares and for calculating industry travel demand, the own-fare and other-fare changes are assumed to be identical. Therefore, the overall price effect is the sum of the two coefficients. The net effect shows that air passenger travel is sensitive to price changes, but not unusually so. The model predicts that a ten percent fare reduction will increase RPMs by 10.7 percent. This implies that after holding other factors constant—such as population and income—changes in air fares will have virtually no effect on total revenues collected by the industry.

2.3.2 Forecasting Changes in Airline Costs

The airline cost equation estimated for the model is shown in (2.3). As shown, total costs are a function of airline outputs, input prices, and aircraft and airline network attributes. Using the supply parameter estimates shown in Table 2.2.1, (2.3) can

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easily be used to produce a time series of predicted changes in airline costs. Using the log-log structure of our translog specification to our advantage, the following forecast equation is derived:

$$\begin{aligned}
\%\Delta\mathrm{TC} \;=\; & \sum_{i=1}^{2}\alpha_i\%\Delta y_i + \sum_{i\le j}^{2}\sum_{j=1}^{2}\alpha_{ij}\%\Delta y_i\%\Delta y_j + \sum_{i=1}^{4}\beta_i\%\Delta w_i \\
& + \sum_{i\le j}^{4}\sum_{j=1}^{4}\beta_{ij}\%\Delta w_i\%\Delta w_j \\
& + \sum_{i=1}^{4}\rho_i\%\Delta\text{aircraft attributes}_i\%\Delta w_{capital} \\
& + \sum_{i=1}^{2}\gamma_i\%\Delta\text{network traits}_i, \qquad (2.11)
\end{aligned}$$

where $\%\Delta$ means annual percentage change in the variable.

As with the demand forecasts, total costs are projected forward from the baseline defined by the reported data. The model increases the costs at the rates predicted by the model, given output forecasts, input price changes, and aircraft and network characteristics.

2.3.3 Forecasting Changes in Aircraft Fleets

Estimating the aircraft fleet required to meet the forecasted travel demand is a somewhat more involved process. Four factors enter into the forecast of aircraft fleets:

1. The changes in total airline costs;

2. The estimated share of aircraft costs in total costs;

3. The forecasted change in aircraft capital costs; and

4. The growth in average aircraft size.

Changes in total airline costs were discussed in the previous section. Referring to (2.5), the aircraft share of total costs is a function of input prices and aircraft

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attributes. As with the costs and demand forecasts, we update the capital share equation through the forecast period as a function of the rates of change in the factor price and aircraft attribute parameters. The equation for changes in the capital cost share is

$$\Delta M_{capital} = \sum_{i=1}^{4} \beta_{capital,j} \% \Delta w_j + \sum_{i=1}^{4} \rho_j \% \Delta \text{aircraft attributes}_j. \tag{2.12}$$

The resulting capital share time series predicts the fraction of total costs that will be spent on aircraft investments. From (2.12), the capital share varies with changes in the price of aircraft and with changes in aircraft characteristics. By multiplying this share estimate by total costs, we obtain a time series of capital investment in aircraft.

The final pieces of information needed to calculate the number of planes in the aircraft fleet are the predicted level of aircraft prices and the average aircraft size. The aircraft price variable can include more than simply the implicit rental price and since it reflects a more comprehensive measure of aircraft ownership costs, it can also be used to reflect the changes in the productivity of aircraft. Aircraft size, as mentioned earlier, is measured by the average number of seats. When the aircraft investment is divided by the product of the aircraft price index and the average size, we obtain the estimated number of planes in each airline's fleet. In equation form, the formula is

$$\text{Number of Planes} = \frac{\text{TC} \cdot M_{capital}}{p_{capital} \cdot \text{Average Size}}. \tag{2.13}$$

2.4 Scenarios and Forecasts

We define a baseline scenario for the supply and demand variables in Table 2.4. Using these values, the aircraft demand model projects annual growth in travel demand of 4.55 percent for the period 1994 through 2005. This prediction compares favor-

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ably with annual growth forecasts of 4.74 percent and 4.69 percent from the Boeing Company (Boeing) and the Federal Aviation Administration (FAA), respectively. In terms of the number of planes required to satisfy this growth in travel demand, the model projects annual growth in the U.S. commercial airline fleet of 2.36 percent for the period 1994 through 2005. This prediction is between Boeing's forecast of 2.13 percent annual growth and the FAA's forecast of 3.28 percent annual growth.

To demonstrate the reasonableness and utility of this model, we evaluate a set of alternative scenarios. These are summarized in Table 2.4 and 2.4.

In a robust economy scenario, economic growth accelerates to three percent per year, as compared to a 2.5 percent growth rate in the baseline scenario. Consequently, the unemployment rate falls from six percent in 1994 to 4.9 percent in 2015. Because of this robust macroeconomic environment, growth in the consumer demand for passenger air travel increases to 5.43 percent. As a result, the derived demand for aircraft improves.

In an oil price shock scenario, the price of oil is assumed to be approximately twice as high by the year 2015 as it would have been in the baseline scenario. As a result, not only do energy prices increase at a faster pace, but real economic growth declines from 2.5 percent per year to zero percent per year. This poor macroeconomic environment causes the demand for passenger air travel to decline dramatically relative to the baseline scenario.

The airlines are assumed to cut fares more rapidly in the fare war scenario than in the baseline scenario. While this stimulates the demand for passenger air travel and the derived demand for aircraft, the scenario is probably self-limiting because negative operating margins would cause many firms to exit the industry and certainly would constrain the availability of credit with which to finance the needed increase in fleets and networks.

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Table 2.6 Baseline Exogenous Variable Growth Rates

Variable	Annual Growth Rate
Fare yield	-1.23%
Income growth	2.50%
Population growth	0.94%
Unemployment rate	0.00%
Labor Price	-1.60%
Energy Price	-1.60%
Materials Price	0.00%
Capital Price	-0.50%
Stage Length	0.35%
Load Factor	0.15%
Average Age	0.00%
Average Size	0.75%
Percentage of jet aircraft	0.00%
Percentage of wide-bodied aircraft	0.04909

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Table 2.7 Baseline and Alternative Scenario Exogenous Variable Growth Rates

Variable	Annual Growth Rate Baseline	Robust Economy	Oil Shock	Fare War
Fare Yield	-1.23%	-1.23%	-1.23%	-2.00%
Income Growth	2.50%	3.00%	0.00%	2.50%
Population Growth	0.94%	0.94%	0.94%	0.94%
Unemployment Rate	0.00%	-1.00%	0.00%	0.00%
Labor Price	-1.60%	-1.60%	-1.60%	-1.60%
Energy Price	-1.60%	-1.60%	2.00%	-1.60%
Materials Price	0.00%	0.00%	0.00%	0.00%
Capital Price	-0.50%	-0.50%	-0.50%	-0.50%
Stage Length	0.35%	0.35%	0.35%	0.35%
Load Factor	0.15%	0.15%	0.15%	0.15%
Average Age	0.00%	0.00%	0.00%	0.00%
Average Size	0.75%	0.75%	0.75%	0.75%
Percentage of Jet Aircraft	0.00%	0.00%	0.00%	0.00%
Percentage of Wide-Bodied Aircraft	0.04909	0.04909	0.04909	0.04909

Table 2.8 Growth in Travel Demand and Aircraft Fleets and Operating Margin Under Various Scenarios for Years 1995–2005.

Scenario	Annual Growth Rate Travel Demand	Aircraft Fleets	Operating Margin
Baseline	4.55%	2.36%	8.0%
Robust Economy	5.34%	3.07%	8.6%
Oil Shock	1.22%	-0.61%	-1.9%
Fare War	5.38%	3.10%	0.4%

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2.5 Conclusions

Our joint model of demand and supply for commercial air service, and the inferences about the demand for airplanes that are embedded 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 characteristics of the planes in service. We are able to simulate the growth in total system demand for service and thus, for factor inputs such as planes. We are able to examine the impact that emerging technologies that focus on engine fuel efficiencies and noise abatement characteristics have on the demand for aircraft. The former will reduce fuel requirements (fuel is one of the factors of production) and the latter will expand the possibilities for increased flight frequency and would lessen the likelihood of flight curtailment in specific urban corridors which would in turn constrain total number of arrivals/departures in selected airports.

Policy considerations are clearly an important component of an aircraft demand model. In the near term, mandating stage three aircraft will lead to the retiring of several older planes, or at the minimum, require retrofitting their engines with hush kits. Though it appears unlikely that such proposals would pass Congress, the recent National Airline Commission has recommended repealing the aircraft excise taxes, modifying the ticket tax, and exempting airlines from the BTU tax. Our model is capable of reflecting the impact of these proposals through their impact on input and output prices in the aircraft investment equation.

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Chapter 3

Competition in the European Airline Industry

3.1 Introduction

It is widely agreed that fares charged on most routes in Europe have been significantly higher than those charged in the U.S. for routes of similar distance. This point was exemplified by the 1984 conference of the Federation of European Consumers where it was decided that it would be cheaper to fly all their delegates to Washington, D.C. than to meet anywhere in Europe (Sampson, 1988).

One possible explanation of the high prices is that European airlines are inefficient relative to U.S. airlines. When compared to the U.S. airline industry, Good, et al. (1993a,b, 1995) found that the European airline industry is highly inefficient. All the European airlines were technically less efficient than all the U.S. airlines for the period 1976–86. Pan Am and Eastern (both of whom have left the industry) had technical efficiency scores higher than those of the European carriers. A high cost structure for the European airline industry has also been noted by McGowan and Seabright (1989) who suggest that high costs in the European airline industry are due to poor utilization of labor and high indirect and overhead costs. They point out that all the non-U.K. airlines have very high labor costs when compared to U.S. airlines. Captain and Sickles (1997), using data largely based on the period 1976 through the mid-1980s, provide support for this in that labor is paid a wage above its marginal revenue product and suggest strong labor unions as a reason.

In this chapter, we also examine another possible reason for relatively high prices in the European airline industry: market power. With schedules set by treaty, the

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airlines in a market would constitute an oligopoly. We examine the European carriers in an oligopoly structure with product differentiation, using a newly developed panel of international carriers (Wingrove, et al., 1996, Kaplan, et al., 1997, and Johnson, et al., 1997) from which we extract data on eight air carriers from Europe with annual observations from 1976 through 1994.

The chapter is organized as follows. In Section 3.2, we discuss the institutional environment in the European industry as it has evolved through the mid-1990s. We next discuss the airline data we use and what it tells us about differences between carriers in Europe, which have operated in a highly regulated, albeit increasingly competitive economic environment, and carriers in the U.S. , which have operated in a deregulated environment over the entire period in Section 3.4. These comparisons point out the substantial differences in total productivity enjoyed by U.S. carriers vis-a-vis their European counterparts, and underscore the need to better understand the sources of these efficiency differentials. We pursue one possible source of productivity difference by considering the implications of a non-competitive model of cartel behavior to characterize the European carriers in Section 3.5. In Section 3.6, we implement this model empirically and test the extent to which European carriers' pricing decisions are at variance with marginal cost pricing. We conclude, in Section 3.7, by suggesting that one way out of the European's conundrum of apparently competitive pricing at the margin and moderate technical inefficiency may be to exploit the low cost structures of U.S. carriers via strategic alliances and code sharing arrangements.

3.2 A Recent History of the European Airline Industry

Since their inception, European "flag carriers," subsidized and even owned by governments, have acted as duopolies: two carriers from two countries would carve up the market on every route and through bilateral agreements determine how many people

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each would carry and charge. Even as late as 1993, European international routes were oligopolistic. The airlines also engaged in "pooling" agreements whereby they would divide revenue, a practice that persisted until the late 1980s on three-fourths of European routes (*The Economist*, 1993). Before deregulation, the airlines had to get permission from national licensing offices and show financial strength to start operating. Established airlines even needed permission to start new routes. Competition was very limited and as a result of strong state protection and aid for five decades, these carriers were inefficient (Lowden, 1996).

This began changing in 1987. Following the lead of Britain, the Aviation Directorate of the European Commission started a staggered set of deregulatory measures that lifted entry to barriers to new airlines and laid the foundations for a competitive environment in the industry (Lowden, 1996). Most significant of the three has been the "Third Package," which the Commission initiated in 1993 (Hotten, 1995) and whose entire provision came into full effect on April 1, 1997 (Lowden, 1996). The third EC liberalization package for air travel, also called the "Open Skies" program, allowed airlines to set fares starting in 1993 (Europe 2000, 1992) and to operate a route between any two EC countries. The open skies program also abolished pooling (*The Economist*, 1993) and allowed an airline to offer "cabotage" services (the right to offer flights within another country for services starting in its own country) (Europe 2000, 1992). As of April 1, 1997 airlines were able to provide full cabotage services regardless of a flight's origin (Lowden, 1996).

In keeping with the liberalization started with the Third Package, the European Commission has also prepared guidelines for state aid to airlines. Although the Commission can not make a unilateral decision that it is the last time it approves aid to an airline, it is to consider further aid to an airline only if "external circumstances" require it (Feldman, 1997). These guidelines, based on the "one time, last

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time" principle, allow for a one time aid, except in unpredictable circumstances, so that airlines can adjust to new liberal market conditions (Lowden, 1996). In addition, the Commission created a subsidy test called the "Market Economy Investor Principle" (MEIP) whereby funds from public authorities will not be considered aid if such funds would have been invested by the private sector (Feldman, 1997).

The above provisions are in the spirit of the counsel of "The Committee of Wisemen" created by the Commission in 1993. The Committee advocated the continuation of deregulation to establish a Single Aviation Market to meet global challenges. Towards this end, it recommended harmonizing national regulations for effective cost cutting, eliminating infrastructural bottlenecks by creating an efficient Single Traffic Management System, enforcing internal market rules to address problems of slots and state aid, and curbing government intervention in the operation of air carriers (Agence Europe, 1994).

The consequences of the deregulatory undertaking have been manifold. The effort has created many challenges for the European established carriers, or "majors." Even without these threats, Europe's majors face a lot of problems including hub congestion, global competition from strong U.S. majors, lack of unlimited state aid and aircraft replacements. Yet, the most threatening issue has been upstarts that have sprung up following deregulation. These market opening efforts encouraged startups such as Gatwick's Air Europe, which failed in 1991, Ryanair of Ireland and easyJet of Greece. For instance, Ryanair's cheap aircraft, low overhead at its Dublin base and use of lower cost airports, such as Luton, allowed it to charge such low prices that British Airways (BA) was forced to pull its service in Dublin in 1991 (Lowden, 1996).

In fact, one may say that the most visible impact of deregulation has been new entrants and lower fares. Like Ryanair, Greek owned easyJet has offered fares that not only undercut BA's prices on British domestic routes, but also those of train

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operators. These upstarts have largely been able to offer cheap fares by keeping sales and distribution costs low through the use of their own telephone reservations and ticket-less travel: these usually account for 15% to 20% of total operating expenses (Lowden, 1996).

Competition in the recent past has also come from low cost air travel made available by charter airlines. These "carriers," which initially catered to the leisure market by selling packed tours, have begun selling tickets only for flights due to the relaxation of the rules. Estimates indicate that such "charter" flights account for about half cross border European travel. Like the recent startups, these carriers also have costs well below those of the scheduled airlines since they employ only 8% of the airline workforce (*The Economist*, 1993).

To compete in the leisure market, which has become increasingly necessary due to the effects of deregulation, the majors realize the need to cut costs drastically: these costs have been high due to expensive service charges, such as those for airport handling and air traffic control fees, and low labor productivity (*The Economist*, 1993). One obvious target of cost cutting effort has been employment. Despite traffic growth and continued financial recovery, including a profit of \$1.8 billion for IATA member European carriers in 1994 (Sparaco, 1995) and a record of 74.8% load factor on long haul routes in 1996 (Fiorino, 1997), job growth has been slow or falling. Prompted by growing competition from deregulation, scheduled airlines had cut about 40,000 jobs between 1990 and 1994, even in the face of social disputes and walkouts. Examples abound. Air France has frozen wages and cut 5,000 jobs to reduce cost by 30%. Alitalia and Iberia have made similar moves by cutting 2,000 and 3,500 jobs, respectively. By acquiring 49% stake in Sabena, Swissair also reduced ground staff to take advantage of synergy above the 1,600 jobs that it had already eliminated in 1994 (Sparaco, 1995).

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The efforts toward greater market reliance have resulted in improvements. With deregulation and commercialization, mostly in northern Europe, airlines there have exhibited productivity and efficiency gains, especially BA, Lufthansa and KLM (Lowden, 1996). In addition, liberalization of aviation services, most advanced in the UK, has allowed BA to establish domestic services in both Germany and France, and British Midland to become a third carrier by breaking traditional duopolies on many routes (Hotten, 1995).

Of course, competition from startups and pressures from liberalization might prompt the majors to retaliate by other than competition enhancing means. They may try to use political power to deter competition, for instance by monopolizing slots at congested airports. They may also launch advertising campaigns at the time of entry of a new startup who will not be able to match these efforts. In reality, the majors have responded by undertaking "cloning strategies" whereby they have formed companies that match competitors' costs and operations; two cases in point of such strategic subsidiaries include Lufthansa's Cityline and BA's Deutsche BA and TAT France. The majors have also tried to increase market share by combining their network power. This concept has been the reason for many of the alliances of the majors in Europe and the U.S. Examples include alliances between KLM and Northwest, Lufthansa and United, Lufthansa and SAS, Delta and Sabena, and BA and American (Lowden, 1996). The benefits of deregulation may also be limited by infrastructural constraints which will aggravate an already congested and intrinsically confusing air traffic control system (Vincent and Stasinopoulus, 1990). As has been documented in a report by the Association of European Airlines, there is no unified air traffic control system for Europe. The situation that existed in the late 1980s and early 1990s of 22 different systems and 44 operating centers based on political boundaries

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and not operational considerations which could seriously disrupt air travel and create intolerable delays.

The outcome of the liberalization effort has not been all as planned. It has improved competition on some domestic routes but not across Europe. Price competition of international routes are limited and only 7% of international routes are operated by more than two carriers. This lack of competitors is reinforced by problems of airport capacity where inadequate landing and take off slots create barriers to entry by new competitors (Hotten, 1995). Proposals for changing slot allocations are often watered down, providing no reprieve from the problem. Other competition hindering forces have been state aid and air traffic control problems; there are too many of the latter, often one for each sovereign state's air space, leading to delays and hence increases in annual cost of flights. Financial pressures from the high cost of operation, including high navigational, airport take off and landing fees and 3% carbon tax, also stifle competition (*The Economist*, 1993).

That the "Open Skies" initiative has not produced more reform has also been due to lack of compliance with the EU Commission's rules. For instance, the EU's effort to provide for competition in airport ground handling (believed to be 30% too high at many airports) by ordering airlines to handle their own effects in large airports has met with resistance. Lufthansa finds the directive unappealing because costs for handling at Frankfurt are twice those of other airports, and more than three times those at London Gatwick and Manchester. German airports also find this rule objectionable because ground handling generates around 40% of revenues. In addition, the Commission's attempts to reduce state aid to airlines has been met with similar difficulties. Airlines have disregarded these rules and some, such as Iberia, have requested repeated help by claiming a presence of "durable adverse conditions" (*The Economist*, 1993).

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3.3 Data

Before we turn attention to our structural model of cartel behavior we will discuss the data on which the structural model's empirical implementation is based. We also discuss some characteristics of the European carriers in terms of partial factor productivities and how these differ from those of carriers in the U.S. where deregulation has a proven track record of some twenty years. We also examine patterns of radial measures of technical inefficiency that have existed over the period based on a simple Cobb-Douglas form for the production function using the Cornwell et al. (1990) time-varying inefficiency model. Differences in partial factor productivities are significant for some inputs while the technical inefficiency gap appears to have closed considerably in the late 1980s and early 1990s.

Our supply data set consists of a panel of the eight air carriers from Europe that were used in Captain and Sickles (1997). A number of data series used therein were extrapolated between 1985–1990. Results presented here are based on a newly constructed and complete data set of 37 international airlines from 1976 to 1994 that are used in Chapter 4. A list of these carriers are presented in Table 3.1. These carriers and countries are followed with annual observations from 1976 through 1994. A complete discussion of the data can be found in Appendix B.

Table 3.1 List of Carriers and Countries

Sabena (Belgium)	Air France (France)
Lufthansa (Germany)	Alitalia (Italy)
KLM (Netherlands)	SAS (Sweden, Norway, Denmark)
Iberia (Spain)	British Air (United Kingdom)

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3.4 Comparison of U.S. and European Carriers

As was pointed out earlier, European airlines' inefficiencies relative to U.S. airlines is one possible explanation of high prices of air travel in Europe since excess costs need to be recouped as direct subsidies are under increased scrutiny. A possibile explanation for the difference in efficiency scores is that European airline industry makes poor use of labor (McGowan and Seabright, (1989)). It is also possible that labor is being paid a wage that is too high (Captain and Sickles (1997)).

In earlier work utilizing data predominately based on the late 1970s and early 1980s, Good et al. (1993a,b, 1994, 1995) noted differences in technical efficiency between Europe and post-regulatory U.S. of between 10 and 15 percent. We can use our newly extended data set to examine whether or not the general trends which manifested themselves as we found them to in the decade following the U.S. experiment with deregulation while Europe was still strongly entrenched in its rich regulatory traditions have continued into the second half of the 1980s and into the 1990s. To that end, we constructed several series of partial productivity indexes and examined their temporal pattern during the 1970s through the 1990s. The U. S. firms used in this comparison were drawn from the same newly created international carrier data set (Good, et al., 1997) and comprise the vast majority of the total U.S. industry. The firms are American, Contenental, Delta, Eastern, Northwest, Pan Am, Trans World, United, USAir, and Western. Figure 3.1 displays the partial productivity index for labor. We found a substantial disparity when our sample period begins in 1976 and this disparity has narrowed substantially by 1994. Although a similar convergence does not appear in the simple partial productivity measure for the residual materials input (Figure 3.2), the capital input series for Europe and the U.S. are indistinguishable by 1994 (Figure 3.3).

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Figure 3.1 Ratio of Labor Quantity to Scheduled Output for Both U.S. and European Airlines

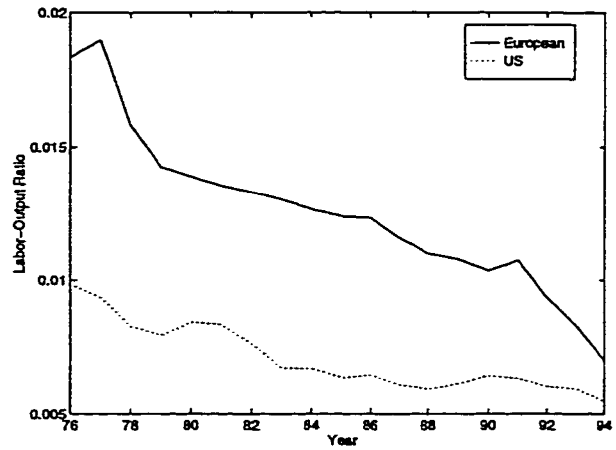

Figure 3.2 Ratio of Materials Quantity to Scheduled Output for Both U.S. and European Airlines

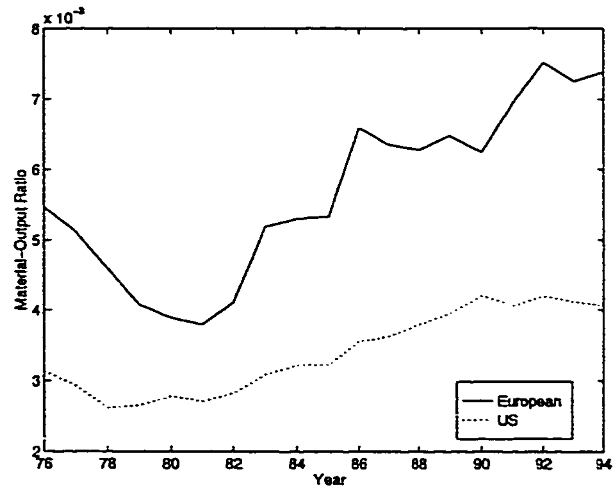

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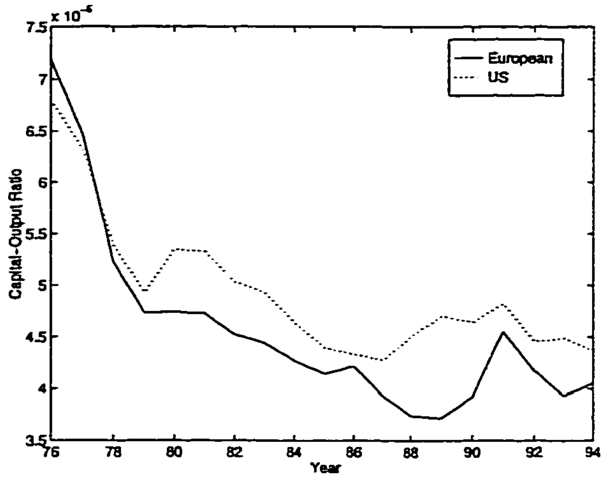
Figure 3.3 Ratio of Capital Quantity to Scheduled Output for Both U.S. and European Airlines



Since it would appear that substantial convergence occurred in the partial productivities of the factor inputs we then ask if a similar convergence has occurred with regard to radial technical efficiency measures. We have estimated a simple Cobb-Douglas model and have constructed time-varying relative technical efficiency measures using the Cornwell, et al. (1990) within estimator and a pooled regression of European and U.S. firms. We then weighted the relative efficiencies by the output share of the particular carrier in the European or U. S. industry to construct the differential between Europe and U.S. over the 1976–1994 period. These are displayed in Figure 3.4.

It is clear that with the addition of data from the mid-1980 through 1994 the story about inefficiency patterns between Europe and the U.S. that is presented in Good, et al. (1993a,b, 1995) and based on the decade earlier appears to have changed. Although there still exists an efficiency difference of about 5% in favor of the U.S., this difference is substantially lower than the average of 10%–15% that appeared to exist in the decade following U.S. deregulation. The remarkable progress of British Air

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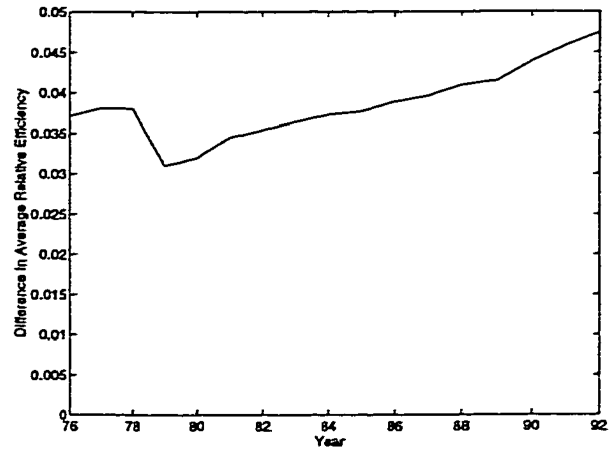
Figure 3.4 Differences in Average Efficiency Scores Between U.S. and European Airlines



after privatization (and its large share of European total revenue passenger miles) and the steady progress of Lufthansa, KLM and Air France from the mid-1980s through the present also has appeared to have flattened the temporal pattern over the entire period 1976–1994.

In the next section we consider a more structured argument based on a model of cartel behavior which was applied to the European industry using data predominantly based on the period 1976–1985 (Captain and Sickles, 1997). A number of data series in that study were not available for later periods through the end of the study period (1990) and were interpolated and/or forecasted using time-series methods. The model will explore whether or not there is evidence of noncompetitive pricing or whether competitive pressures in Europe have also had their way in reducing price/marginal cost markups.

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3.5 Econometric Model of Cartel Behavior

We will study the European carriers in an oligopoly structure with product differentiation.[1] Consider an industry with N firms that produce a differentiated output q. The output is produced using n inputs $x = (x_1, x_2, \ldots, x_n)$. Market demand for firm k at time t is given by

$$q_{kt} = q_k(p_t, p_{mt}, Y_t, \psi, \epsilon_{dt}), \tag{3.1}$$

where p_t is the average price charged by firm k, p_{mt} is an index of all other firms' prices, Y_t are other variables that shift demand, ψ are unknown parameters of the demand function, and ϵ_{dt} are the random errors. The "perceived" marginal revenue function is

$$\text{PMR} = p_t + D_1 q_{kt}, \tag{3.2}$$

where $D_1 = \partial p_{kt} / \partial q_{kt}$.

The cost function for firm k is

$$C_{kt} = C_k(q_{kt}, W_{kt}, Z_t, \omega, \epsilon_{ct}), \tag{3.3}$$

where W_{kt} is a vector of input prices that firm k pays at time t, Z_t are industry variables that shift cost, ω are the unknown parameters in the cost function, and ϵ_{ct} are the random errors. Marginal cost is

$$\text{MC} = C_1(q_{kt}, W_t, Z_t, \gamma). \tag{3.4}$$

In an oligopolistic industry, a firm chooses output where marginal cost is equal to "perceived" marginal revenue (in a perfectly competitive industry, MC = p). We equate marginal cost and "perceived" marginal revenue to get the quantity setting condition

$$C_1(q_{kt}, W_t, Z_t, \gamma) = p_t + D_1 q_{kt} \theta, \tag{3.5}$$

[1]This section is based on Captain and Sickles (1997)

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where θ is an index of the competitive nature of the firm. That is, when $\theta = 0$, the industry is perfectly competitive since marginal cost equals price. A θ value of unity is consistent with Nash behavior. Thus, (3.5) is referred to as the behavioral equation.

The profit function for airline k at time t is

$$\Pi_{kt} = q_{kt}(p_{kt}; p_{1t}, \ldots, p_{k-1,t}, p_{k+1,t}, \ldots, p_{Nt}) \cdot p_{kt} - C_{kt}(q_{kt}(\cdot)). \tag{3.6}$$

Taking the derivative of this function with respect to p_{kt} and holding all other prices constant, we have the first order conditions for profit maximization in a price setting game:

$$\frac{\partial q_{kt}}{\partial p_{kt}} p_{kt} + q_{kt} - \frac{\partial C_{kt}}{\partial q_{kt}} \frac{\partial q_{kt}}{\partial p_{kt}} = 0. \tag{3.7}$$

By summing over the N firms, we have

$$\frac{\partial Q_t}{\partial p_t} p_t + Q_t - \sum_k \frac{\partial C_{kt}}{\partial q_{kt}} \frac{\partial q_{kt}}{\partial p_{kt}} = 0, \tag{3.8}$$

where $Q_t = \sum_k q_{kt}$. Assuming symmetry in cost, (3.5) reduces to

$$p_t = \frac{\partial C_{kt}}{\partial q_{kt}} - \frac{Q_t}{\frac{\partial Q_t}{\partial p_t}} \theta. \tag{3.9}$$

With this, we can estimate θ by specifying a demand and a cost equation.

For the market demand equation, we specify a semi-logarithmic function:

$$\begin{aligned} \log q_{kt} &= \delta + \delta_P P_{kt} + \delta_{P_i} P_{ikt} + \delta_{GDP} GDP_{kt} \\ &\quad + \delta_{GASP} GASP_{kt} + \delta_{GCONS} GCONS_{kt} \\ &\quad + \delta_{RAILP} RAILP_{kt} + \epsilon_d, \end{aligned} \tag{3.10}$$

where q_{kt} is the output of firm k at time t, P_{kt} is the price charged by firm k, P_{ikt} is an index of the price charged by the other $N-1$ firms, GDP is the gross domestic product, $GASP$ is the retail price of gas including taxes, $GCONS$ is the growth in consumer expenditures and $RAILP$ is the price of rail travel.

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For the cost function, we use a trans-logarithmic specification. After we impose symmetry, the cost function is given by

$$\begin{aligned}
\log C &= \alpha + \sum_{i=1}^{3} \beta_i \log p_i + \sum_{j>i}^{3} \sum_{i=1}^{2} \beta_{ij} \log p_i \log p_j + \frac{1}{2} \sum_{i=1}^{3} \beta_{ii} \log^2 p_i \\
&\quad + \gamma_q \log q + \frac{1}{2} \gamma_{q^2} \log^2 q + \sum_{i=1}^{3} \gamma_{qi} \log q \log p_i \\
&\quad + \beta_{TP} TP + \beta_{WB} WP + \beta_{SL} \log SL + \beta_{LF} \log LF \\
&\quad + \beta_{Netsize} \log Netsize + \sum_{i=1}^{7} \alpha_i AIR_i + \epsilon_c \qquad (3.11)
\end{aligned}$$

where p_i is the i^{th} input price, q is output, PT is the percentage of the fleet which are turbo-prop aircraft, WB is the percentage of the fleet which are wide-body aircraft, SL is the stage length, LF is the load factor, and $Netsize$ is the size of the network.

The $\alpha_i AIR_i$ represent fixed firm effects in the cost equation. These firm effects can be given the reduced form interpretation of omitted variables which 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, et al., 1990).

The cost shares must add to unity and we must have linear homogeneity in input prices. The following restrictions are thus applied on the cost function:

$$\begin{aligned}
\beta_K + \beta_L + \beta_M &= 1 \\
\beta_{Ki} + \beta_{Li} + \beta_{Mi} &= 0, \qquad \text{for all}\, i \in \{K, L, M\} \\
\gamma_{qK} + \gamma_{qL} + \gamma_{qM} &= 0.
\end{aligned}$$

Summary statistics based on the translog and its associated share equations are provided by the Allen-Uzawa, Morishima and own- and cross-price substitution elasticities, and a measure of returns to scale. The Allen-Uzawa elasticities of substitution

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and own-price elasticities are given by

$$\begin{aligned}\zeta_{ij} &= \frac{\beta_{ij} + S_i S_j}{S_i S_j} \\ \zeta_{ii} &= \frac{\beta_{ii} + S_i(S_i - 1)}{S_i^2},\end{aligned} \tag{3.12}$$

where S_i is the fitted share for input i. Morishima elasticities are given by

$$\sigma_{ij} = (\zeta_{ji} - \zeta_{ii})S_i, i \neq j. \tag{3.13}$$

The own- and cross-price elasticities are

$$\begin{aligned}\nu_{ii} &= \zeta_{ii} S_i \\ \nu_{ij} &= \zeta_{ij} S_j, i \neq j \\ \nu_{ji} &= \zeta_{ij} S_i, i \neq j.\end{aligned} \tag{3.14}$$

Returns to scale are computed as the inverse of the cost elasticity of output. This is give by

$$\mu = [\beta_q + \beta_{qq} \log q + \beta q L \log p_L + \beta q M \log p_M + \beta q K \log p_K]^{-1}. \tag{3.15}$$

The behavioral equation we estimate is

$$P = \mathrm{MC} - \frac{\theta}{\delta} + \epsilon_b. \tag{3.16}$$

We then estimate a system of five equations using iterated non-linear three-stage least squares (ITNL3SLS). The five equations are the demand, cost, labor share, capital share and the behavioral equation. We treat the price of air travel, quantity, total cost, labor share, capital share, and labor price as endogenous variables. All other variables are treated as exogenous.

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3.6 Empirical Results

The parameter estimates for the system of equations given in Section 3.5 can be found in Table 3.2. Fitted share values, returns to scale, and various elasticities calculated from these estimates are in Tables 3.3 through 3.7.

We identify the market structure by testing the null hypothesis that $\theta = 1$ versus the alternative that $\theta < 1$. The null hypothesis is rejected at the 95% level of significance. The European airlines industry does not behave consistently with Nash behavior.

In the demand equation, all the parameters (with the possible exception of gas price) have the expected sign and are significant. The output price elasticity of -0.55 means that demand for air travel is inelastic and consumers will decrease air travel demand proportionally less with price increases. However, the elasticity of the price index is positive and quite large (1.98), so airlines in Europe are thought of as substitutes and any product differentiation is quite small. The rail price cross-price elasticity is positive so rail travel is also a substitute for air travel. The output GDP elasticity is also positive, so countries with higher GDPs have a larger demand for air travel, which is expected. The gas price output elasticity is negative which may be due to a link between gas price and aircraft fuel price.

The cost function estimates produce fitted share values that are positive at all the observations. The estimated cost function is concave in input prices at the data mean and at 60% of the data points. The estimated returns to scale at the data mean is 1.29. Of the five airline specific variables included in the cost function, only stage length and percentage of wide bodied aircraft are significant. The parameter estimates for both stage length and load factor do not have their expected signs.

Labor, capital and materials are all substitutable inputs as measured with the Allen-Uzawa elasticities of substitution (see Table 3.5). Likewise, the Morishima

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Table 3.2 Nonlinear IT3SLS Parameter Estimates

Cost Equation

Variable	Parameter Estimate	T-Ratio	Variable	Parameter Estimate	T-Ratio
$\log p_K$	0.044	2.30	$\log p_L$	1.163	14.35
$\log p_M$	-0.207	-2.38	$\log Q$	-2.174	-27.31
$\log^2 Q$	0.198	27.62	$\log Q \log p_K$	-0.007	-5.36
$\log Q \log p_L$	-0.043	-7.70	$\log Q \log p_M$	0.050	8.42
$\log^2 p_L$	0.117	17.47	$\log^2 p_K$	0.041	21.49
$\log^2 p_M$	0.158	60.41	$\log p_K \log p_L$	-0.016	-8.28
$\log p_K \log p_M$	-0.025	-13.52	$\log p_L \log p_M$	-0.133	-21.17
$\log SL$	0.309	6.19	LF	0.514	1.82
$\log Netsize$	0.036	0.72	PWB	-1.247	-6.16
PT	0.004	0.66	Iberia	20.628	23.63
Air France	20.590	22.98	Lufthansa	20.689	23.53
Alitalia	20.438	23.52	KLM	20.420	23.63
British Airways	20.499	23.32	SAS	20.620	23.93
Sabena	19.929	23.12			

Demand Equation

Variable	Parameter Estimate	T-Ratio	Variable	Parameter Estimate	T-Ratio
Intercept	12.726	78.94	P	-0.490	-3.70
$Pindex$	0.249	9.44	$Gasp$	-0.822	-4.22
GDP	0.001	10.25	$Prail$	9.265	7.80

Behavioral Equation

Variable	Parameter Estimate	T-Ratio
θ	0.112	3.58

Table 3.3 Fitted Share Values and Returns to Scale at Data Mean

Labor	0.322
Capital	0.069
Materials	0.609
Returns to scale	
1.29	

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Table 3.4 Output Price Elasticities at Data Mean

Price	-0.551
Price Index	1.976
Gas Price	-0.588
GDP	0.391
Rail Price	0.494

elasticities of substitution (see Table 3.6) show that capital, labor and materials are all substitutable inputs.

Finally, we compute the average θ values and mark-ups over the sample, by year, and airline in Tables 3.8 through 3.10. Over the entire period, mark-ups averaged 22.8%. For the years 1976–86, mark-ups averaged 23.1%. Mark-ups started the period at near 25% level and only declined slightly over the period. In 1987, when the European market was opening to a more competitive environment, mark-ups started to increase (this trend actually starts in 1986). However, after three years, this trend stops, and mark-ups start to decline to levels lower than before 1986. The average mark-up for the years 1989–93 is 17.8%. Despite inelastic demand, with other airlines and railroads as close substitutes, high mark-ups in the European market could not be sustained.

Table 3.5 Allen-Uzawa Elasticities of Substitution at Data Mean

	Labor	Materials	Capital
Labor	-0.975	×	×
Materials	0.485	-0.304	×
Capital	0.271	0.411	-4.872

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Table 3.6 Morishima Elasticities of Substitution at Data Mean

	Labor	Materials	Capital
Labor	×	0.470	0.401
Materials	0.480	×	0.435
Capital	0.356	0.366	×

Table 3.7 Input Price Elasticities at Data Means

	Labor	Materials	Capital
Labor	-0.314	0.295	0.019
Materials	0.156	-0.185	0.028
Capital	0.087	0.250	-0.337

Table 3.8 Competition Variable (θ) Estimates,
Average Prices, Mark-Ups and Marginal Costs

θ	P	Mark-up	MC
0.112	1.123	0.228	0.895

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Table 3.9 Competition Variable (θ) Estimates by Year with Average Prices, Mark-Ups and Marginal Costs

Year	θ	P	Mark-up	MC
76	0.120	0.755	0.244	0.511
77	0.125	0.815	0.255	0.560
78	0.122	0.862	0.248	0.614
79	0.118	0.979	0.240	0.739
80	0.120	1.135	0.245	0.890
81	0.106	1.060	0.216	0.844
82	0.120	1.037	0.224	0.813
83	0.102	1.002	0.209	0.794
84	0.097	0.969	0.198	0.771
85	0.095	0.989	0.194	0.795
86	0.133	1.142	0.271	0.872
87	0.149	1.300	0.304	0.996
88	0.149	1.313	0.303	1.010
89	0.129	1.320	0.262	1.058
90	0.135	1.417	0.275	1.143
91	0.095	1.572	0.193	1.379
92	0.055	1.446	0.113	1.333
93	0.023	1.252	0.046	1.206

Table 3.10 Competition Variable (θ) Estimates by Airline with Average Prices, Mark-Ups and Marginal Costs

Airline	θ	P	Mark-up	MC
Air France	0.086	1.111	0.175	0.935
Alitalia	0.145	1.114	0.295	0.818
British Airways	0.053	0.976	0.107	0.869
Iberia	0.105	0.974	0.213	0.761
KLM	0.073	0.875	0.150	0.725
Lufthansa	0.073	1.328	0.150	1.179
SAS	0.182	1.435	0.371	1.063
Sabena	0.185	1.129	0.376	0.753

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3.7 Conclusions

In this chapter we have examined the productivities, efficiencies, and market conduct of firms in the European airline industry. We have found what appears to be convergence in several of the major sources of factor productivity to the standard of the unregulated industry in the U.S., inefficiency differentials that are substantially moderated by the competitive pressures induced by measures put in place through the European Union, and little evidence that competitive pricing is violated on average. Whether or not selected firms in the industry are candidates for takeover or what potential exists for selected firms to join in strategic alliances, mergers, and/or simple code-sharing arrangements is not explored in this paper. It would appear, however, that a combination of aggressive cost-cutting, exploitation of the production capacity of lower-cost U.S. carriers and marketing alliances will continue to drive the European industry as the dynamic of the competitive market continues to rationalize airline firm decision-making.

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Chapter 4

A Model of World Aircraft Demand

In this chapter, we outline a procedure that examines airframe and engine innovations and the benefits of those innovations that accrue to equipment manufacturers, airlines and passengers. We focus on the gross characteristics of an airframe/engine combination: its size and operating characteristics as well as more detailed characteristics of an airline's fleet and individual aircraft within it (e.g., improved avionics or benefits of maintenance that results from fleet standardization). The benefits that occur through altering the menu of potential aircraft choices will be measured on both a carrier specific and industry-wide level of aggregation.

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 to a cost analysis of the carriers in term of the prices of the firms' factors of production—labor, fuel, materials, and flight equipment. Flight equipment will be modeled in an especially detailed way by incorporating characteristics of the aircraft.

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 (for flying capital energy prices will be of particular interest), characteristics of the aircraft used by the airline system, and the level of passenger and cargo service.

Our research is both comprehensive and methodologically innovative. We look at both the evolution of the demand and cost structure of the international airline firms in Europe, North America and Asia in response to the integration processes underway and the potential for expansion of air services in the Pacific Rim.

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We describe previous studies on airline cost in section 4.1. The data is described in section 4.2. Section 4.3 describes the demand functions that we estimate using the world data set. The cost function is explained in section 4.4. The forecasts of the number of aircraft in a particular carrier's fleet are given in section 4.5. Section 4.6 concludes.

4.1 Previous Research

Captain (1993) and Roeller and Sickles (1994) have studied static and dynamic demand and supply models for the European industry from 1976 to 1990. Production and cost data on the eight largest European carriers—Air France, Alitalia, British Airways, Iberia, KLM, Lufthansa, Sabena, and SAS—are linked to demand data for the same period collected for the respective countries—France, Italy, Great Britain, Spain, Netherlands, Germany, Belgium and the three Scandinavian countries, Denmark, Sweden, and Norway. The demand facing firm k (from country k) at time t is

$$\begin{aligned} \log Q_{kt} &= \beta_0 + \beta_1 P_{kt} + \beta_2 P_{other,t} + \beta_3 P_{rail,kt} \\ &\quad + \beta_4 P_{gas,kt} + \beta_5 GDP_{kt} + \beta_6 \Delta \log Cons_{kt} + \varepsilon_{kt}, \end{aligned} \tag{4.1}$$

where P is the average own-ticket price, P_{other} is index for the other $n-1$ firms' prices, P_{rail} is the price of rail travel, P_{gas} is the retail price of gasoline (used as a proxy for car travel expenses), GDP is the gross domestic product, and $\Delta \log Cons$ is the growth rate in consumer expenditures. Their findings were based on a demand quantity variable that corresponds to a carrier's annual revenue ton kilometers. The European data were collected from the International Energy Agency, the OECD, and from Jane's World Railways. The gasoline prices and growth rate of consumer expenditure for Denmark, Sweden, and Norway were weighted by their respective

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GDP's in order to create single representative indices for the Scandinavian countries that share a 50% equity stake in SAS.

A stochastic frontier cost function (TC) was specified as a nonhomothetic translog in factor prices of labor, planes, and materials (including energy), average stage length, load factor, network size, with additive treatments for percentage of fleet that is wide-bodies and turboprop. A nonlinear system of cost, shares, and a behavioral equation that allowed for deviations in marginal cost pricing was estimated jointly. Estimates of the technological parameters of interest (returns to scale, substitution elasticities, etc.) were comparable to those for U.S. carriers. Demand elasticities indicated that air travel is elastic (−1.483 with a t-statistic of −8.93). On the aggregate industry level, the cross-price elasticity (2.33 with a t-statistic of 8.94) indicated that all the airlines were close substitutes and that the level of product differentiation was minimal. The cross-price elasticity for rail travel was also relatively large (5.47 with a t-statistic of 3.34). The estimated conduct parameter was 0.042 with a t-statistic of 0.64, indicating no evidence of monopoly power. However, despite the popular belief that competition marginally increased in the European industry after 1983, the markups (P-MC) rose from 0.98% of average fares in 1982 to 8.99% in 1986. Elsewhere (Good et al., 1992, 1993a,b, 1994, 1995; Park et al., 1993) the relative efficiency differences between European and American airlines have been found to be in the range of 15–18% for the 1976–86 period. The relatively higher prices charged by European carriers may thus be due to the need to cover the partially subsidized losses due to the technical inefficiencies engendered by the protected national carrier status given to these firms (excepting British Air) during the period 1976–86 and not to their ability to exploit their market power. Their results also point to cost reductions on the order of 28% for wide-bodied aircraft while costs for turboprop aircraft are on the order of 35% higher given a network configuration that had the

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same stage length and network size. Comparable models for the U.S. industry require hub specific demand factors as well as the percentage of originating passengers that travel from a hub on a particular carrier (for recent comprehensive studies of city-pair demand see, e.g., Borenstein and Rose, 1992; Brueckner and Spiller, 1992).

4.2 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 percent of the scheduled passenger traffic in the world. The carriers and countries are presented in Table 4.1. These carriers are followed with annual observations from 1976 through 1994. A complete discussion of the data appears in Appendix B.

4.3 Demand Equation

We develop a specific model of the international demand for an airline firm's provision of passenger and cargo service. 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

$$\begin{aligned} \log Y_{tk} &= \alpha + \sum_{i=1}^{N-1} \alpha_i \mathrm{CARRIER}_i + \beta_Y \log P_{Y,tk} \\ &\quad + \beta_{POP} \log \mathrm{POP_{tk}} + \beta_{\mathrm{PCI}} \log \mathrm{PCI_{tk}} \\ &\quad + \beta_{LFP} \log \mathrm{LFP_{tk}} + \varepsilon_{\mathrm{tk}}, \end{aligned} \tag{4.2}$$

where Y is revenue passenger mile originating at time t in 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,

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Table 4.1 List of Carriers and Countries by Geographic Area

Europe	
Sabena (Belgium)	Finnair (Finland)
Air France (France)	Lufthansa (Germany)
Alitalia (Italy)	KLM (Netherlands)
TAP (Portugal)	SAS (Sweden, Norway, Denmark)
Iberia (Spain)	Swissair (Switzerland)
British Air (United Kingdom)	

Asia	
Qantas (Australia)	Air India (India)
Indiana Airlines (India)	Garuda (Indonesia)
Japan Asia Airways (Japan)	JAL (Japan)
Air New Zealand (New Zealand)	Air Pakistan (Pakistan)
Philippines Airlines (Philippines)	KAL (Korea)
SIA (Singapore)	Thai International (Thailand)

North America	
Air Canada (Canada)	C P Air (Canada)
American (United States)	USAir (United States)
Continental (United States)	Delta (United States)
Eastern (United States)	Northwest (United States)
Pan Am (United States)	Trans World (United States)
United (United States)	Western (United States)

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LFP_{tk} is the labor force participation rate at time t for country k. The $CARRIER_i$ represents the conventional treatment for firm fixed effects. This equation was estimated for Europe, Asia and North America separately. The countries included in these areas are shown in Table 4.1.

Equation 4.2 was estimated using ordinary least squares (OLS)[1]. Estimates for the three world demand equations are shown in Table 4.2. The estimates from these three equations do not seem to be reasonable, given previous studies. The Europe equation has a price variable that 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 estimate 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 airport travel would improve the estimates. Also, having a variable for competitors' prices on competing routes could only improve the quality of the estimates.

4.4 Cost Equation

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

- The carriers are cost minimizers.
- The carriers are profit maximizers.

[1]OLS estimation of a least squares dummy variable (LSDV) model such as (4.2) allows for correlation between the regressors and the effects.

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Table 4.2 Demand Equation Parameter Estimates

Europe

Variable	Parameter Estimate	T Value
Price	-0.121	-1.423
Population	-2.646	-13.173
Income	2.721	13.154
Labor Force	0.0137	5.533
R^2 value 0.9813		

Asia

Variable	Parameter Estimate	T Value
Price	0.290	3.715
Population	1.398	5.112
Income	1.579	10.840
Labor Force	-0.007	-2.115
R^2 value 0.9735		

North America

Variable	Parameter Estimate	T Value
Price	-0.682	-2.963
Population	6.511	3.320
Income	1.046	1.241
Labor Force	0.010	1.736
R^2 value 0.8534		

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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. This is the most widely used of the flexible functional forms (Green, 1993). The translog functional form was introduced by Christensen, et al., (1973) as a production function that did not impose homotheticity or separability. However, we do impose homotheticity in the cost function. We also imposing symmetry of the cross-price derivatives.

4.4.1 Cost Minimization

After we impose symmetry, the cost function is given by

$$\begin{aligned}
\log C \quad & \sum^{4} \quad \sum^{4}\sum^{3} \quad \frac{1}{\cdot}\sum_{i=1}^{4} \delta_{ii} \log^2 p_i \\
& + \sum^{2} \gamma_i \log Y_i + \frac{1}{2} \sum^{3} \gamma_{ii} \log^2 Y_i + \gamma_{12} \log Y_1 \log Y_2 \\
& + \sum_{i=1}^{2} \gamma_i \log Y_i + \frac{1}{2} \sum_{i=1}^{3} \gamma_{ii} \log^2 Y_i + \gamma_{12} \log Y_1 \log Y_2 \\
& + \delta_A \log p_k \log AA + \delta_S \log p_k \log AS \\
& + \delta_J PJ \log p_k + \delta_W PW \log p_k + \beta_{sl} \log SL \\
& + \beta_{lf} \log LF + \sum_{i=1}^{36} \alpha_i AIR_i + \epsilon_c \qquad (4.3)
\end{aligned}$$

where p_i is the i^{th} input price, Y_i is one of the two outputs (scheduled output, 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 the fleet that are jet aircraft, PWB is the percentage of the fleet that are wide-body aircraft, SL is the stage length, and LF is the load factor.

The $\alpha_i AIR_i$ represent 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

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structural interpretation as time-invariant technical inefficiencies from a stochastic frontier cost function (Schmidt and Sickles, 1984; Cornwell, et al., 1990).

The cost shares must add to unity and we must have linear homogeneity in input prices. The following restrictions are applied to impose these conditions on the cost function:

$$\sum_i \beta_i = 1; \sum_j \delta_{ij} = 0; \sum_{i \in \{A,S,J,W\}} \delta_i = 0 \tag{4.4}$$

Our restrictions do not affect the way that outputs, output characteristics, capital or its characteristics enter into the input share equations. Further, we still can construct shadow prices of the output and technology attributes, but we assume that any variation in these shadow prices due to variations in measured outputs, the quasi-fixed capital stock, or in other attributes have second-order effects that can be neglected or do not change appreciably during the sample period.

The cost share of capital is given by

$$\begin{aligned} S_k &= \beta_k + \sum_{i=1}^{4} \delta_{ik} \log p_i + \delta_A \log AA \\ &\quad + \delta_S \log AS + \delta_J PJ + \delta_W PW. \end{aligned} \tag{4.5}$$

Summary statistics based on the translog and its associated share equations are provided by the Allen-Uzawa, Morishima and own- and cross-price substitution elasticities, and several measures of returns to scale that extend from the short-run to the long-run. The Allen-Uzawa elasticities of substitution and own-price elasticities are given by

$$\begin{aligned} \theta_{ij} &= \frac{\delta_{ij} + S_i S_j}{S_i S_j} \\ \theta_{ii} &= \frac{\delta_{ii} + S_i(1 - S_i)}{S_i^2}. \end{aligned} \tag{4.6}$$

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Morishima elasticities are given by

$$\sigma_{ij} = (\theta_{ji} - \theta_{ii})S_i, i \neq j. \tag{4.7}$$

The own- and cross-price elasticities are

$$\begin{aligned} \epsilon_{ii} &= \theta_{ii}S_i \\ \epsilon_{ij} &= \theta_{ij}S_j, i \neq j \\ \epsilon_{ji} &= \theta_{ij}S_i, i \neq j. \end{aligned} \tag{4.8}$$

Before we do any estimation, we normalize the data so that all the variables are unity at the data median. We estimate each of these cost functions using the cost function and all but one (materials) of the cost share equations using iterated seemingly unrelated regression (ITSUR). Asymptotically, upon convergence, ITSUR will be equivalent to the maximum likelihood estimates, that are invariant to that cost share equation we leave out of the estimation. In addition to the restrictions imposed for linear homogeneity in input prices, we restrict the price variables to equal the mean of the data for the variable. The parameter estimates (excluding the fixed effects), returns to scale and elasticity estimates are found in Tables 4.3, 4.4.1, 4.4.1, 4.4.1 and 4.4.1.

These equations produced estimates that are 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.

4.4.2 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

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Table 4.3 Cost Equation Parameter Estimates Under Cost Minimization

Variable	Parameter Estimate	T-Ratio
Labor price	0.286	na
Labor price squared	0.008	1.117
Labor × energy	-0.010	-2.369
Labor × materials	0.007	1.089
Labor × capital	-0.005	-1.386
Energy price	0.202	na
Energy price squared	0.037	7.804
Energy × materials	-0.007	-1.187
Energy × capital	-0.020	-6.728
Materials price	0.429	na
Materials price squared	0.010	1.058
Materials × capital	-0.011	-3.166
Capital price	0.083	na
Capital price squared	0.036	11.848
Scheduled demand	0.908	33.028
Scheduled demand squared	0.062	1.504
Nonscheduled demand	0.016	2.542
Nonscheduled demand squared	0.011	2.333
Scheduled × nonscheduled demand	-0.032	-3.033
Stage length	0.137	3.061
Load factor	-0.533	-4.765
Average seats	0.004	0.866
Average age	0.022	4.605
Percentage jets	-0.014	-6.075
Percentage wide-bodied aircraft	-0.012	-2.465
Returns to Scale is 1.082		

Table 4.4 Fitted Share Equation Values at Data Mean Under Cost Minimization

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

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Table 4.5 Allen-Uzawa Partial Elasticities of Substitution at Data Mean Under Cost Minimization

	Labor	Energy	Materials	Captial
Labor	-2.393	×	×	×
Energy	0.819	-3.036	×	×
Materials	1.060	0.922	-1.274	×
Capital	0.729	-0.511	0.629	-5.902

Table 4.6 Price Elasticities at Data Mean Under Cost Minimization

	Labor	Energy	Materials	Captial
Labor	-0.685	0.165	0.455	0.048
Energy	0.235	-0.613	0.396	-0.034
Materials	0.303	0.186	-0.547	0.042
Capital	0.209	-0.103	0.270	-0.392

Table 4.7 Morishima Partial Elasticities of Substitution at Data Mean Under Cost Minimization

	Labor	Energy	Materials	Captial
Labor	×	0.920	0.871	0.894
Energy	0.778	×	0.799	0.509
Materials	1.002	0.943	×	0.817
Capital	0.440	0.358	0.433	×

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method to estimate the cost function above. We keep the same normalization and the restriction on the parameter estimates. The estimation procedure we use is a modification of iterated three-stage lease squares(I3SLS).

With I3SLS, right hand side endogenous variables are replaced by their predicted value from a regression on these variables on a set of instruments. We have five such right hand side endogenous variables in our cost function, and the predicted values were not as good as desired. Therefore, we ran OLS using the log of one of the two outputs and an the instrument set as the set of regressors. With the predicted values from these regressions, we constructed the squared- and cross-output variables. The results are shown in tables 4.8, 4.4.2, 4.4.2, 4.4.2 and 4.4.2.

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.

4.5 Prediction

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

- Predict the growth of service demand over the period using an estimated demand function;
- Predict the change in total cost per carrier over the time period using our predicted demand growth and an estimated cost function;
- Use the capital share equation to predict what the total capital expense will be over the period;

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Table 4.8 Cost Equation Parameter Estimates Under Profit Maximization

Variable	Parameter Estimate	T-Ratio
Labor price	0.287	na
Labor price squared	-0.018	-1.589
Labor × energy	-0.024	-4.440
Labor × materials	0.053	5.312
Labor × capital	-0.011	-2.574
Energy price	0.204	na
Energy price squared	0.039	8.313
Energy × materials	0.004	0.659
Energy × capital	-0.019	-6.301
Materials price	0.426	na
Materials price squared	-0.046	-3.768
Materials × capital	-0.011	-3.081
Capital price	0.082	na
Capital price squared	0.040	13.154
Scheduled demand	0.884	19.494
Scheduled demand squared	0.407	9.634
Nonscheduled demand	-0.009	-0.771
Nonscheduled demand squared	0.011	2.846
Scheduled × nonscheduled demand	-0.025	-1.143
Stage length	0.014	0.182
Load factor	-0.464	-2.353
Average seats	0.003	0.590
Average age	0.019	4.022
Percentage jets	-0.013	-5.856
Percentage wide-bodied aircraft	-0.009	-1.849
Returns to Scale is 1.132		

Table 4.9 Fitted Share Equation Values at Data Mean Under Profit Maximization

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

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Table 4.10 Allen-Uzawa Partial Elasticities of Substitution at Data Mean Under Profit Maximization

	Labor	Energy	Materials	Captial
Labor	-2.702	×	×	×
Energy	0.589	-2.966	×	×
Materials	1.429	1.045	-1.597	×
Capital	0.456	-0.348	0.628	-5.060

Table 4.11 Price Elasticities at Data Mean Under Profit Maximization

	Labor	Energy	Materials	Captial
Labor	-0.775	0.120	0.609	0.031
Energy	0.169	-0.606	0.446	-0.024
Materials	0.410	0.213	-0.681	0.042
Capital	0.131	-0.071	0.268	-0.342

Table 4.12 Morishima Partial Elasticities of Substitution at Data Mean Under Profit Maximization

	Labor	Energy	Materials	Captial
Labor	×	0.944	0.989	0.906
Energy	0.726	×	0.819	0.535
Materials	1.290	1.127	×	0.949
Capital	0.373	0.319	0.385	×

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

It should be noted that we assume that capital prices remain constant over the period. A baseline scenario is used to evaluate the model. Other scenarios are easily implemented and can be used to forecast aircraft demand with any number of shocks. The baseline changes in variables is given in Table 4.13.

From our estimates shown in Table 3, this scenario leads to an annual service increase of 3.64% in Asia, 1.98% in Europe, and 8.32% in North America (see Tables 8–13). 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.

Table 4.13 Baseline Variable Rates of Change

Variable	Percentage Change
Ticket Price	−0.75
Per Capita Income	2.55
Population Growth	0.94
Labor Cost	−1.60
Energy Cost	1.05

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4.5.1 Cost Minimization

Using the cost minimization procedure, we predict a 1.58% increase in planes in Europe, a 3.10% increase in Asia, and a 7.65% increase in North America. These results are being biased by the demand results. The 7.65% increase in fleet size in North America is about two times as large as predicted in previous studies that looked only at the US. Also, since the Asia demand growth seems to be too low, growth in fleet size would be biased downward. The projected number of total aircraft, by region, are given in tables 4.14 through 4.16.

4.5.2 Profit Maximization

For profit maximization, 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 4.36% increase in Asia, and a 12.6% increase in North America. As with the cost minimization, the results also rely on questionable demand functions. The projected number of total aircraft, by region, is given in tables 4.17 through 4.19.

4.6 Conclusions

In this essay, we develop a method to forecast fleet size in the international airline industry. The 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 endogeneity of outputs.

While our cost model seems to be adequate, our demand data is somewhat lacking. Our estimates of demand growth seem unreasonable. Less aggregated world demand data may be necessary to successfully forecast demand growth. Ticket prices

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Table 4.14 Total European Aircraft Demand and Air Travel Demand Under Cost Minimization

Year	Number of Aircraft	Scheduled Service	Non-scheduled Service
1997	1256.29	32965811.36	3983023.17
1998	1276.04	33619911.04	4062053.37
1999	1296.15	34286989.23	4142651.65
2000	1316.60	34967303.40	4224849.16
2001	1337.35	35661116.23	4308677.58
2002	1358.47	36368695.51	4394169.33
2003	1379.95	37090314.40	4481357.38
2004	1401.77	37826251.47	4570275.40
2005	1423.97	38576790.83	4660957.69
2006	1446.53	39342222.21	4753439.28

Table 4.15 Total Asian Aircraft Demand and Air Travel Demand Under Cost Minimization

Year	Number of Aircraft	Scheduled Service	Non-scheduled Service
1997	684.49	28868095.58	3187401.66
1998	705.69	29918593.76	3303389.90
1999	727.58	31007319.12	3423598.91
2000	750.16	32135662.75	3548182.28
2001	773.44	33305066.32	3677299.15
2002	797.47	34517024.04	3811114.57
2003	822.27	35773084.38	3949799.48
2004	847.86	37074852.27	4093531.05
2005	874.26	38423990.94	4242492.97
2006	901.50	39822224.22	4396875.54

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Table 4.16 Total North American Aircraft Demand and Air Travel Demand Under Cost Minimization

Year	Number of Aircraft	Scheduled Service	Non-scheduled Service
1997	4993.28	115760228.11	2897669.36
1998	5373.53	125386999.54	3138643.32
1999	5783.16	135814345.81	3399656.99
2000	6224.45	147108843.78	3682376.89
2001	6699.86	159342606.94	3988608.14
2002	7212.12	172593745.78	4320306.00
2003	7764.06	186946866.60	4679588.27
2004	8358.87	202493611.61	5068748.96
2005	8999.84	219333244.23	5490272.71
2006	9690.62	237573282.63	5946850.93

Table 4.17 Total Europe Aircraft Demand and Air Travel Demand Under Profit Maximization

Year	Number of Aircraft	Scheduled Service	Non-scheduled Service
1997	1275.92	32965811.36	3983023.17
1998	1301.46	33619911.04	4062053.37
1999	1327.71	34286989.23	4142651.65
2000	1354.69	34967303.40	4224849.16
2001	1382.42	35661116.23	4308677.58
2002	1410.94	36368695.51	4394169.33
2003	1440.26	37090314.40	4481357.38
2004	1470.40	37826251.47	4570275.40
2005	1501.41	38576790.83	4660957.69
2006	1533.28	39342222.21	4753439.28

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Table 4.18 Total Asian Aircraft Demand and Air Travel Demand Under Profit Maximization

Year	Number of Aircraft	Scheduled Service	Non-scheduled Service
1997	713.39	28868095.58	3187401.66
1998	743.16	29918593.76	3303389.90
1999	774.59	31007319.12	3423598.91
2000	807.71	32135662.75	3548182.28
2001	842.64	33305066.32	3677299.15
2002	879.51	34517024.04	3811114.57
2003	918.43	35773084.38	3949799.48
2004	959.52	37074852.27	4093531.05
2005	1002.91	38423990.94	4242492.97
2006	1048.79	39822224.22	4396875.54

Table 4.19 Total North American Aircraft Demand and Air Travel Demand Under Profit Maximization

Year	Number of Aircraft	Scheduled Service	Non-scheduled Service
1997	5509.93	115760228.11	2897669.36
1998	6146.73	125386999.54	3138643.32
1999	6873.97	135814345.81	3399656.99
2000	7706.01	147108843.78	3682376.89
2001	8659.77	159342606.94	3988608.14
2002	9755.15	172593745.78	4320306.00
2003	11015.62	186946866.60	4679588.27
2004	12468.82	202493611.61	5068748.96
2005	14147.47	219333244.23	5490272.71
2006	16090.34	237573282.63	5946850.93

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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 the OECD countries, unemployment data is hard to find. While it may be difficult to get better data on air travel demand, this will be of the greatest benefit with 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 a 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 considerably more flexibility in the disposition of owned equipment than either equipment acquired through an operating lease or 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

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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 detail for our modeling approach is that it be able to address a wide range of characteristics of the fleet including a behavioral model that 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, or very fuel efficient engines), although they have been discussed for many years. Further, it is clear that equipment is chosen to serve a particular route structure.

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Chapter 5

Bootstrap and Heteroscedasticity and Autocorrelation Consistent Covariance Estimators

5.1 Introduction

Bootstrapping has become a powerful technique for estimating sampling distributions of statistics since its introduction by Efron (1979). There are good reasons for the substantial interest in bootstrapping methodologies. One is that it allows a researcher an alternative to computing asymptotic distributions of statistics that are intractable. Under some regularity conditions, bootstrapping will provide distributions to test statistics and estimators that are at least as good as first-order asymptotics. Indeed, when bootstrapping asymptotically pivotal statistics, bootstrapping will provide an asymptotic refinement over standard first-order asymptotic theory (Hall, 1992; Horowitz, 1997, 1999). Manski (1975, 1985), Härdle, et al. (1991), West (1990), and Brown and Newey (1992), among others, have adopted the bootstrap as an alternative to utilizing the asymptotic distribution.

Bootstrapping procedures have been expanded to cover the case where errors are conditionally heteroscedastic. Liu (1988) introduced the "wild" bootstrap by extending a bootstrapping procedure proposed by Wu (1986). Härdle and Marron (1991) and Härdle and Mammen (1993) use the wild bootstrap in nonparametric regression.

There are also bootstrapping procedures to cover the case where there is temporal dependence in the error structure. These methods are based on blocking the data,

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and are divided into methods that have non-overlapping or overlapping blocks. Both methods were first suggested by Hall (1985) for use with spatial data. For univariate time series data, Carlstein (1986) suggested non-overlapping blocks, while Künsch (1989) proposed overlapping blocks. Hall, et al. (1996) suggest rules for optimal block length given ones objective of the bootstrapping procedure. Politis and Romano (1994) suggest using random block lengths. They point out that fixed block lengths causes nonstationarity in the bootstrapping process.

While the wild bootstrap and blocking procedures are a great improvement when dealing with non-iid errors, results obtained from these procedures will be misleading when they are used in inappropriate settings. For example, the wild bootstrap will not reproduce any time dependence in the error structure. Block procedures will not capture any conditional heteroscedasticity in the data. These problems will produce unreliable results when either the wild or block bootstraps are used in inappropriate settings.

Kernel-based heteroscedastic and autocorrelation consistent (HAC) covariance matrix estimator are alternatives to bootstrapping t-statistics. The general covariance structure can be estimated by a HAC covariance matrix estimator and therefore eliminate the need for bootstrapping. Hansen (1982), White (1984), Gallant (1987), Newey and West (1987), Robinson (1991), Andrews (1991), Andrews and Monahan (1992), and Hansen (1992), among others, have utilized kernel estimators to produce HAC covariance matrix estimators. However, there are problems with the HAC covariance matrix estimators as well. Kernel based HAC estimation has been shown to perform quite poorly in certain contexts (Andrews, 1991). Also, these kernel-based estimators will converge at rates slower than $o_p(n^{-1/2})$.

Data seldom display only serial dependence or heteroscedasticity. Elements of both are often present. The specification of correlation patterns and the structure

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of variance heterogeneity on *a priori* grounds is problematic. Moreover, samples are rarely large enough to justify the slow rates of convergence which plague the HAC kernel-based alternatives to bootstrapping. We also examine parametric methods using inferences based on ordinary and generalized least squares. Our results question the robustness and usefulness of bootstrapping procedures when the data suffer from the standard problems of serial correlation and/or heteroscedasticity which plague most econometric models.

The chapter is organized as follows. In section 5.2 we discuss the bootstrapping procedures that have been proposed to handle a variety of data generating processes. Section 5.3 outlines the design of a set of Monte Carlo simulations comparing these various inferential methods as well as those based on conventional asymptotic formulas, in particular the ordinary least squares and the generalized least squares estimators. Section 5.3.2 discusses the results of the simulations.

5.2 Inferences Based on Bootstrapping and Kernel Based Procedures When the Data Exhibits Temporal Dependencies and Variance Heterogeneity

Throughout this paper we consider the linear regression model

$$Y = X\beta + \epsilon, \tag{5.1}$$

where Y is $N \times 1$, X is $N \times k$, and ϵ is $N \times 1$. We assume that the regressors are strictly exogenous and that $\mathrm{E}(\epsilon) = 0$, $\mathrm{Cov}(\epsilon) = \Omega$.

5.2.1 The Standard Bootstrap

The bootstrap introduced by Efron (1979) is quite well known and easy to implement. Equation (5.1) is first estimated by ordinary least squares (OLS) to obtain the

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residuals

$$\widehat{\epsilon} = Y - X\widehat{\beta}, \tag{5.2}$$

These are used to construct a bootstrap sample

$$Y^* = X\widehat{\beta} + \widehat{\epsilon}^*, \tag{5.3}$$

where $\widehat{\epsilon}^*$ is an $N \times 1$ vector of residuals drawn randomly, with replacement, from the OLS residuals $\widehat{\epsilon}$. The naive bootstrap estimates β as

$$\widehat{\beta}^* = (X'X)^{-1}X'Y^*. \tag{5.4}$$

By repeating the construction of bootstrap data sets the distribution of the parameter estimates are constructed. Variance estimates and/or confidence intervals are based on this distribution.

Let F_ϵ be the true cumulative distribution function (CDF) of the errors ϵ in (5.1). If the errors in (5.1) are iid, then feasible nonparametric estimate of the CDF of ϵ is given by the empirical CDF of $\widehat{\epsilon}$ where each residual has a probability of $\frac{1}{N}$. If we take B bootstraps from the empirical CDF, where B is suitably large, then for the b^{th} bootstrap,

$$P(\widehat{\epsilon}_n^* = \widehat{\epsilon}_n) = \frac{1}{N}. \tag{5.5}$$

Then,

$$\mathrm{E}\left(\widehat{\beta}^*\right) = \mathrm{E}\left((X'X)^{-1}X'Y^*\right) = \widehat{\beta}.$$

The variance of the bootstrapped residuals is

$$\sigma_{\widehat{\epsilon}}^2 = \mathrm{E}\left(\widehat{\epsilon}_n^{2*}\right) = \frac{1}{N}\sum_{n=1}^{N} \epsilon_n^2 = s^2\frac{N-k}{N},$$

where $s^2 = \frac{1}{N-k}\sum_{n=1}^{N} \epsilon_n^2$. The bootstrap variance estimator differs from the MLE estimator under the assumption of normality by only a scale factor. In this ideal case, the standard bootstrap does not buy us much. However, if the assumption of normality can not be made, then the bootstrap is of use.

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5.2.2 The Pair Bootstrap

In cases where (5.1) have nonconstant variances, the bootstrap can be implemented by resampling observations (Y, X) randomly with replacement. This is known as the pair bootstrap. Equation (5.1) is first estimated by OLS to obtain

$$\widehat{\beta} = (X'X)^{-1}X'Y. \tag{5.6}$$

Then, we construct a bootstrap sample (Y^*, X^*) by resampling observations with replacement. From these bootstrap samples, we obtain

$$\widehat{\beta}^* = (X'^*X^*)^{-1}X'^*Y^*. \tag{5.7}$$

By repeating the construction of bootstrap data sets the distribution of the parameter estimates are constructed. As with the standard bootstrap, variance estimates and/or confidence intervals are based on this distribution. Since ϵ in (5.1) is assumed to be heteroscedastic, the standard bootstrap cannot be implemented by resampling OLS residuals independently of X.

5.2.3 The Wild Bootstrap

The wild bootstrap was originally developed by Liu (1988) to deal with the problem of replicating a data generating process in which variances are nonconstant.

First let F_i, $i = 1, \ldots, N$ be the unique two-point distribution such that

$$\begin{aligned} \mathrm{E}(Z|\,\mathrm{F}_i) &= 0 \\ \mathrm{E}(Z^2|\,\mathrm{F}_i) &= \widehat{\epsilon}_i^2 \\ \mathrm{E}(Z^3|\,\mathrm{F}_i) &= \widehat{\epsilon}_i^3 \end{aligned}$$

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Here, Z is a random variable with distribution F_i. The distribution of Z is given by

$$P(Z=z)=\begin{cases} \frac{1+\sqrt{5}}{2\sqrt{5}}, & z=\frac{(1-\sqrt{5})\widehat{e}_i}{2} \\ 1-\frac{1+\sqrt{5}}{2\sqrt{5}}, & z=\frac{(1+\sqrt{5})\widehat{e}_i}{2} \\ 0, & \text{otherwise} \end{cases} \tag{5.8}$$

The wild bootstrap is carried out by drawing random samples $\widehat{\epsilon}_i^*$ from F_i.

5.2.4 The Blocked Bootstrap

When the structure of serial correlation in a regression model is not known, the bootstrap can be implemented by dividing the data into blocks. Carlstein (1986) suggested that the blocks be non-overlapping, while Künsch (1989) used overlapping blocks. Overlapping block structures have higher bootstrap estimation efficiency than non-overlapping blocks. However, the efficiency gain from using overlapping blocks is small. Hall, et al. (1995) compared the two blocking methods for computing the distribution of the sample mean. They reported that the asymptotic root mean squared error was reduced less than ten percent as a result of using overlapping blocks as opposed to non-overlapping ones. Since there is no computational burden, overlapping blocks are used in the experiments below.

A bootstrap sample is again constructed from the OLS residuals. First, form blocks of length l, $L_k=\{\widehat{\epsilon}_k,\widehat{\epsilon}_{k+1},\ldots,\widehat{\epsilon}_{k+l-1}\}$ for $k=1,2,\ldots,b$, where $b=N-l+1$ and N is the length of $\widehat{\epsilon}$. Next sample the blocks with replacement to create $\widehat{\epsilon}^*=(L_1^*,L_2^*,\ldots,L_{N/l}^*)$. These block bootstrapped residuals are then used to construct a bootstrap sample

$$Y^*=X\widehat{\beta}+\widehat{\epsilon}^*. \tag{5.9}$$

and the bootstrap estimate $\widehat{\beta}^*$:

$$\widehat{\beta}^*=(X'X)^{-1}X'Y^*. \tag{5.10}$$

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This process is repeated many times to build up the distribution for the parameters.

Asymptotic refinements cannot be gained by using independent bootstrap samples if the data generating process produces dependent data. If one has a parametric model, such as an ARMA model, that allows the data generating process to be reduced to a transformation of iid random variables, then the standard bootstrapping procedure can be used. However, if the process cannot be transformed suitably, or a parametric model is not known, then blocking allows the use of the bootstrap.

5.2.5 Heteroscedasticity and Autocorrelation Consistent (HAC) Covariance Estimators

White (1982) was the first to note that consistent estimation of the variance of the (inefficient) least squares estimator of β did not require a consistent estimator of all unique elements of the $N \times N$ matrix Ω, only the unique elements of the $k \times k$ matrix $X'\Omega X$. However, this is just the variance of $v = x'\epsilon$. If we could consistently (at the rate $n^{-1/2}$) estimate the variance of ν then we could construct a root-n consistent estimator for the variance of the least squares estimator of β without requiring the structure of the variance to be specified *a priori*, or with an estimator that converges at a slower than $n^{1/2}$ rate. The motivation behind the heteroscedastic and autocorrelation consistent (HAC) estimator is that the ordinary least squares estimator of β has an asymptotic variance that can be consistently estimated by a finite number of parameters. Specifically, since the distribution of

$$\widehat{\beta}_{ols} \longrightarrow \mathrm{N}(\beta, (X'X)^{-1}(X'\Omega X)(X'X)^{-1}) \tag{5.11}$$

and since $X'\Omega X$ can be consistently estimated by a finite number of parameters, a kernel based smoother is a good candidate for such a consistent estimator. One such HAC estimator developed by Andrews and Monahan (1992) utilizes a first-order

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vector autoregressive (VAR) prewhitening scheme. First let[1]

$$\widehat{\Upsilon} = \begin{bmatrix} x_{11}\widehat{\epsilon}_1 & x_{12}\widehat{\epsilon}_1 & \cdots & x_{1k}\widehat{\epsilon}_1 \\ x_{21}\widehat{\epsilon}_2 & x_{22}\widehat{\epsilon}_2 & \cdots & x_{2k}\widehat{\epsilon}_2 \\ \vdots & \vdots & \ddots & \vdots \\ x_{T1}\widehat{\epsilon}_T & x_{T2}\widehat{\epsilon}_T & \cdots & x_{Tk}\widehat{\epsilon}_T \end{bmatrix}, \tag{5.12}$$

where $\widehat{\epsilon}_t$ is the tth OLS residual from the estimation of (5.1). The VAR is specified as

$$\widehat{\Upsilon}_t = \widehat{\Upsilon}_{t-1}A + \psi_t, \qquad t = 2, 3, \ldots, T, \tag{5.13}$$

and can be estimated by ordinary least squares. This estimator for A is adjusted using a single value decomposition so that $I_k - \widehat{A}$ is not singular. Next, the whitened kernel HAC estimator, $\widehat{X'\Omega X}_w$ is computed

$$\widehat{X'\Omega X}_w = \frac{T}{T-k}\sum_{j=-T+1}^{T-1} k_{Qs}\left(\frac{j}{\widehat{S}_T}\right)\widehat{\Gamma}^*(j),$$

where

$$\widehat{\Gamma}^*(j) = \begin{cases} \frac{1}{T}\sum_{t=j+1}^{T} \widehat{\psi}_t\widehat{\psi}'_{t=j}, & j \geq 0 \\ \frac{1}{T}\sum_{t=-j+1}^{T} \widehat{\psi}_{t+j}\widehat{\psi}'_t, & j < 0 \end{cases}$$

and $\widehat{S}_T$ is a data-dependent bandwidth parameter. A data-dependent plug-in estimate of the optimal value determined by Andrews (1991), given the QS kernel $k_{QS}(\cdot)$ defined by

$$k_{QS}(x) = \frac{25}{12\pi^2x^2}\left(\frac{\sin(6\pi x/5)}{6\pi x/5} - \cos(6\pi x/5)\right)$$

is given by

$$\widehat{S}_T = 1.3221(\widehat{\alpha}^*(2)T)^{1/3}$$

[1]When considering temporal dependence it is more natural to utilize the time subscript. Clearly this is just a labeling convention. The distinction between the i and t subscripts is apparent for the particular type of model we consider.

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where

$$\widehat{\alpha}^*(2) = \left(\sum_{a=1}^{k} w_a \frac{4\widehat{\rho}_a \widehat{\sigma}_a^4}{(1-\widehat{\rho}_a)^8}\right) / \left(\sum_{a=1}^{k} w_a \frac{\widehat{\sigma}_a^4}{(1-\widehat{\rho}_a)^4}\right).$$

The parameters (ρ_a, σ_a^2) are the autoregressive and variance parameters and the w_a are the weights attached to estimates of each of the k diagonal elements of Ω. We use the weights used by Andrews and Monahan (1992), where $w_1 = 0$, $w_i = 1$, $i = 2, ..., k$.

The estimator of $\widehat{X'\Omega X}_w$ is then recolored to obtain the VAR prewhitened HAC kernel estimator of

$$\widehat{X'\Omega X}_{hac} = \widehat{D}\widehat{X'\Omega X}_w \widehat{D}'$$

where

$$\widehat{D} = (I_k - \widehat{A})^{-1}$$

5.3 Monte Carlo Evidence

5.3.1 Design of the Experiments

In order to determine the usefulness of these procedures in finite samples, we conducted a set of Monte Carlo experiments. A single equation model was constructed. The model is

$$Y = X\beta + \epsilon, \tag{5.14}$$

where X is a $T \times k$ matrix and $k = 3$ with the last column of X being a constant. The first two regressors are i.i.d. normal random variables.[2]

[2]To speed up computational speed, the $x's$ are then transformed in the following way. We start with two vectors of normally distributed data, x_1 and x_2, which we use as our exogenous variables. These two vectors are combined into a $T \times 2$ vector $\widetilde{x}$. Let $\overline{x}_i$ be the mean of vector x_i and $\overline{x} = (\overline{x_1}, \overline{x_2})$. We new construct $\overline{\overline{x}} = \widetilde{x} - \overline{x}$ which provides us with a transformation

$$x^* = \overline{\overline{x}} \left(\frac{1}{t} \overline{\overline{x}}' \overline{\overline{x}}\right)^{\frac{1}{2}}$$

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The vector $\beta = [2, 0, 3]$. The same β was used in all the experiments. The sample sizes of the experiments were set to 30, 60 and 120. Several different error structures were used. Each experiment was replicated 2500 times.

For each replication, we test the hypothesis that $\beta_2 = 0$ using one of seven methods. All the methods use a t-statistic and either the asymptotic critical value or a bootstrapped critical value to either accept or reject the null hypothesis. All the tests are two-sided.

The first four methods utilize the bootstraps to find a critical value z_α to determine whether to reject the null hypothesis of $\beta_2 = 0$. We use the standard bootstrap, the pair bootstrap, the wild bootstrap, and the block bootstrap.

In each of the Monte Carlo replications, the following procedure was followed:

1. Generate a data set to be estimated from equation (5.14) where β_2 is set equal to 0. Estimate β using OLS and compute the

2. Generate a bootstrap sample of size t from the residuals of the constrained OLS estimate of β. The method of constructing the bootstrap sample depends on the bootstrap method used. That is, the bootstrap sample is $Y^* = X\widehat{\beta}_c + \widehat{\epsilon}^*$, where $\widehat{\beta}_c$ are the constrained OLS estimates of β and $\widehat{\epsilon}^*$ are generated from the standard, block, or wild bootstrap. For the pair bootstrap, we generate a bootstrap sample of size t by drawing observations $(Y, X)^*$ randomly, with replacement, from the original data set.

3. From this bootstrap sample, estimate a bootstrapped $\widehat{\beta}^*$ using unconstrained OLS and $\widehat{\widehat{\epsilon}^*} = Y^* - X\widehat{\beta}^*$.

---

such that if $\imath$ is a vectors of ones, and $x = (\imath, x^*)$, then

$$(x'x)^{-1} = \frac{1}{T}I$$

where I is the identity matrix.

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4. Next, compute the bootstrapped t-statistic, T^*, for testing $H_0^* : \beta_2 = 0$. T^* for the standard bootstrap is the standard t-statistic
$$T^*_{std} = \frac{\widehat{\beta}_i^*}{s^*_{22}},$$
where s^*_{22} is based on $\widehat{\epsilon}^*$ using the standard covariance estimator. For the pair bootstrap, T^* is
$$T^*_{wild} = \frac{\widehat{\beta}_i - \widehat{\beta}_i^*}{sw^*_{22}},$$
where $\widehat{\beta}_i$ is the unconstrained OLS estimate and sw^*_{22} is estimated using the White heteroscedastic consistent covariance matrix using $\widehat{\epsilon}^*$ and X. For the wild bootstrap, T^* is
$$T^*_{wild} = \frac{\widehat{\beta}_i^*}{sw^*_{22}},$$
where sw^*_{22} is estimated using the White heteroscedastic consistent covariance matrix using $\widehat{\epsilon}^*$ and X. The block bootstrap calculates T^* as
$$T^*_{block} = \frac{\widehat{\beta}_i^*}{sh^*_{22}},$$
where sh^*_{22} is estimated using the HAC covariance matrix, again using $\widehat{\epsilon}^*$ and X. Hall, et al. (1995) note that the optimal block length for estimating a two-sided distribution function is $l \sim n^{1/5}$. Optimality is defined as minimizing the asymptotic mean-squared error of the block bootstrap estimator. Therefore, in our simulations, we use a block of length two, since $30^{1/5} \approx 1.97$, $60^{1/5} \approx 2.27$ and $120^{1/5} \approx 2.61$. For $n = 120$, perhaps a block length of three would be better, but we kept the length two for consistency between simulations.

5. By repeating this step B times, we have four bootstrap distributions for T^*, one for each of the bootstrapping methods used.

6. With the B bootstrap estimates of $T_b^*, b = 1, ..., B$, we find the critical values z_α by ordering $|T_b^*|$ and finding the p^{th} percentile $|T_p^*| = (1-g)|T_j^*| + g|T_{j+1}^*|$,

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where $j = int\left[(B+1)\,p\right]$ and $g = (B+1)\,p - j$. Then, we set $z_\alpha = |T_p^*|$, where $\alpha = 1 - p$. So, for a nominal five-percent rejection rate, we find the 95^{th} percentile of the ordered T_b^* statistics and reject the null hypothesis when $|T| > z_\alpha = |T_p^*|$.

The fourth method used is the standard t-statistic for testing $H_0 : \beta_i = 0$:

$$T_{std} = \frac{\widehat{\beta}_i}{s_{ii}}, \tag{5.15}$$

where s_{ii} is the square-root of the iith element of $s^2(X'X)^{-1}$. Here, $s^2 = \widehat{\epsilon}'\widehat{\epsilon}/(T-k)$. We then reject the null hypothesis if $|T_{std}| > 1.96$ at the five-percent confidence level and $|T_{std}| > 2.575$ at the one-percent confidence level. The results of the simulations using this method are shown in the table rows labeled *std.asy*.

The fifth method used the t-statistic based on the White (1980) heteroscedastic consistent covariance matrix estimator. We calculate T_{white} as in (5.15), except the term s_{ii} is replaced with the square root of the iith element of

$$(X'X)^{-1}\widehat{X'\Omega X}_{white}(X'X)^{-1}$$

and where

$$\widehat{X'\Omega X}_{white} = \frac{1}{T}\sum_t \epsilon_t^2 x_t x_t'.$$

As with the standard t-statistic, we reject the null hypothesis if $|T_{white}| > 1.96$ at the five-percent confidence level and $|T_{white}| > 2.575$ at the one-percent confidence level.

In the sixth method, the t-statistic is based on the Andrews and Monahan (1992) HAC estimator $\widehat{X'\Omega X}_{hac}$. Thus T_{hac} is computed as T_{std} except that s_{ii} is now the square root of the iith element of the estimated HAC covariance matrix

$$(X'X)^{-1}\widehat{X'\Omega X}_{hac}(X'X)^{-1}.$$

This too is an asymptotic test so we reject the null hypothesis if $|T_{hac}| > 1.96$ at the five-percent confidence level and $|T_{hac}| > 2.575$ at the one-percent confidence level.

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5.3.2 Monte Carlo Results

The results of the Monte Carlo study are shown in Tables 5.1 through 5.6. Note that if the the true size of the test is 5%, then the standard error of a particular simulation based on NS=2500 simulations is 0.44%. Therefore, a 95% confidence interval on a 5% rejection rate is [4.15%, 5.85%] . When our experimental results yield rejection probabilities within such a range, we indicate those experiments with a *. For a test of one-percent, the 95% confidence interval for 2500 Monte Carlo simulations is [0.61%, 1.39%]. Heteroscedasticity and serial dependencies are modeled as

$$\epsilon_t = \left(1 + x_{1t}^2 + x_{2t}^2\right)^{1/2} \nu_t, \tag{5.16}$$

where $\nu_t = \rho\nu_{t-1} + u_t$ and $u_t \sim \mathrm{N}(0, 1)$.

In Table 5.1, the errors in our model are iid, $\mathrm{N}(0,1)$ random variables. The standard asymptotic test performs quite well, even in small samples. The other asymptotic test did not do as well, however. In small samples ($t = 30$), the White and HAC asymptotic tests reject from two to five times too much, depending on the nominal size of the test. The standard bootstrap performs as well, or better, as the asymptotic test. The other bootstrap methods performed very well. These methods seemed to perform as well as the standard bootstrap. The one exception is the pair bootstrap. It performs better than the White or HAC asymptotic tests, but not as well as the other bootstrapping methods.

In Table 5.2, the errors in our model are iid random variables. The distribution is t_3. The standard bootstrap performs well, as do the pair, the wild and block bootstraps. The HAC estimator does not perform well, but it improves as sample size gets larger. These results hold for the case where the errors are t_5, as seen in Table 5.3. The pair bootstrap does well in these tests, though it does not perform as well as the wild bootstrap.

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Table 5.1 Homoscedastic Normal Errors with $\sigma^2 = 1$

	$t = 30$		$t = 60$		$t = 120$	
method	5%	1%	5%	1%	5%	1%
std.asy	5.64*	1.52	5.68*	1.84	5.04*	1.20*
white.asy	10.40	4.08	7.56	2.48	5.92	1.48
hac.asy	12.28	5.16	7.64	3.00	6.36	1.80
std	5.16*	1.48	5.92	2.00	5.08*	1.36*
wild	4.76*	0.72*	5.44*	1.24*	5.24*	1.40
block	5.64*	1.00*	6.08	2.32	5.04*	1.60
pair	6.00	1.40	6.60	2.20	5.90	1.80

Table 5.2 Homoscedastic t-Distributed Errors with 3 Degrees of Freedom

	$t = 30$		$t = 60$		$t = 120$	
method	5%	1%	5%	1%	5%	1%
asy.std	5.60*	1.80	5.20*	1.30*	5.40*	1.40
asy.white	8.40	2.50	6.00	1.80	5.70*	1.40
asy.hac	11.20	4.80	7.20	2.20	6.90	1.40
std	4.84*	0.88*	5.14*	1.08*	4.88*	0.94*
wild	6.92	1.72	6.72	1.60	5.64*	1.30*
block	4.82*	0.98*	5.34*	0.92*	4.76*	1.12*
pair	3.80	0.60	5.00*	1.60	5.50*	1.70

Table 5.3 Homoscedastic t-Distributed Errors with 5 Degrees of Freedom

	$t = 30$		$t = 60$		$t = 120$	
method	5%	1%	5%	1%	5%	1%
asy.std	5.10*	1.50	6.20	1.20	5.20*	1.30*
asy.white	9.10	2.60	7.60	2.20	6.00	2.10
asy.hac	10.20	4.60	8.00	2.70	6.60	2.80
std	4.34*	1.04*	4.96*	1.02*	5.02*	0.96*
wild	6.24	1.38*	5.66*	1.40	5.06*	1.20*
block	4.86*	0.86*	5.26*	1.20*	4.68*	1.06*
pair	5.20*	1.70	5.50*	1.20*	5.90	1.60

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In Tables 5.4, 5.5, and 5.6, the errors are both autocorrelated and heteroscedastic. These errors are generated from (5.16). The wild bootstrap seems to be the best method in this situation. Its size tends to be closer to the nominal size in small samples. When the sample sizes get larger and the HAC estimator improves, the wild bootstrap still performs well. The pair bootstrap works well in cases where $t = 60$ and the autocorrelation coefficient is close to zero.

Table 5.4 Autocorrelated Heteroscedastic Errors with $t = 30$

	$\rho = -0.99$		$\rho = -0.9$		$\rho = -0.7$		$\rho = -0.5$	
method	5%	1%	5%	1%	5%	1%	5%	1%
asy.std	22.30	5.30	28.50	12.60	31.80	16.30	33.00	17.70
asy.white	10.60	2.30	11.10	4.00	13.80	6.20	15.90	5.40
asy.hac	33.20	14.32	4.00	1.16*	10.86	3.92	14.72	6.88
std	3.58	0.58	4.28*	1.12*	11.60	2.86	12.56	3.40
wild	9.36	1.64	4.00	0.94*	6.44	0.98*	4.92*	0.90*
block	2.72	0.52	3.96	1.14*	12.66	3.64	14.36	4.24
pair	1.50	0.20	3.60	0.80*	4.30*	1.10*	3.90	0.90*
	$\rho = -0.3$		$\rho = -0.1$		$\rho = 0.1$		$\rho = 0.3$	
method	5%	1%	5%	1%	5%	1%	5%	1%
asy.std	32.10	18.00	32.40	19.00	33.70	19.60	33.60	19.60
asy.white	15.70	6.00	16.30	6.20	16.80	6.60	16.50	6.30
asy.hac	17.60	9.08	12.90	5.74	15.64	7.86	13.74	5.90
std	15.04	4.58	8.48	2.34	11.78	3.72	10.30	2.78
wild	5.30*	1.04*	6.28	1.64	7.16	2.16	5.96	1.26*
block	13.38	4.04	8.46	2.12	11.58	3.52	10.96	3.06
pair	3.60	1.00*	3.80	1.00*	4.10	1.00*	3.60	0.90*
	$\rho = 0.5$		$\rho = 0.7$		$\rho = 0.9$		$\rho = 0.99$	
method	5%	1%	5%	1%	5%	1%	5%	1%
asy.std	34.30	18.80	36.00	20.00	38.50	20.00	27.10	10.20
asy.white	16.10	5.50	16.50	4.30	16.30	3.40	17.00	2.50
asy.hac	18.70	9.58	12.46	5.14	17.14	5.78	41.72	19.94
std	12.34	4.08	9.64	2.84	1.00	0.08	0.74	0.10
wild	7.36	1.84	10.40	3.58	1.48	0.18	3.50	0.68
block	15.70	5.58	7.94	1.66	1.98	0.14	0.94	0.12
pair	3.60	0.60	3.20	0.60	3.00	0.40	0.90	0.00

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Table 5.5 Autocorrelated Heteroscedastic Errors with $t = 60$

	$\rho = -0.99$		$\rho = -0.9$		$\rho = -0.7$		$\rho = -0.5$	
method	5%	1%	5%	1%	5%	1%	5%	1%
asy.std	5.30*	0.90*	14.60	4.20	19.20	8.10	20.10	8.80
asy.white	2.30	0.40	7.40	1.70	10.60	3.30	10.40	3.70
asy.hac	4.52*	0.92*	25.64	12.94	5.36*	1.66	7.66	2.74
std	2.36	0.24	23.96	8.70	7.24	1.48	13.14	4.30
wild	2.04	0.38	11.18	3.00	4.00	0.82*	7.96	2.22
block	2.04	0.32	29.34	13.46	6.38	1.56	12.04	3.80
pair	0.70	0.20	3.30	0.90*	5.60*	1.50	5.00*	1.60

	$\rho = -0.3$		$\rho = -0.1$		$\rho = 0.1$		$\rho = 0.3$	
method	5%	1%	5%	1%	5%	1%	5%	1%
asy.std	18.50	8.20	16.70	7.50	16.40	7.30	16.60	6.80
asy.white	10.30	3.40	9.40	3.00	8.60	2.80	8.50	2.40
asy.hac	10.34	3.92	8.32	2.94	10.30	3.46	9.76	3.08
std	16.98	5.62	11.48	3.36	11.72	3.42	9.04	2.08
wild	7.72	2.04	6.66	1.68	5.42*	1.14*	5.40*	1.14*
block	15.16	4.98	11.54	3.14	11.30	2.98	9.26	2.38
pair	5.00*	1.20*	4.50*	1.20*	4.10	1.30*	4.10	1.20*

	$\rho = 0.5$		$\rho = 0.7$		$\rho = 0.9$		$\rho = 0.99$	
method	5%	1%	5%	1%	5%	1%	5%	1%
asy.std	16.80	7.00	17.10	6.00	12.90	3.80	3.00	0.80
asy.white	9.10	2.50	7.90	2.40	6.10	1.30	1.60	0.40
asy.hac	8.74	3.04	13.12	4.90	14.02	5.06	5.24*	1.34*
std	9.54	2.60	15.78	4.88	19.30	6.66	3.18	0.54
wild	4.32*	0.84*	11.00	3.68	6.34	1.12*	1.04	0.10
block	9.86	2.78	13.48	4.38	16.56	5.04	3.06	0.72
pair	4.00	1.00*	3.50	0.70*	2.90	0.50	1.10	0.30

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Table 5.6 Autocorrelated Heteroscedastic Errors $t = 120$

	$\rho = -0.99$		$\rho = -0.9$		$\rho = -0.7$		$\rho = -0.5$	
method	5%	1%	5%	1%	5%	1%	5%	1%
asy.std	6.20	2.70	20.50	8.40	15.30	6.60	15.10	5.90
asy.white	1.90	0.40	6.50	1.40	5.50*	1.00*	4.90*	1.10*
asy.hac	6.10	2.04	3.20	0.54	4.56*	0.88*	8.10	2.84
std	4.12	1.02*	6.86	1.80	10.12	2.54	14.72	5.62
wild	1.72	0.38	2.58	0.40	4.66*	1.12*	7.42	2.06
block	5.18*	1.24*	5.50*	1.18*	7.82	1.86	13.30	4.68
pair	0.60	0.00	1.60	0.20	1.30	0.20	1.70	0.40
	$\rho = -0.3$		$\rho = -0.1$		$\rho = 0.1$		$\rho = 0.3$	
method	5%	1%	5%	1%	5%	1%	5%	1%
asy.std	16.20	6.30	16.60	7.40	17.70	8.10	19.90	8.80
asy.white	5.40*	1.40	6.50	1.60	7.30	1.50	8.00	2.60
asy.hac	7.54	1.96	6.88	1.78	8.74	2.50	7.96	2.36
std	13.04	4.48	11.80	3.62	14.12	4.82	13.30	3.70
wild	4.58*	1.00*	5.48*	1.12*	5.74*	1.12*	5.10*	1.14*
block	14.86	4.82	11.58	3.48	13.78	4.38	12.90	3.96
pair	1.90	0.50	2.20	0.60	2.60	0.70*	3.80	0.90*
	$\rho = 0.5$		$\rho = 0.7$		$\rho = 0.9$		$\rho = 0.99$	
method	5%	1%	5%	1%	5%	1%	5%	1%
asy.std	23.70	11.30	31.80	17.90	42.20	29.80	60.90	40.70
asy.white	10.20	3.40	16.20	5.90	26.10	13.80	25.00	5.20
asy.hac	8.84	2.74	6.74	1.94	9.36	3.38	64.26	50.68
std	9.16	2.60	12.94	4.00	9.06	2.34	57.08	20.58
wild	4.24*	0.70*	3.62	0.62	1.60	0.12	52.08	26.12
block	9.42	2.46	14.24	5.00	11.54	3.84	52.72	14.98
pair	4.90*	1.50	8.20	2.50	15.40	6.40	3.20	0.90*

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5.4 Conclusions

In this chapter, we examined four bootstrapping procedures: the standard bootstrap; the pair bootstrap; the wild bootstrap; and, the block bootstrap. We also examined the heteroscedasticity and autocorrelation consistent covariance matrix estimator of Andrews and Monahan (1992). We briefly outlined the procedure for using all four bootstrap procedures. We explained how to use the Andrews and Monahan (1992) HAC covariance matrix estimator.

To determine the usefulness of the different bootstrap procedures, as well as the HAC covariance matrix estimator, we conducted several Monte Carlo experiments. These experiments were designed to examine the performance of the bootstrap estimators where the ideal conditions for all the methods was violated to some degree. However, we conducted some experiments for the iid random error case.

We found that when the errors of a single-equation model were iid, the standard asymptotic test works quite well, even in very small samples. The standard and wild bootstraps both performed well in these cases. When errors were drawn independently from a t-distribution, the standard and block bootstraps both worked well.

When our model included errors that were both heteroscedastic and autocorrelated, the performance of all the estimators suffered. In small samples ($t = 30$), the HAC estimator rejected a null hypothesis that was true about three times the nominal rejection rate.

The pair and wild bootstraps did not perform too badly in the cases where the autocorrelation coefficient was small ($|\rho| \leq 0.3$). The standard bootstrap never worked well in these cases. The block bootstrap did not perform well in these cases.

Our results suggest that the bootstrap does not work well when the data generation process violates the assumptions of the bootstrap method in some fashion. Also, the HAC estimators are of little use when sample sizes are not large.

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Chapter 6

Bootstrapped Aircraft Cost Model Confidence and Prediction Intervals

6.1 Introduction

Panel data sets, data sets that contain both time series and cross sections, are very common in economics. Our U.S. and world data sets are two examples of such data sets. There are often complex covariance structures that make calculating asymptotic distributions difficult at best.

In addition, we often calculate elasticities and other functions of the parameters that are highly non-linear. It is sometimes impossible to work out asymptotic distributions for such estimates. The bootstrap is a technique that allows us to find confidence intervals for these estimates.

6.1.1 Bootstrap Confidence Intervals

There are several detailed comparisons of bootstrap confidence intervals [*e.g.*, Diciccio and Romano, 1988 and Hall, 1988, 1992]. We will briefly review some of the ideas. Let $\widehat{\beta}$ be an estimate of a parameter β based on the sample X. Let $\widehat{\beta}^*$ be a bootstrap estimate of β. One $(1-2\alpha)100$ percent confidence interval for β is

$$CI_B = \left[\widehat{F}^{-1}(\alpha), \widehat{F}^{-1}(1-\alpha)\right], \tag{6.1}$$

where $\widehat{F}(x) = \Pr(\widehat{\beta}^* \leq x|X)$ is the bootstrap distribution function of $\widehat{\beta}^*$. This method is known as the percentile method. It has been shown in Diciccio and Romano (1988) to have some problems in small samples.

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Efron (1982) introduced the bias correction or BC method to improve upon the percentile method. The method "centers" the empirical distribution $\widehat{F}(x)$ so that $\widehat{F}(1/2) = \widehat{\beta}$. The $(1-2\alpha)100$ percent confidence interval is

$$CI_{BC} = \left[\widehat{F}^{-1}(\Phi(2\widehat{m} + z_{\alpha})), \widehat{F}^{-1}(\Phi(2\widehat{m} + z_{1-\alpha}))\right], \tag{6.2}$$

where $\widehat{m} = \Phi^{-1}(\widehat{F}(\widehat{\beta}))$ and $z_{\alpha} = \Phi^{-1}(\alpha)$. Schenker (1985) showed that the BC method has coverage probabilities that are bias downward substantially in small samples.

To improve the confidence intervals, Efron (1987) introduced the accelerated bias correction or ABC (sometimes BC_a) method to adjust for bias and skewness. With this method, the confidence interval becomes

$$CI_{ABC} = \left[\widehat{F}^{-1}(\Phi(g[\alpha])), \widehat{F}^{-1}(\Phi(g[1-\alpha]))\right], \tag{6.3}$$

where

$$g(x) = \widehat{m} + \frac{\widehat{m} + z_x}{1 - \widehat{a}(\widehat{m} + z_x)} \tag{6.4}$$

and a is the estimate of the acceleration constant, which is a measure of skewness.

Another method for finding confidence intervals is the percentile-t method. The procedure is to bootstrap a sample and then calculate the usual t-statistic $t^* = \frac{\widehat{\beta}^* - \widehat{\beta}}{s^*}$ using the formulas from asymptotic theory. We then use the distribution of t^* to construct the confidence interval

$$CI_{Bt} = \left[\widehat{\beta} - \widehat{\sigma} t^*_{1-\alpha}, \widehat{\beta} + \widehat{\sigma} t^*_{\alpha}\right]. \tag{6.5}$$

Hall (1992) shows that the percentile-t method produces confidence intervals that are closer to nominal values than those produced by first-order asymptotic theory.

6.1.2 Bootstrap Forecasts

Forecasting is an important use (and often the objective) of econometric models. However, point forecasts are usually of little value by themselves. Standard errors of

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the forecasts or prediction intervals for the point forecasts are also important. Stine (1985) suggests the bootstrap as a distribution-free prediction interval estimator. Again, consider (5.1). We wish to predict y_{N+1} with known x_{N+1}. To bootstrap the prediction interval, we first obtain $\widehat{\epsilon}$ from OLS estimation of (5.1). Then, we construct a bootstrap sample $[\widehat{\epsilon}_1^*, \ldots, \widehat{\epsilon}_N^*, \widehat{\epsilon}_{N+1}^*]$. The bootstrap forecast is then

$$y_{N+1}^* = x_{N+1}\widehat{\beta} + \widehat{\epsilon}_{N+1}^*. \tag{6.6}$$

We then use $[\widehat{\epsilon}_1^*, \ldots, \widehat{\epsilon}_N^*]$ to construct the bootstrap data set

$$Y^* = X\widehat{\beta} + \widehat{\epsilon}^* \tag{6.7}$$

and compute the bootstrap estimate $\widehat{\beta}^*$. The prediction error is then

$$PE_b = y_{N+1}^* - x_{N+1}\widehat{\beta}^*. \tag{6.8}$$

By repeating these steps many times, we can construct an empirical distribution for the prediction errors. Let $\widehat{F}(\alpha)$ be the CDF of the bootstrap distribution. The $(1-2\alpha)100$ percent prediction interval is

$$PI_B = \left[x_{N+1}\widehat{\beta} + \widehat{F}^{-1}(\alpha), x_{N+1}\widehat{\beta} + \widehat{F}^{-1}(1-\alpha)\right]. \tag{6.9}$$

Stine (1985) shows that the coverage of the bootstrap prediction intervals are quite good in small samples. He also proves that the bootstrap prediction interval is asymptotically correct. Veall (1987) use the bootstrap to obtain forecast errors for peak electricity demand. Prescott and Stengos (1987) use the method with lagged dependent variables. Peters and Freedman (1985) use the bootstrap to find multi-period prediction errors to evaluate between forecasting models.

6.2 The Cost Model

We use a translog functional form for our cost equations. This is the most widely used of the flexible functional forms (Green, 1993). The translog functional form

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was introduced by Christensen, et al., (1973) as a production function that did not impose homotheticity or separability. However, we do impose homotheticity in the cost function. We also imposed symmetry of the cross-price derivatives.

The short-run technology has three variable inputs, two quasi-fixed factor, three characteristics of the aircraft, two measured output quantities, and two output service characteristics. We control for cost-neutral seasonal variations by including three seasonal dummy variables in the cost equation. We also control for fixed firm effects by including firm dummy variables 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, et al., 1990).

After we impose symmetry, the cost function is given by

$$\begin{aligned}
\log C \quad = \quad & \alpha + \sum_{i=1}^{4} \beta_i \log p_i + \sum_{j>i}^{5} \sum_{i=1}^{4} \delta_{ij} \log p_i \log p_j + \frac{1}{2} \sum_{i=1}^{5} \delta_{ii} \log^2 p_i \\
& + \sum_{i=1}^{2} \gamma_i \log Y_i + \frac{1}{2} \sum_{i=1}^{2} \gamma_{ii} \log^2 Y_i + \gamma_{12} \log Y_1 \log Y_2 \\
& + \sum_{i \in \{shk, lhk\}} \delta_{AAi} \log p_i \log AA + \delta_{ASi} \log p_i \log AS + \delta_{FUi} \log p_i \log FU \\
& + \delta_{SLi} \log p_i \log SL + \delta_{LFi} \log p_i \log LF \\
& + \sum_{i=1}^{15} \delta_i AIR_i, \qquad (6.10)
\end{aligned}$$

where p_i is the i^{th} input price, Y_i is one of the two outputs (scheduled output and non-scheduled output), AA is the average age of an airframe in months, AS is the average size in seats of the fleet, FU is the fuel efficiency index, SL is the stage length, and LF is the load factor.

The cost shares must add to unity and we must have linear homogeneity in input prices. The following restrictions are applied to impose these conditions on the cost

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function:

$$\sum_i \beta_i = 1; \sum_j \delta_{ij} = 0; \sum_{i \in \{AA,AS,FU,SL,LF\}} \delta_i = 0 \tag{6.11}$$

The cost share of short-haul capital is given by

$$\begin{aligned} S_{ksh} &= \beta_{ksh} + \sum_{i=1}^{5} \delta_{ik} \log p_i + \delta_{AA} \log AA \\ &+\delta_{AS} \log AS + \delta_{FU} \log FU + \delta_{SL} \log SL + \delta_{LF} \log LF. \end{aligned} \tag{6.12}$$

The long-haul capital share equation is

$$\begin{aligned} S_{klh} &= \beta_{klh} + \sum_{i=1}^{5} \delta_{ik} \log p_i + \delta_{AA} \log AA \\ &+\delta_{AS} \log AS + \delta_{FU} \log FU + \delta_{SL} \log SL + \delta_{LF} \log LF. \end{aligned} \tag{6.13}$$

The three remaining share equations are

$$S_j = \beta_j + \sum_{i=1}^{5} \delta_{ij} \log p_i. \tag{6.14}$$

Summary statistics based on the translog and its associated share equations are provided by the Allen-Uzawa, Morishima and own- and cross-price substitution elasticities, and a measure of returns to scale. The Allen-Uzawa elasticities of substitution are given by

$$\begin{aligned} \theta_{ij} &= \frac{\delta_{ij} + S_i S_j}{S_i S_j} \\ \theta_{ii} &= \frac{\delta_{ii} + S_i(S_i - 1)}{S_i^2}. \end{aligned} \tag{6.15}$$

Morishima elasticities are given by

$$\sigma_{ij} = (\theta_{ji} - \theta_{ii}) S_i, i \neq j. \tag{6.16}$$

The own- and cross-price elasticities are

$$\begin{aligned} \epsilon_{ii} &= \theta_{ii} S_i \\ \epsilon_{ij} &= \theta_{ij} S_j, i \neq j \\ \epsilon_{ji} &= \theta_{ij} S_i, i \neq j. \end{aligned} \tag{6.17}$$

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6.3 Model Estimation

We estimated (6.10), (6.12), (6.13) and the labor and energy share equations using iterated seemingly unrelated regressions (ITSUR). The parameter estimates of the cost equation are shown in Table 6.3. The returns to scale at the data mean is 1.058. The fitted cost function is concave at 91.9 percent of the data points and is positive at all of the data points. The fitted share equation values at the data mean are shown in Table 6.3.

The Allen-Uzawa partial elasticities of substitution are shown in Table 6.3. From these estimates, we see that labor and energy are substitutes, as are labor and materials, labor and long-haul capital, energy and short-haul capital, materials and short-haul capital, and short-haul capital and long-haul capital. All other combinations are complements.

As can be seen in (6.15), these elasticities are non-linear functions of the parameter estimates. Even if the parameter estimates are normal random variables, finding confidence intervals will be no easy task. One possible way to deal with this non-linearity is to calculate a linear approximation of the elasticities and then find an approximation to the true variance using standard statistical procedures. However, Krinsky and Robb (1986) point out that linear approximations greatly understate the the variance of the elasticities. They recommend using a simulation procedure, assuming that the parameter estimates are normally distributed. The covariance matrix from the estimation is used for this procedure. Since Eaton (1985) proves that the conventional estimator of the covariance matrix is downwardly biased in the general SUR model, and Atkinson and Wilson (1992) show that the bootstrap estimator has a smaller bias, in some cases, we will bootstrap the confidence intervals for elasticities instead of using the simulation procedure.

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Table 6.1 Cost Function Variable Estimates

Variable	Parameter Estimate	T-Ratio
Labor price	0.379	158.486
Labor price squared	-0.008	-0.539
Labor × energy	-0.008	-1.788
Labor × materials	0.044	3.284
Labor × short-haul	-0.035	-5.777
Labor × long-haul	0.008	1.297
Energy price	0.169	117.579
Energy price squared	0.149	53.089
Energy × materials	-0.134	-37.319
Energy × short-haul	0.014	4.500
Energy × long-haul	-0.021	-7.967
Materials price	0.329	174.935
Materials price squared	0.106	7.260
Materials × short-haul	0.008	1.511
Materials × long-haul	-0.024	-4.156
Short-haul price	0.082	38.993
Short-haul price squared	-0.010	-1.543
Short-haul × long-haul	0.024	5.716
Long-haul price	0.041	29.326
Long-haul price squared	0.013	3.094
Scheduled demand	0.871	62.366
Scheduled demand squared	-0.070	-2.116
Nonscheduled demand	0.081	6.497
Nonscheduled demand squared	-0.103	-2.281
Scheduled × nonscheduled demand	0.123	3.139
Stage length	-0.263	-11.316
Load factor	-0.797	-20.135
Average seats × short-haul	0.019	1.666
Average age × short-haul	0.030	1.588
Fuel × short-haul	-0.039	-2.880
Average seats × long-haul	0.001	0.118
Average age × long-haul	-0.034	-3.886
Fuel × long-haul	0.033	3.412

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Table 6.2 Fitted Share Equation Values at Data Mean

Labor Share	0.377
Energy Share	0.214
Materials Share	0.288
Short Haul Capital Share	0.086
Long Haul Capital Share	0.035

Table 6.3 Allen-Uzawa Partial Elasticities of Substitution at Data Mean

	Labor	Energy	Materials	Short Haul	Long Haul
Labor	-1.712	$\times$	$\times$	$\times$	$\times$
Energy	0.904	-0.431	$\times$	$\times$	$\times$
Materials	1.405	-1.167	-1.200	$\times$	$\times$
Short Haul	-0.086	1.729	1.323	-11.941	$\times$
Long Haul	1.582	-1.803	-1.423	9.084	-16.976

To obtain bootstrap values for the Allen-Uzawa partial elasticities, we draw randomly, with replacement, from

$$\widehat{\epsilon} = Y - X\beta_{ITSUR} \tag{6.18}$$

such that on the b^{th} draw, we select randomly with replacement an integer i from $\{1, \ldots, N\}$, where N is the number of observations in our data set. The i^{th} residual is used from each of the equations in our system. When N draws have been made, we construct the bootstrap data set

$$Y^* = X\beta_{ITSUR} + \widehat{\epsilon}^*,$$

where $\widehat{\epsilon}^*$ are the bootstrapped residuals. We then estimate this system using ITSUR to find β^*_{ITSUR}. From these bootstrap estimates, we calculate the Allen-Uzawa partial elasticities. We continue creating and estimating the pseudo-data many times to build

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a distribution of the Allen-Uzawa partial elasticities. In this case, we drew 6,420 bootstrap samples. We also use the wild bootstrap to find bootstrap estimates by drawing $\hat{\epsilon}^*$ in the appropriate manner.

The bootstrapped confidence intervals for the Allen-Uzawa partial elasticities of substitution are shown in Table 6.4 and 6.5. These confidence intervals confirm most of our beliefs given the point estimates. However, labor and short-haul capital are no longer unambiguous substitutes. The confidence interval using the wild bootstrap also suggests that materials and short-haul capital are not unambiguous substitutes. The wild bootstrap confidence intervals are wider than those produced by the standard bootstrap. The differences range from approximately 8% to 69% wider.

The Morishima partial elasticities of substitution are shown in Table 6.3. All but three combinations of inputs are substitutes. The energy-materials, energy-long haul and materials-long haul combinations are complements.

The bootstrapped confidence intervals for the Morishima partial elasticities of substitution are shown in Table 6.3 and 6.3. The materials-long haul capital combination is no longer an unambiguous complement. As opposed to the Allen-Uzawa partial elasticities, the wild bootstrap does not produce longer confidence intervals in all cases.

Table 6.4 Standard Bootstrapped Allen-Uzawa Partial Elasticities of Substitution Confidence Intervals at Data Mean

	Labor	Energy	Materials	Short Haul	Long Haul
Labor	(-1.913, -1.506)	×	×	×	×
Energy	(0.798, 1.009)	(-0.547, -0.308)	×	×	×
Materials	(1.171, 1.650)	(-1.305, -1.043)	(-1.557, -0.862)	×	×
Short Haul	(-0.461, 0.264)	(1.410, 2.074)	(0.908, 1.744)	(-13.769, -10.347)	×
Long Haul	(0.713, 2.474)	(-2.575, -1.065)	(-2.590, -0.267)	(6.218, 11.892)	(-23.884, -10.206)

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Table 6.5 Wild Bootstrapped Allen-Uzawa Partial Elasticities of Substitution Confidence Intervals at Data Mean

	Labor	Energy	Materials	Short Haul	Long Haul
Labor	(-1.973, -1.446)	×	×	×	×
Energy	(0.790, 1.018)	(-0.590, -0.276)	×	×	×
Materials	(1.042, 1.777)	(-1.384, -0.961)	(-1.908, -0.548)	×	×
Short Haul	(-0.468, 0.302)	(1.353, 2.133)	(0.462, 2.190)	(-13.603, -10.350)	×
Long Haul	(0.507, 2.698)	(-2.968, -0.643)	(-3.843, 0.846)	(6.175, 12.216)	(-28.922, -5.789)

Table 6.6 Morishima Partial Elasticities of Substitution at Data Mean

	Labor	Energy	Materials	Short Haul	Long Haul
Labor	×	0.986	0.395	0.613	1.241
Energy	0.286	×	-0.158	0.462	-0.294
Materials	0.750	0.009	×	0.726	-0.064
Short Haul	1.025	1.182	1.147	×	1.818
Long Haul	0.641	0.524	0.537	0.900	×

Table 6.7 Standard Bootstrapped Morishima Partial Elasticities of Substitution Confidence Intervals at Data Mean

	Labor	Energy	Materials	Short Haul	Long Haul
Labor	×	(0.882, 1.092)	(0.322, 0.470)	(0.439, 0.777)	(0.898, 1.608)
Energy	(0.242, 0.326)	×	(-0.196, -0.122)	(0.382, 0.545)	(-0.469, -0.124)
Materials	(0.593, 0.914)	(-0.095, 0.116)	×	(0.553, 0.903)	(-0.432, 0.310)
Short Haul	(0.852, 1.197)	(1.007, 1.350)	(0.969, 1.317)	×	(1.387, 2.223)
Long Haul	(0.402, 0.890)	(0.288, 0.765)	(0.289, 0.790)	(0.590, 1.223)	×

Table 6.8 Wild Bootstrapped Morishima Partial Elasticities of Substitution Confidence Intervals at Data Mean

	Labor	Energy	Materials	Short Haul	Long Haul
Labor	×	(0.852, 1.118)	(0.298, 0.491)	(0.451, 0.775)	(0.807, 1.687)
Energy	(0.243, 0.331)	×	(-0.218, -0.099)	(0.370, 0.559)	(-0.557, -0.037)
Materials	(0.477, 1.033)	(-0.196, 0.219)	×	(0.346, 1.117)	(-0.855, 0.703)
Short Haul	(0.876, 1.168)	(1.046, 1.316)	(0.945, 1.347)	×	(1.517, 2.129)
Long Haul	(0.243, 1.046)	(0.127, 0.929)	(0.099, 0.971)	(0.487, 1.337)	×

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Table 6.9 Price Elasticities at Data Mean

	Labor	Energy	Materials	Short Haul	Long Haul
Labor	-0.645	0.193	0.404	-.007	0.055
Energy	0.340	-0.092	-0.336	0.150	-0.062
Materials	0.530	-0.250	-0.345	0.114	-0.049
Short Haul	-0.032	0.370	0.381	-1.033	0.314
Long Haul	0.596	-0.386	-0.409	0.785	-0.586

Table 6.10 Standard Bootstrapped Price Elasticities Confidence Intervals at Data Mean

	Labor	Energy	Materials	Short Haul	Long Haul
Labor	(-0.726, -0.567)	(0.171, 0.215)	(0.338, 0.472)	(-0.039, 0.023)	(0.025, 0.085)
Energy	(0.301, 0.382)	(-0.117, -0.066)	(-0.374, -0.301)	(0.120, 0.178)	(-0.087, -0.038)
Materials	(0.440, 0.626)	(-0.277, -0.224)	(-0.445, -0.249)	(0.077, 0.151)	(-0.088, -0.010)
Short Haul	(-0.174, 0.099)	(0.302, 0.442)	(0.262, 0.499)	(-1.181, -0.881)	(0.220, 0.408)
Long Haul	(0.268, 0.937)	(-0.550, -0.228)	(-0.743, -0.077)	(0.524, 1.030)	(-0.824, -0.358)

Table 6.11 Wild Bootstrapped Price Elasticities Confidence Intervals at Data Mean

	Labor	Energy	Materials	Short Haul	Long Haul
Labor	(-0.749, -0.541)	(0.170, 0.217)	(0.303, 0.506)	(-0.041, 0.026)	(0.018, 0.092)
Energy	(0.297, 0.385)	(-0.126, -0.059)	(-0.397, -0.278)	(0.118, 0.183)	(-0.101, -0.023)
Materials	(0.390, 0.674)	(-0.296, -0.206)	(-0.543, -0.160)	(0.040, 0.193)	(-0.130, 0.030)
Short Haul	(-0.177, 0.114)	(0.290, 0.457)	(0.135, 0.623)	(-1.173, -0.888)	(0.220, 0.409)
Long Haul	(0.192, 1.018)	(-0.634, -0.138)	(-1.104, 0.243)	(0.536, 1.051)	(-0.986, -0.196)

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6.4 Forecasting

Using our cost model along with the appropriate share equation, we can forecast the future quantities of aircraft (either short- or long-haul) in a particular airline's fleet. For example, if the forecast period explanatory variables are known, we can find the number of short-haul planes for airline j at time $t+k$ as

$$q_{j,t+k} = \frac{C_{j,t+k} \cdot S_{j,t+k}}{p_{j,t+k}}, \tag{6.19}$$

where $C_{j,t+k}$ is the total cost for airline j at time $t+k$, $S_{j,t+k}$ is the short-haul expense share for airline j at time $t+k$, $p_{j,t+k}$ is the short-haul price for airline j at time $t+k$, and $q_{j,t+k}$ is the number of short-haul planes.

As important as the point forecasts, it is important to get standard errors for the forecasts. The bootstrap, as is pointed out by Stine (1985), can be used as a distribution-free method for getting forecast errors. In our model, we bootstrap forecast errors as follows. We assume that X_{t+1} is known, so our point-estimate forecast is found by calculating $q_{j,t+1}$ in (6.19). Our forecast errors are then calculated by drawing randomly, with replacement, from

$$\widehat{\epsilon} = Y - X\beta_{ITSUR} \tag{6.20}$$

such that on the b^{th} draw, we select randomly with replacement an integer i from $\{1, \ldots, N\}$, where N is the number of observations in our data set. The i^{th} residual is used from each of the equations in our system. When $N+1$ draws have been made, we find our bootstrap forecasts:

$$q^*_{j,N+1} = \frac{C_{j,N+1} \cdot S_{j,N+1}}{p_{j,N+1}}, \tag{6.21}$$

where $C_{j,N+1}$ and $S_{j,N+1}$ are based on

$$Y^*_{N+1} = X_{N+1}\beta_{ITSUR} + \widehat{\epsilon}^*_{N+1}. \tag{6.22}$$

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We then construct the bootstrap data set

$$Y^* = X\beta_{ITSUR} + \widehat{\epsilon}^*, \tag{6.23}$$

where $\widehat{\epsilon}^*$ are the first N bootstrapped residuals. We then estimate this system using ITSUR to find β^*_{ITSUR}. The bootstrap forecast error is

$$FE_b = q^*_{j,N+1} - \frac{C^*_{j,N+1} \cdot S^*_{j,N+1}}{p_{j,N+1}},$$

and $C^*_{j,N+1}$ and $S^*_{j,N+1}$ are forecasts based on β^*_{ITSUR}. We continue creating and estimating the pseudo-data many times to build a distribution of the forecast errors. Here, we drew $1,340$ bootstrap samples. Let z^*_α be the $100 \cdot \alpha$th percentile from the distribution of the bootstrapped forecast errors. The $1-2\alpha$ bootstrap prediction interval for Y_{N+1} is $[q_{j,N+1} + z^*_\alpha, q_{j,N+1} + z^*_{(1-\alpha)}]$.

One can extend this bootstrapping technique to k step-ahead prediction intervals by increasing the number of residuals drawn in each of the bootstraps from $N+1$ to $N+k$ and proceeding as above. If there were a lagged endogenous variable, then one would need to recursively find each new Y^*.

To generate our forecasts, we first project the exogenous variables for four quarters, using the growth rates in Table 6.4. We then calculate the fitted value for total cost and capital share. Using these values and the projected cost of capital, we find the short-haul fleet size forecasts, which are shown in Table 6.4.

These forecasts are not as good as those calculated in Chapter 2. In that chapter, we allowed the average of the last year total cost and capital share to grow at the rate projected using elasticities. Here, we use the fitted values.

The standard bootstrap prediction intervals are shown in Table 6.4. These prediction intervals are very large. They range from about 200 planes to over 1,800 planes. The intervals do include the value for the actual number of planes in the quarter prior

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Table 6.12 Baseline Exogenous Variable Growth Rates

Parameter	Annual Growth Rate
Labor Price	-1.6%
Energy Price	0.9%
Materials Price	—
Short-haul Capital Price	-0.5%
Long-haul Capital Price	-0.5%
Scheduled Service	4.5%
Non-scheduled Service	4.5%
Stage Length	0.35%
Load Factor	0.15%
Average Age	—
Average Size	0.75%
Fuel Efficiency	2.5%

Table 6.13 Carrier Short-Haul Capital at 1994Q3 and Point Forecasts

Airline	1994Q3	1994Q4	1995Q1	1995Q2	1995Q3
American	424.79	644.24	661.33	653.20	657.02
Eastern	144.48	257.28	263.96	260.58	261.96
Trans World	302.86	391.66	401.94	396.90	399.11
Continental	258.39	248.76	255.34	252.19	253.65
Delta	325.00	915.60	940.36	929.28	935.20
Northwest	257.48	371.58	381.47	376.82	379.06
USAir	398.55	318.81	327.45	323.62	325.70
Southwest	174.38	91.06	93.53	92.43	93.03

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to the projection in all cases. It is not unreasonable for these intervals to be as large as they are, given the problems with the point forecasts.

6.5 Conclusions

In this chapter, we applied the bootstrap to calculate confidence intervals for Allen-Uzawa and Morishima partial elasticities of substitution and for price elasticities. We also used the bootstrap to find prediction intervals for forecasts of airline fleet size.

We began by explaining four methods for calculating bootstrap confidence intervals: the percentile method; bias correction (BC) method; the accelerated bias correction (ABC) method; and the percentile-t method. An explanation is also presented on how to construct prediction intervals using the standard bootstrap.

We estimated a translog cost function using the U.S. data set. We calculated the Allen-Uzawa and Morishima partial elasticities of substitution from the parameter estimates. We then bootstrapped confidence intervals for the Allen-Uzawa and Morishima partial elasticities using both the standard and wild bootstrap. Allen-Uzawa partial elasticities confidence intervals were longer using the wild bootstrap. The Morishima partial elasticity confidence intervals were not longer in all cases using the wild bootstrap. The confidence intervals for price elasticities had the correct signs.

We also forecast the fleet size for eight U.S. airlines. The forecast were not as good as those produced in Chapter 2. This is because we used fitted values for the total costs and capital shares instead of using the elasticity property of our parameter estimates to "grow" the actual total costs and share values.

In addition to these forecasts, we produced prediction intervals using the standard bootstrap. These intervals were quite large, and ranged between 200 to 1,800 planes.

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Table 6.14 Carrier Short-Haul Capital Forecasts with Bootstrapped Confidence Intervals

Airline	Type	1994Q4	1995Q1	1995Q2	1995Q3
	Lower	152.29	150.56	157.43	151.65
American	Point	644.24	661.33	653.20	657.02
	Upper	1602.50	1645.83	1635.85	1632.76
	Lower	56.82	61.64	53.57	59.00
Eastern	Point	257.28	263.96	260.58	261.96
	Upper	630.62	657.69	647.10	645.52
	Lower	35.69	34.20	35.41	36.05
Trans World	Point	391.66	401.94	396.90	399.11
	Upper	1040.73	1079.66	1025.13	1075.17
	Lower	53.10	57.29	54.69	55.86
Continental	Point	248.76	255.34	252.19	253.65
	Upper	592.08	604.26	592.96	601.92
	Lower	304.63	311.72	305.05	315.64
Delta	Point	915.60	940.36	929.28	935.20
	Upper	2140.68	2156.97	2061.98	2119.69
	Lower	8.01	8.39	5.94	3.46
Northwest	Point	371.58	381.47	376.82	379.06
	Upper	1054.68	1117.82	1062.58	1111.21
	Lower	72.63	74.79	73.55	74.23
USAir	Point	318.81	327.45	323.62	325.70
	Upper	767.19	797.00	794.48	797.30
	Lower	20.94	22.15	20.75	21.88
Southwest	Point	91.06	93.53	92.43	93.03
	Upper	213.93	220.41	215.35	216.62

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An improvement to the forecasts needs to be made. This is easily done by using the methods of Chapter 2. However, this does cause a problem with the bootstrapping procedure. A method for applying the bootstrap to find prediction intervals when using the methods of Chapter 2 needs to be found.

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Chapter 7

Applications of the Growth Literature to the Airline Industry

7.1 Introduction

All outputs that can be produced by a given input vector constitute a production technology. The frontier technology consists of those combinations that maximize output given a set of inputs, under the existing production process. Conversely, the frontier technology can minimize the usage of inputs given an output set. We identify firms as technically inefficient if they do not operate on this frontier.

The frontier literature has largely been concerned with documenting inefficiency of firms in various markets. Technical efficiency techniques have a wide-spread appeal because both government policy makers and industry managers are concerned about productive performance. More importantly, upon determination of efficiency differentials, these techniques can be used as decision making tools since they indicate areas of deficiency and direction for change.

We are interested in the link between market structure and performance first made explicit in Leibenstein (1966) article on X-efficiency which states that, given "proper motivations," firms can achieve increased efficiency. A prime motivational factor is the degree of competitive pressure. This hypothesis takes on heightened importance in today's global economy. World markets are becoming less regulated and more integrated leading to intensified international competition. From the European Union to the former Soviet Bloc to the North American Free Trade Agreement to the emerging markets in Asia, there is an increase in market contestibility and in

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competition for all the markets in all these economies. Whether rising competition will lead to efficiency improvements, as managers are increasingly pressed to cut costs, improve products and maintain or expand market share, is a question worthy of global concern and attention.

With the introduction of technical efficiency measurement techniques to measure and partition X-inefficiency (Leibenstein and Maital, 1992), studies on this topic have become more formalized. Caves and Barton (1990), for example, consider the relationship between technical efficiency levels and competitive conditions for 285 US industries. Overall, they find support for public policies designed to maintain competition among producers since these policies promote efficiency. Other studies focus on sectors such as utilities (e.g., Reifschneider and Stevenson, 1991), since the dependency between efficiency and competitive pressure has significant regulatory relevance. Button and Weyman-Jones (1992) find, in their literature survey, that those industries subject to bureaucratic control generally exhibit lower efficiency levels than those which are competitive or weakly regulated.

Alam and Sickles (1999) take a unique approach to empirically examine the relationship between competitive forces and the time pattern of technical efficiency. They do this by bringing together the technical efficiency literature (Schmidt and Sickles, 1984; Cornwell, et al., 1990; Kumbhakar, 1990; Gong and Sickles, 1992; Tulken and Vanden Eeckaut, 1995), developments in cointergration (Kwiatkowski, et al., 1992) and convergence literatrue (Faȑe, et al., 1994). As a case study, they examine the U.S. airline industry between 1970 and 1990. They find evidence that the efficiency scores of U.S. airlines are, in fact, cointergrated and that these scores are converging.

In Hultberg and Postert (1998), three measures of rank movements were developed and used to explain leapfrogging in the per capita income of OECD countries. We can use these measures to report on the level of rank movements of efficiency

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scores between airlines, whether domestic or international. These measures provide an objective and concise way to discuss the amount of leapfrogging and a possible test for the ability of economic models to explain the data.

7.2 Evidence of Leapfrogging

We implement our model using parameters and growth rates that equate the industrial performances of the national flag carriers (or industrial aggregate) to their respective country's performance. This provides us with a transparent illustration of our methodology and its implementation.

Looking at the OECD sample it is apparent that the nations' airline industrys' growth paths cross. Figure 7.1 shows the countries' airline industries income over the period 1960-90. The U.S. is the income leader for most of the years [Switzerland obtained the leader position a few times over the sample period]. As can be seen in Figure 7.1, three countries' airline industry in particular shifted income positions. Japan went from being one of the poorest airline industries in 1960 (rank 19) to become quite wealthy (rank 8) in 1990. Japan appears to be a growth miracle. The same can be said for Norway which advanced from rank 12 to 4 over the sample period. In contrast, New Zealand made a rapid descent through the relative income positions (from 3 to 17), earning the title growth disaster. However, most of the rank movements take place among the middle countries' airline industry (those ranked 3 to 16 in 1960) which are close in income levels. For these countries' airline industries leapfrogging could be due to random disturbances or heterogeneous shocks.

In fact, a closer examination of the rankings reveals that it is very common for two countries' airline industries to switch positions, only to immediately switch back. A few examples are: Germany and the U.K. from 1961 to 1968, Japan and Italy between 1971 and 1980 (these two countries' airline industries changed positions six times only

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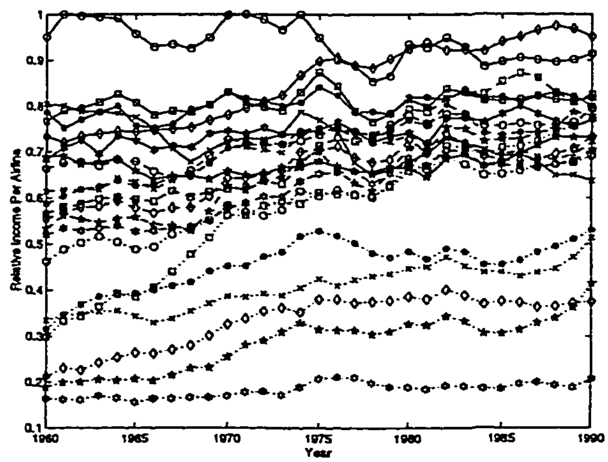
Figure 7.1 Country Airline Industry's Relative Income Distribution



to end up at the same place in 1980), and the U.S. and Switzerland up until 1975. This shows that much of the rank dynamics are driven by short-term fluctuations. These rank movements are most likely due to country-specific fluctuations, such as lagged business cycles, and represent what this paper calls randomness. One way to remove this from the data is to consider a longer time period than one year for the analysis. Panel studies often consider 3–5 year time intervals to side-step the influence of business cycles.

We adopt the methodology of Quah (1993) and Chari et al. (1996) in presenting the evidence in the form of a mobility matrix. Their papers are concerned with the world income distribution and, therefore, group countries in transition states based on their incomes relative to the world average. This approach only indirectly reveals the amount of leapfrogging since, for example, the mere fact that one country's airline industry's income is 1/4 of world average in 1960 but 1/2 of world average in 1990 does not imply a shift in relative position (especially if the sample simultaneously display convergence). In contrast, the Markov transition matrix used here directly

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addresses the changes in ranks since countries airline industries are grouped according to rank instead of incomes relative to world average.

A cell in our mobility or transition matrix represents the average number of transitions for the sample; i.e. the probability of moving a specified number of ranks within a specific time interval calculated for each consecutive time interval and averaged over the 30-year period. Each column and row thus represents the ranking of a country's airline industry (1 through 22 in a sample of 22 countries' airline industries), so that each entry in the Markov transition matrix represents the probability of moving from the column rank to the row rank during the specified time period. If there is no leapfrogging at all, then the matrix will be an identity matrix. All off-diagonal entries show a probability of shifts in relative positions, and the more probability mass off the diagonal the more common is rank movements. We consider average annual, 3-year, and 5-year transition matrices, as well as a 30-year transition matrix.

The main characteristic of the data, whether presented annually or for 3(5)-year intervals, is persistence, especially at the extremes. There is more mobility among the "middle airline industries"; these are the airlines which were initially close in income levels. As the time interval is extended, the mobility matrix shows more and more off-diagonal probability mass, which indicates that these movements are not driven by business cycles alone. The probability of jumping more than one state is also increased, once again indicating sustained movements of countries.

7.2.1 Measures of Rank Mobility

We feel the need for an index to quantify the amount of leapfrogging contained in the transition matrix. The advantage of an index is that we obtain one number as opposed to N^2 numbers, where N is the number of states in the transition matrix. For example, the 22-by-22 matrix yields 484 numbers to be interpreted. The disadvantage

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is that an entry in the transition matrix is easy to interpret, while the mobility index might not be. It is also important to note that these measures provide an index of the amount of leapfrogging in the sample, not of the "nature" of leapfrogging. That is, two samples may have the same amount of leapfrogging, but behave quite differently in terms of actual growth patterns. We discuss a possible use of the measures to approach the question of the nature of rank movements, but in the end one must look at the end period rankings displayed in the data and the simulation to determine if the model actually captures the source of rank mobility. Hence, there are two questions, one, whether the model allows for the amount of leapfrogging observed, and two, whether the model allows for leapfrogging through the right channels.

We propose the use of two measures of mobility recently introduced by Buchinsky and Hunt (1996). Both measures are based on the transition matrix. The first is a measure of expected or average "jump" (AJ) and is given by

$$AJ = \frac{\sum_{i=1}^{S} \sum_{j=1}^{S} |i - j| p_{ij}}{AJ^*},$$

where S is the number of states in the Markov transition matrix, and AJ* is the maximum attainable value for the numerator of AJ, i and j represent the column and row numbers (i.e. ranks), and p_{ij} is the probability of going from rank i to rank j in one time period. The AJ measure thus calculates the average off-diagonal movements in the Markov transition matrix.

The second measure is different in that it does not take into account the entire transition matrix. Since p_{ii} is the probability of remaining in the same state [i.e. probability of no shift in relative income positions], $\frac{1}{1-p_{ii}}$ is the mean exit time from that state. Buchinsky and Hunt's second measure of mobility is defined as

$$MP = \frac{\sum_{i=1}^{S}(1 - p_{ii})}{MP^*},$$

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where MP* is the maximum attainable value of the numerator of MP. The MP measure provides the average likelihood of a country's airline industry leaving its original position without considering the number of "size" of the jump. Both AJ and MP will range from 0 to 1, where 0 represents no mobility at all.

Both of these measures lack a crucial feature which concerns us; namely, that countries' airline industries close in income levels are more likely to shift income positions. The size and uniformity of the earnings data set used by Buchinsky and Hunt (1996) allows one to ignore this factor. For our sample of airline industries, however, it ought to be explained. Therefore, we suggest the use of a mobility index which discounts rank movements between industries close to each other, while it puts a premium on leapfrogging between countries' airline industries that are far apart. The measure used is constructed so that if airlines are closer than the average relative income distance $\left[\frac{(Y^{MAX}-Y^{MIN})}{(N-1)}\right]$ between the airline industries in the sample, then the probability of leapfrogging is discounted, and vice versa. Thus, for two countries ranked i and j the "income gap weight", d_{ij}, becomes

$$d_{ij} = \frac{Y_i - Y_j}{\frac{(Y^{MAX}-Y^{MIN})}{(N-1)}\,|i-j|}, \quad i \neq j$$

where Y is the per capita income of the country's airline industry and N is the number of countries in the sample. This income weight is then added to the AJ measure yielding a weighted average jump [WAJ] measure

$$WAJ = \frac{\sum_{i=1}^{S}\sum_{j=1}^{S}|d_{ij}|\,|i-j|\,p_{ij}}{WAJ^*},$$

where WAJ^* is the maximum attainable value of the numerator which occurs when the airline industries are clustered in a bimodal fashion and switch as many positions as possible.

Again, these mobility indexes are constructed to obtain a summary measure of the amount of movement in our samples. Theoretically, they can range from 0 to

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1, as the number increases the more transitions are evidenced. There is a question of what constitutes a large number and what constitutes a small number. Also, we need to be able to compare two measures and determine when they are statistically (significantly) different. For both of these reasons, we need to establish confidence intervals around the various rank measures. This, in turn, requires knowledge of the distributions of the rank mobility statistics. Although the mobility statistics are simple to implement and understand, they are based on very complex dynamics which makes calculating the asymptotic distributions difficult, if not impossible. To get around the intractability of the asymptotics, we use bootstrapping techniques to find their distributions. This is one of the main uses of the bootstrap, which was mentioned in Chapter 5.

Specifically, from an approximate model of the data (in which all countries' airline industries have linear growth paths with a trend break in 1972-73). Next, we bootstrap these residuals (using the random length block technique from Politis and Romano (1994)) to generate pseudo data which is subsequently used to recalculate the various rank measures. The bootstrapping and the consequent simulations are replicated extensively. The resulting distributions are shown in Figures 7.2, 7.3, and 7.4.

These distributions, and the 95 percent confidence intervals in Table 7.2, show that even small values for the measures may be statistically significant, especially for the AJ and WAJ measures, and that the measures need to increase over time in order for us to judge movements not due to randomness. Note again that, although we attempt to determine whether rank movements are random or deterministic, the measures only indicate the amount of rank movements but cannot distinguish between persistent one-way leapfrogging and deterministic up-and-down rank movements.

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Figure 7.2 Bootstrap Distribution of AJ Rank Mobility Measure

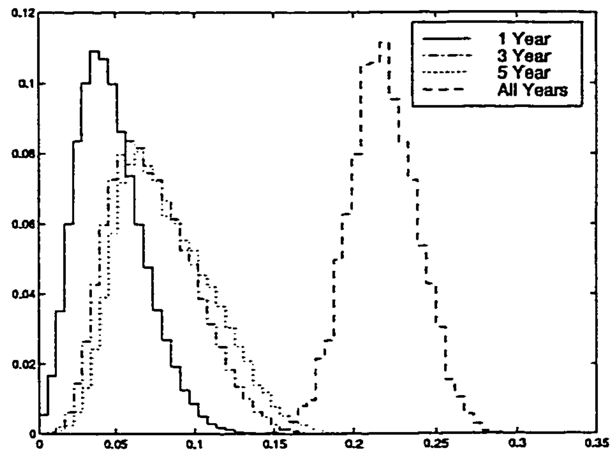

Figure 7.3 Bootstrap Distribution of WAJ Rank Mobility Measure

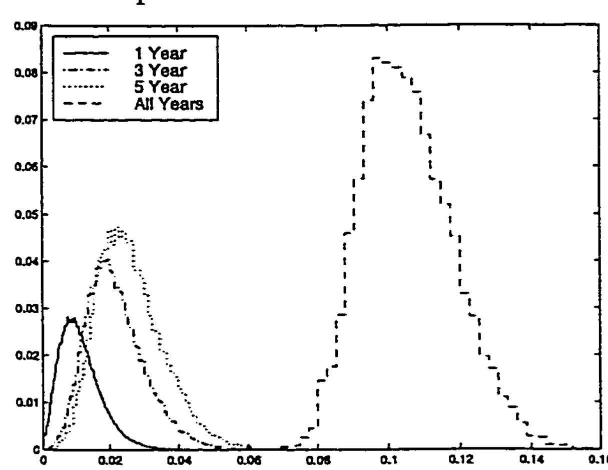

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Figure 7.4 Bootstrap Distribution of MP Rank Mobility Measure

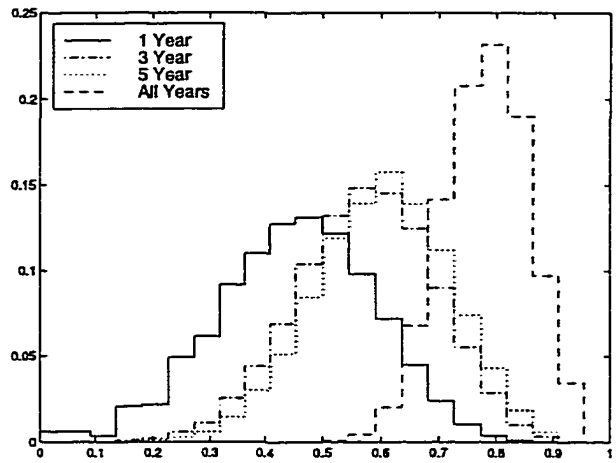

Table 7.1 WAJ, AJ, and MP Mobility Measures for the Data

	Yearly	3-Year	5-Year	1960–1990
WAJ	0.0056	0.0118	0.0201	0.1099
	(0.0052–0.0060)	(0.0096–0.0141)	(0.0171–0.0231)	
AJ	0.0277	0.0430	0.0682	0.1818
	(0.0238–0.0315)	(0.0341–0.0546)	(0.0549–0.0814)	
MP	0.3636	0.4876	0.6061	0.6818
	(0.3394–0.3879)	(0.3909–0.4818)	(0.5455–0.6667)	

Note: The numbers in parentheses show the measures for 1960–75 and 1975–90, respectively.

Table 7.2 95-Percent Confidence Intervals for the Rank Mobility Measures

	Yearly	3-Year	5-Year	1960–1990
WAJ	0.0020–0.0258	0.0072–0.0410	0.0096–0.0470	0.0808–0.1318
AJ	0.0144–0.0975	0.0310–0.1345	0.0367–0.1490	0.1784–0.2631
MP	0.1880–0.7306	0.3507–0.8219	0.3846–0.8476	0.6478–0.9467

Note: The Table shows the upper and lower limits for the 95-percent confidence intervals.

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7.2.2 Results from the Data

We report all three mobility measures (obtained from a 22-by-22 transition matrix) since their relative sizes reveal information about the type of leapfrogging. In general, a large WAJ or AJ value could be due to a relatively small probability of a big jump, or a large probability of a small jump. The MP-measure would be small in the former case and large in the latter, thus, their relative sizes tell us something about the type of movements. Hence, when comparing simulation results with the data all three measures should be used when determining the fit of the model.

Table 7.1 presents our three mobility measures calculated from the one-year Markov transition matrices. For the WAJ measure, the relative income differentials are also calculated annually. As expected, the indices for annual amounts of leapfrogging are small in absolute values, but, according to our simulated distributions, significantly different from zero (see Table 7.2). The 30-year annual averages are: WAJ=0.0056, AJ=0.0277, and MP=0.3636. The measures of leapfrogging appear to evolve over time. When considering separate measures for the periods 1960–75 and 1975–90, all measures show a larger value in the second half, but this observation may be due to the OECD sample converging in the post-war period leading to the airline industries getting proportionally closer to each other. The WAJ measure's proportional increase is smaller than the AJ measure's proportional increase, indicating that this might in fact be the case. This is then consistent with the Easterly et al. (1993) argument that as countries get closer to each other the random shocks become more important relative to the transitional effects.

In Table 7.1 the measures of leapfrogging are also shown when every third year or every fifth year (to remove business cycle effects) is used when calculating the mobility matrix. For the WAJ measure the income weight at the beginning of the 3(5)-year period is used. All three measures for both 3-year and 5-year data increase

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relative to the annual data. Thus, the number of rank movements appear to increase as the time period is extended, a fact most clearly observed when we consider the entire sample period (1960–90). To calculate the WAJ measure for the 30-year period we use the income differentials which exist in the initial period (1960). The measures are then much larger in absolute terms, and again, statistically significant. The WAJ measure becomes 0.1099, the AJ measure is 0.1818 and the MP measure grows to 0.6818.

The statement that the mobility measures increase with the extended time interval needs statistical support. Using our simulated distributions of the rank measures, we obtain 95-percent confidence intervals for each measure and time interval. The results are shown in Table 7.2. For the AJ measure, for example, the 3-year interval approach yields a 95-percent confidence interval of [0.0130 – 0.1345] while the entire sample period results in a confidence interval of [0.1781 – 0.2631]. The fact that these intervals are not overlapping allows us to conclude that the AJ measure does in fact increase with the time interval. The same result is found for the WAJ measure. However, although the average MP measure increases with the time interval, we are not able to conclude with 95 percent confidence that the MP measures for different time intervals are statistically different .

The MP measure does not distinguish between large and small rank changes (as it only considers diagonal elements of the Markov transition matrix) while the AJ and WAJ measures do, it appears as if the changes in relative income positions are generally small. However, the small jumps are not likely due to randomness, because the AJ measure increases proportionately more than the MP measure as the time period is extended. Again, the larger magnitudes for longer time intervals carry some important implications. If rank movements are *only* due to randomness, then the time period should not affect the mobility measures at all. Since this is not the case,

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we conclude that there are additional sources for the observed leapfrogging. In our simulation we explore if these additional factors are differing accumulation rates.

7.3 The Human Capital Augmented Solow Model

The empirical analysis reaches two main conclusions: the data justifies a study of leapfrogging, and the observed leapfrogging cannot be explained by randomness alone. The goal of the simulation is then to explore whether differing accumulation rates of factor inputs are the additional sources behind the rank movements as predicted by the standard neoclassical model. Our prediction is that rank movements due to differing accumulation rates (i.e. different steady states) will surface over time, while an added productivity shock will accommodate short run rank movements. The working hypothesis is that the neoclassical model will achieve two goals, one, yield rank measures similar to the data, and two, yield growth paths consistent with the observed.

Consider a simple Solow model extended to include human capital as in Mankiw et al. (1992). For each airline industry, let output Y be produced by physical capital K, human capital H, and labor L according to the production function

$$Y_t = K_t^{\alpha} H_t^{\beta} (A_t L_t)^{1-\alpha-\beta},$$

where A represents labor-augmenting technological progress. The economy is also subject to the usual transition equations where labor growth (n), physical capital investment rate (s_K), and the human capital investment rate (s_H) are allowed to differ across countries.

Expressing the model in terms of per unit of effective labor (AL), and finding the solution for the balanced growth path yields the steady state output per effective unit

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of labor

$$y^* = \left[\frac{s_K^\alpha s_H^\beta}{(n+g+\delta)^{\alpha+\beta}}\right]^{\frac{1}{1-\alpha-\beta}} .$$

We derive the predictions for the augmented Solow model for its behavior out of steady state to obtain the following differential equation

$$\ln y_{t_2} = (1-e^{-\lambda\tau})\ln y^* + e^{-\lambda\tau}\ln y_{t_1},$$

where $\tau = t_2 - t_1$ and $\lambda = (1-\alpha-\beta)(n+g+\delta)$.

Before the simulation is carried out the model is put into relative terms [similar to Jones (1995)]. All variables are considered relative to the U.S., the 1960 income leader:

$$\tilde{y}_t = \frac{y_t}{y_t^{US}}$$

Substituting and rearranging yields

$$\ln \hat{y_{t_2}} = (1-e^{-\lambda\tau})\ln y^* + e^{-\lambda\tau}\ln \hat{y_{t_1}} + (1-e^{-\lambda\tau})\ln A_0 + g(t_2 - e^{-\lambda\tau}t_1)$$

where y now represents income. This equation can be expressed as the following differential equation which we use in the simulations

$$\ln \tilde{y}_{t+\tau} = (1-e^{-\lambda\tau})\ln \tilde{y}^* + e^{-\lambda\tau}\ln \tilde{y}_{t_0} + (1-e^{-\lambda\tau})\ln \tilde{A}_0 \qquad (7.1)$$

where τ goes from 1 to 30 (corresponding to the 1960 to 1990 period).

7.4 Simulations

All simulations are based on (7.1) in which all variables are expressed relative to the United States. Each country's airline industry's relative steady state parameters $\tilde{s_K}$, $\tilde{s_H}$, $\tilde{A}$, and n, as well as the actual relative income levels of 1960, are substituted for $\tilde{y^*}$. Thus we assume that countries are out of their steady states in 1960, but over

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the 30-year-period they grow toward their own steady states. Therefore one would like to estimate the steady state values for each country. Again, the model allows the investment rates, the population growth rate, and the relative technology level to endogenously evolve over time to the steady state levels. However, estimating the steady state values based on "fundamentals", such as preferences, taxes, political instability etc., is extremely difficult. Instead we follow Jones (1995) in using recent data from each country to proxy for the steady state values [see Table 7.3]. In fact, we use the same definitions and numbers as Jones, which are:

- For the physical investment rates and the population growth rates, Jones uses the data for the period 1980-90 from Summers and Heston, PWT 5.6.
- For the human capital investment rate, he uses the SCHOOL variable from Mankiw et al. (1992).
- For the relative technology level, an estimate of the relative level of Harrod-neutral multifactor productivity in 1990 is used. This is the "levels" equivalent of the Solow residual and therefore captures everything not already included in the production function.

The resulting model is then allowed to grow over a thirty year period at which point the simulation results are compared to the data. Six different simulations are performed. The benchmark is based on the assumptions of Mankiw et al. (1992), while the additional five are carried out in order to test whether different error structures can aid in explaining the data.

7.4.1 Benchmark

From the human capital augmented Solow model it is clear that we need a few parameters. Based on Mankiw et al. (1992), we make the following assumptions: α, β,

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Table 7.3 Estimates of Steady State Variables

Country	$\widetilde{Y_0}$	$\tilde{A}$	s_K	$\widetilde{s_K}$	s_H	$\widetilde{s_H}$	n
USA	1	1	0.210	1	0.119	1	0.011
Canada	0.73	0.92	0.253	1.20	0.106	0.92	0.011
Japan	0.30	0.41	0.338	1.61	0.109	0.89	0.008
Austria	0.52	0.80	0.247	1.18	0.080	0.67	0.008
Belgium	0.56	0.93	0.207	0.99	0.093	0.78	0.005
Denmark	0.68	0.44	0.215	1.02	0.117	0.90	0.006
Finland	0.53	0.47	0.320	1.52	0.115	0.97	0.007
France	0.59	1.02	0.252	1.20	0.089	0.75	0.010
Germany	0.66	0.72	0.245	1.17	0.084	0.71	0.013
Greece	0.21	0.40	0.199	0.95	0.079	0.66	0.005
Ireland	0.33	0.65	0.238	1.13	0.114	0.96	0.007
Italy	0.46	1.12	0.244	1.16	0.071	0.60	0.007
Netherlands	0.61	0.93	0.210	1.00	0.107	0.90	0.013
Norway	0.57	0.53	0.276	1.31	0.100	0.84	0.009
Portugal	0.19	0.79	0.207	0.99	0.058	0.49	0.003
Spain	0.32	1.04	0.239	1.14	0.080	0.67	0.009
Sweden	0.77	0.67	0.212	1.01	0.079	0.66	0.007
Switzerland	0.95	0.71	0.306	1.46	0.048	0.40	0.010
Turkey	0.16	0.24	0.221	1.05	0.055	0.46	0.024
UK	0.69	0.85	0.171	0.81	0.089	0.75	0.005
Australia	0.79	0.63	0.269	1.28	0.098	0.82	0.019
New Zealand	0.80	0.36	0.241	1.15	0.109	1.00	0.015

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and $g + \delta$ are assumed to be constant across countries, and n, s_K, s_H, and $\tilde{A}$ are assumed to vary across countries

The production parameters, α and β, are assumed to be 1/3, according to recent convergence literature. The other constant parameters, g, which reflects primarily the advancement of knowledge which is not country-specific, and δ, the depreciation rate, are assumed to add up to 0.05, which are the numbers used in Mankiw et al. (1992). However, Jones (1995) assumes that they sum to 0.075.

7.4.2 Simulation with an Error Term

We add random noise to the human capital augmented Solow model to determine whether the cross-country data, with respect to rank movements, can be explained by the standard neoclassical growth model with different accumulation rates and a random disturbance. The covariance matrix is constructed from the data using five different assumptions of the error structure: homoscedasticity, heteroscedasticity, heteroscedasticity with cross-country correlations, autocorrelation, and autocorrelation with half the variance.

Each covariance matrix is constructed using the OLS residuals of the model

$$Y_{it} = t\beta_i + \epsilon_i,$$

where Y_{it} is the log of country i's relative GDP value at time t and β_i is the time trend for country i. That is, we model relative GDP values as a linear time trend. Further, we fix the relative GDP value of the US at one, and do not include it in the estimation of the covariance matrices.

From our estimate, we construct a coveriance matrix Ω, which is used to add random noise to (7.1). We construct bootstrap samples

$$\ln \tilde{y}^b_{t+\tau} = (1 - e^{-\lambda\tau}) \ln \tilde{y}^* + e^{-\lambda\tau} \ln \tilde{y}_{t_0} + (1 - e^{-\lambda\tau}) \ln \tilde{A}_0 + \epsilon^b, \tag{7.2}$$

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where ϵ^b is a normal random variable drawn from $N(0, \Omega)$ and $\ln \tilde{y}^b_{t+\tau}$ is our bootstrapped relative income. This is a parametric bootstrap. The covariance matrix Ω, estimated from the least squares residuals, is based on one of five models explained below.

The first covariance matrix is constructed under the assumption that errors are homoscedastic; that is, the variance of each country's airline industry is constant and equal over all time periods. The second covariance matrix is constructed based on the assumption that the errors are heteroscedastic so that each country's airline industry has a different variance, but remain constant over time. For the third covariance matrix, we keep the assumption of heteroscedastic error, but add cross-country correlation. This cross-country correlation is fixed over time, but varies over each pair of countries. Fourth, we estimate a covariance matrix where each country's airline industry has its own AR(1) disturbance. Our estimate of the ρ is given by

$$\hat{r}_i = 1 - \frac{d_i}{2},$$

where d_i is the Durbin-Watson statistic for the hypothesis that $\rho = 0$. There are no cross-country effects in this covariance matrix. Finally, we use the AR(1) model covariance matrix with half the variance.

7.5 Simulation Results

Figure 7.5 shows the growth paths of all the countries' airline industries for the benchmark model. From the picture, it is apparent that the benchmark model displays some leapfrogging, which the mobility measures in Tables 7.4-7.6 confirm. However, Table 7.4 shows that the annual mobility measures for the benchmark are much below the data. These results remain for the every third year mobility measures (Table 7.5). The disparity is declining, however, when we consider the entire

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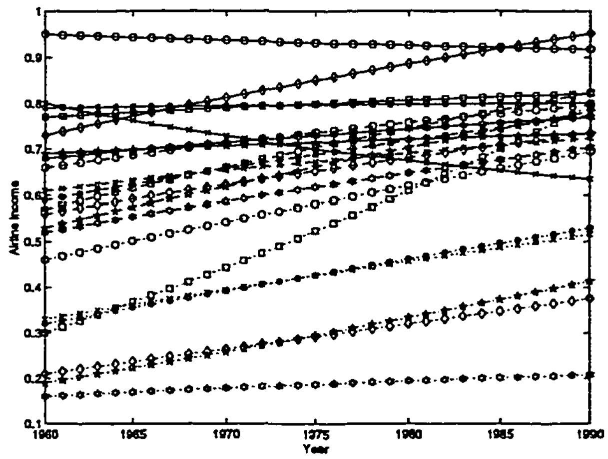
Figure 7.5 Benchmark Growth Path



time interval (Table 7.6), the measures are actually greater for the benchmark. This finding can be explained by the growth paths of the benchmark being determined by the countries' airline industries' differing steady states, an effect which slowly surfaces as time passes. The benchmark simulation thus shows that leapfrogging is a definite feature of the standard neoclassical model, especially in the long run. When we add an error to the benchmark model, the mobility measures all improve relative to the benchmark. The annual, 3-year and 5-year Markov transition matrices now display more leapfrogging, while the measures decline over the entire time period. Both effects bring the measures closer to the data results. Again, the neoclassical model succeeds in accommodating the amount of leapfrogging shown in the data; over the short periods, the fit can be explained by random shocks, while over longer periods an explanation is provided by countries' airline industries transitions to differing steady states. The results for the simulated mobility measures are also given in Tables 7.4-7.6. We believe it possible to approximate the data mobility measures by changing the error structures appropriately.

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Table 7.4 Measures Using Annual Markov Matrices

	Data	1	2	3	4	5	6
WAJ	0.0056	0.0006	0.0180	0.0150	0.0094	0.0126	0.0079
			(0.0058)	(0.0061)	(0.0056)	(0.0047)	(0.0033)
AJ	0.0277	0.0089	0.0861	0.0678	0.0525	0.0648	0.0496
			(0.0274)	(0.0227)	(0.0237)	(0.0212)	(0.0178)
MP	0.3636	0.1273	0.6045	0.5768	0.4958	0.5384	0.4720
			(0.1065)	(0.1184)	(0.1432)	(0.1108)	(0.1157)

Note: 1. Benchmark model, 2. with homoscedastic error, 3. with heteroscedastic error, 4. with heteroscedastic error and cross-country correlation, 5. with autocorrelated error, 6. with autocorrelated error, half the variance. Standard errors in parenthesis.

Table 7.5 Measures Using Third Year Markov Matrices

	Data	1	2	3	4	5	6
WAJ	0.0118	0.0051	0.0186	0.0156	0.0105	0.0221	0.0148
			(0.0060)	(0.0062)	(0.0058)	(0.0069)	(0.0049)
AJ	0.0430	0.0250	0.0872	0.0701	0.0560	0.0944	0.0733
			(0.0290)	(0.0243)	(0.0251)	(0.0286)	(0.0241)
MP	0.4876	0.3045	0.6032	0.5808	0.5078	0.6241	0.5653
			(0.1088)	(0.1232)	(0.1441)	(0.1033)	(0.1086)

Note: 1. Benchmark model, 2. with homoscedastic error, 3. with heteroscedastic error, 4. with heteroscedastic error and cross-country correlation, 5. with autocorrelated error, 6. with autocorrelated error, half the variance. Standard errors in parenthesis.

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Table 7.6 Measures Using Entire Period Markov Matrices

	Data	1	2	3	4	5	6
WAJ	0.1099	0.1115	0.0872	0.0874	0.0878	0.0920	0.0879
			(0.0093)	(0.0092)	(0.0100)	(0.0135)	(0.0100)
AJ	0.1818	0.1875	0.2170	0.2159	0.2165	0.2209	0.2180
			(0.0224)	(0.0186)	(0.0197)	(0.0277)	(0.231)
MP	0.6818	0.7273	0.7943	0.7926	0.8021	0.7987	0.7957
			(0.0596)	(0.0670)	(0.0601)	(0.0655)	(0.0610)

Note: 1. Benchmark model, 2. with homoscedastic error, 3. with heteroscedastic error, 4. with heteroscedastic error and cross-country correlation, 5. with autocorrelated error, 6. with autocorrelated error, half the variance. Standard errors in parenthesis.

The question remains of whether the measured mobility is of the right "nature". In fact, a problem appears when we consider the actual income levels and rankings of the benchmark simulation. Table 7.7 shows the last year rankings for data and the benchmark; although some countries' airline industries' rankings are close (especially at either extreme), it is evident that the model fails in exactly replicating the data in this respect. Adding an error to the benchmark does not, on average, improve the last year rankings. This is the result of the error being assumed normally distributed with zero mean. Therefore, the model might not capture the correct kind of leapfrogging. Most noteworthy is the fact that the benchmark predicts that Japan will not advance in ranking, while the data shows Japan as a growth miracle. The same is true for Norway, and conversely so for Belgium, France, and the Netherlands. This is a failure that we feel is potentially important, and which may also be present in studies of convergence.

Based on these results, we conclude that the human capital augmented Solow model shows good results in accommodating the data with respect to the amount of

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rank movements. Also, the Solow model does remarkably well for the most productive countries' airline industries (U.S. and Canada) and for the least productive countries' airline industries (Turkey, Greece, Portugal, Ireland, and Spain). At the same time, the neoclassical model provides poorer results in terms of giving a complete picture of the origin of leapfrogging as the model fails in explaining the movements of most of the other nations' industries, such as Japan and Norway (see Table 7.7). Having said that, one feat of the model is that it picks up New Zealand as a growth disaster. In the end, we feel it is fair to state that the model is not quite sufficient in explaining the rank movements observed in the data. However, it is true that the simulations are only as good as our estimated parameters. In particular, we feel the estimated relative efficiency levels given to us by the model appear somewhat nonsensical for some of the countries. For instance, the main reason the benchmark fails in explaining the advancement of Japan is that its steady state efficiency compared to the U.S. is 0.41 (see Table 7.3). At the same time, Italy appears destined to become the most efficient country in the steady state.

7.6 Conclusions

The OECD sample does display a fair amount of leapfrogging. Based on our results from the data, annually, there is a low probability for rank movements, whether or not one accounts for the relative "closeness" of income levels. However, as the time period under consideration is extended, more leapfrogging is observed. This implies that relative income shifts are not random (which we verify statistically). The relative size of the three rank measures indicate quite a few income shifts, which are generally small "jumps". The measures of leapfrogging might have increased between the first half and the second half of our sample period, as predicted by a neoclassical model with an added random shock. However, this increase is not statistically significant.

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The introduced rank mobility measures are able to establish rank movements, but perform much better in terms of the amount as opposed to the nature of leapfrogging. The question remains whether leapfrogging is a significant part of the growth process of the OECD sample? It has been shown that rank movements do exist, and they are not purely random. The fact that the amount of shifts is not enormous is not as relevant; if we believe that countries' airline industries follow the same growth process then even the small amount of movements shown here are pertinent.

The simulation of the human capital augmented Solow model, allowing for different accumulation rates, provide us with mobility results which are annually poor, but which improve with the time interval. However, simulated last period rankings are often quite different from the observed ones. As randomness is added to the model, we obtain better mobility measures; they are now closer both annually and for longer time periods. Final period rankings do not improve over the benchmark since random shocks cancel out over time. Therefore, the neoclassical model is able to supply the amount of rank movements for the OECD airline industries, but it seems as if the origin of leapfrogging that it accommodates (random shocks in the short run and steady state transitions in the long run) does not quite agree with what is observed in the data. There appears to be more to leapfrogging than random shocks and factor input accumulations. Also, although this chapter does not deal with the convergence issue, it has been shown elsewhere that the OECD countries display both convergence and catch-up. However, the human capital augmented Solow model remains largely unable to replicate actual growth patterns of the OECD sample in the postwar period.

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Table 7.7 Last Year Rankings for Data and Simulations

Country	Data	1	2	3	4	5	6
USA	1	1	1.0 (0.03)	1.0 (0.00)	1.0 (0.00)	1.0 (0.00)	1.0 (0.03)
Canada	2	2	2.0 (0.19)	2.0 (0.08)	2.0 (0.00)	2.1 (0.34)	2.0 (0.19)
Japan	8	19	19.0 (0.22)	18.8 (0.53)	18.9 (0.28)	17.2 (3.12)	19.0 (0.23)
Austria	15	14	12.9 (2.14)	12.3 (1.68)	13.7 (1.08)	13.0 (2.83)	12.8 (2.23)
Belgium	12	5	6.1 (2.21)	5.7 (1.93)	5.6 (1.16)	6.2 (2.88)	6.1 (2.22)
Denmark	10	15	13.5 (2.08)	14.1 (1.14)	14.2 (1.08)	14.1 (1.28)	13.5 (2.04)
Finland	9	10	9.5 (2.60)	9.5 (2.46)	9.5 (1.78)	9.5 (3.02)	9.5 (2.66)
France	11	3	3.6 (1.10)	3.3 (0.75)	3.1 (0.32)	4.0 (1.78)	3.6 (1.10)
Germany	7	12	11.3 (2.54)	11.6 (1.59)	11.6 (1.00)	11.6 (2.14)	11.3 (2.60)
Greece	21	21	21.0 (0.14)	20.9 (0.34)	21.0 (0.12)	20.6 (0.70)	21.0 (0.14)
Ireland	19	18	17.5 (0.64)	17.6 (0.65)	17.6 (0.62)	17.7 (0.85)	17.5 (0.69)
Italy	16	11	11.1 (2.57)	11.3 (2.05)	11.3 (1.58)	11.2 (2.69)	11.0 (2.62)
Netherlands	14	4	5.4 (1.99)	5.1 (1.80)	5.0 (1.45)	6.2 (3.50)	5.5 (2.03)
Norway	4	13	13.0 (2.29)	13.3 (1.89)	13.5 (1.73)	13.1 (2.95)	12.9 (2.34)
Portugal	20	20	20.0 (0.14)	20.1 (0.34)	20.2 (0.12)	20.2 (0.57)	20.0 (0.14)
Spain	18	17	17.4 (0.65)	17.4 (1.01)	17.3 (0.86)	16.4 (3.57)	17.4 (0.67)
Sweden	5	8	8.5 (2.61)	8.2 (1.74)	8.2 (1.25)	8.3 (2.04)	8.6 (2.74)
Switzerland	3	7	7.0 (2.47)	6.6 (1.91)	6.3 (1.43)	6.7 (2.28)	7.0 (2.51)
Turkey	22	22	22.0 (0.00)	22.0 (0.00)	22.0 (0.00)	22.0 (0.00)	22.0 (0.00)
UK	13	6	6.9 (2.38)	6.5 (1.77)	6.4 (2.17)	6.7 (2.42)	6.9 (2.39)
Australia	6	9	9.0 (2.55)	8.9 (1.58)	8.9 (1.35)	8.9 (1.92)	9.1 (2.66)
New Zealand	17	16	15.5 (1.16)	15.9 (0.87)	16.0 (0.67)	15.7 (1.73)	15.5 (1.32)

Note: 1. Benchmark model, 2. Benchmark plus homoscedastic error, 3. Benchmark plus heteroscedastic error, 4. Benchmark plus heteroscedastic error and cross-country correlation, 5. Benchmark plus autocorrelated error, 6. Benchmark plus autocorrelated error, half variance. The values in parentheses are the standard deviations of the estimates of rankings from the simulations.

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Chapter 8

General Conclusions

This dissertation has addressed several issues in domestic and international airline economics, as well as some applications of the bootstrap to empirical analysis. In the first Chapter, we presented a model of U.S. aircraft demand. Our joint model of demand and supply for commercial air service and the inferences about the demand for airplanes that are embedded in that model allowed us to simulate the effects of emerging technologies in engine design capabilities and in airframe capacities in terms of modifications in the characteristics of the planes in service. We were able to simulate the growth in total system demand for service and, thus, for factor inputs such as planes. We also were able to examine the impacts that emerging technologies that focus on engine fuel efficiencies and noise abatement characteristics on the demand for aircraft.

In Chapter 3, Competition in the European Airline Industry, we examined the productivities, efficiencies, and market conduct of firms in the European airline industry. We found what appears to be convergence in several of the major sources of factor productivity to the standard of the unregulated industry in the U.S., inefficiency differentials that are substantially moderated by the competitive pressures induced by measures put in place through the European Union, and little evidence that competitive pricing is violated on average. Whether or not selected firms in the industry are candidates for takeover or what potential exists for selected firms to join in strategic alliances, mergers, and/or simple code-sharing arrangements is not explored in this chapter. It would appear, however, that a combination of aggressive cost-cutting, exploitation of the production capacity of lower-cost U.S. carriers and

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marketing alliances will continue to drive the European industry as the dynamic of the competitive market continues to rationalize airline firm decision-making.

The third Chapter, A Model of World Aircraft Demand, developed a method to forecast fleet size in the international airline industry. The model used a demand model for air travel and linked this to a cost model for air travel production. From derived demand equations for the factors of production, we could predict fleet size given any number of possible scenarios. Our method allowed for endogeneity of outputs. The cost model seemed fine, but our demand data was somewhat lacking. Our estimates of demand growth seemed unreasonable. We will need to obtain 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 were problems, however. Except for the OECD countries, unemployment data is difficult to find. While it may be difficult to obtain better data on air travel demand, this will be of the greatest benefit with our model, and we will be able to better predict world aircraft demand.

The fourth chapter examines bootstrap estimators and heterogeneous and autocorrelation consistent (HAC) covariance estimators. We detailed the method for doing standard, pair, wild and block bootstraps, as well as the Andrews and Monahan (1991) HAC covariance estimator. The Monte Carlo evidence suggested that the bootstrapping techniques work well in small samples and is more suitable than asymptotic approximations.

In Chapter 6, Bootstrapped Aircraft Cost Model Confidence and Prediction Intervals, we used the bootstrap to compute confidence intervals for Allen-Uzawa and Morishima partial elasticities of substitution as well as price elasticities. We also used the bootstrap to find prediction intervals for forecasts of U.S. airline fleet sizes.

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The sixth Chapter, Applications of the Growth Literature to the Airline Industry, suggested an application of leapfrogging measures to the airline industry. A detailed look at Hultberg and Postert (1998) was presented. We found that the OECD sample does display a fair amount of leapfrogging. The measures of leapfrogging might have increased between the first half and the second half of our sample period as predicted by a neoclassical model with an added random shock. However, this increase is not statistically significant. The introduced rank mobility measures were able to establish rank movements, but performed much better in terms of the amount as opposed to the nature of leapfrogging. We also simulated the human capital augmented Solow model, allowing for different accumulation rates, which provided us with mobility results that are annually poor, but improve with the time interval. However, simulated last period rankings are often quite different from the observed ones. As randomness was added to the model we obtained better mobility measures; they were closer both annually and for longer time periods. Final period rankings did not improve over the benchmark since random shocks cancel out over time. Therefore, the neoclassical model was able to supply the amount of rank movements for the OECD airline industries, but it seems as if the origin of leapfrogging it accommodates did not quite agree with what was observed in the data.

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Appendix A

U.S. Data

The airline production data set includes four inputs: labor; energy; flight capital; and a residual category called materials that includes supplies, outside services, and nonflight capital. The data set also includes two outputs: scheduled and a nonscheduled revenue passenger-miles. Additionally, it includes two network traits: stage length and load factor. Flight capital is described by four aircraft attributes; the average size (measured in seats); the average age; and the separate proportions of aircraft in the fleet that are jet powered or wide-bodied designs.

The most comprehensive data set includes information for the 17 largest U.S. air carriers that were operating at the time of deregulation, or their descendant airlines. The carriers included are American, Eastern, Trans World, United, Braniff International, Continental, Delta, Northwest, Western, USAir, Frontier, North Central, Piedmont, Ozark, Southern, Republic and Texas International. This provides nearly total coverage of scheduled air traffic by 1990, the data set's end. This information is quarterly, air-carrier-specific information and results in 1,137 total observations. Attention was restricted to the traditional certificated carriers because routine data reporting was well-established for them at the time of deregulation. New entrants can be added to this data set with some difficulty. However, it should be remembered that these carriers have little experience in providing the often burdensome reporting required by DOT Form 41 and that noncompliance results in virtually no sanctions. Consequently, new entrant data tend to be of significantly lower quality. The version

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of the data described in more detail below provides the largest, cleanest data available on the production of U.S.-scheduled passenger air transport.

The procedure used in constructing the data set has changed considerably over the last decade. As more and more data sources become available, it will change further. One of the most significant factors in these changes has been an adaptation to the changes in the reporting requirements of DOT Form 41. In order to maintain comparability over time, data form all versions of Form 41 must be mapped into a single version. The latest significant revision, which occurred in 1987, eliminated many of the specific functional accounts that were used previously. The most significant changes occurred in the areas of labor, supplies and outside services. This latest version Form 41 data is the most restrictive in that it provides the least detail in most cases. In other instances, the 1985 revision of Form 41 data is somewhat more restrictive. However, many of these changes were in place for only a short period of time. Where the 1985 restrictions were most severe, the 1987-equivalent accounts were estimated. This occurred most seriously in the area of ground-based capital, where lease payments and capitalized leases had to be allocated between flight and ground capital. In other cases, it seemed reasonable to estimate 1985 accounts from the 1987 data provided. The objective was to maintain as much detail as possible in all areas of air carrier production.

The construction of the individual input and output categories is described in the next several sections. In cases where price and quantity pairs for a specific input or output are constructed, several subcomponents to that input or output are first constructed. Then, these are aggregated into a single input or output using a multilateral Tornqvist-Theil index number procedure.[1] The result of this procedure is a

[1]This mathematical technique derives indexes from underlying utility, cost, production, revenue, profit or transformation functions. In this case, the translog cost function is underlying, and the

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price index (much like the consumer price index) that aggregates price information for commodities having disparate physical units. When total expenditures of the input or output category are divided by this price index, an implicit quantity index is produced.

Labor

The labor input was composed of 93 separate labor accounts aggregated into five major employment classes (flight deck crews, flight attendants, mechanics, passenger/cargo/aircraft handlers, and other personal). We do not attempt to correct for differing utilization rates since we do not have information on the number of hours worked by the labor inputs. Expenditures in these five subcomponents are constructed from the expenditure data in DOT Form 41 Schedules P5, P6, P7, and P8.

Following the 1987 modification in Form 41, Schedules P7 and P8 were dramatically simplified, eliminating many separate expense accounts. Mechanics and Handlers appear as line 5 and 6 of the new Schedule P6. In order to be more compatible with the new Schedule P6, trainees and instructors were moved into the Other Personnel category. Flight attendant expense was calculated by subtracting accounts 5123 and 5124 from Schedule P5 from line 4 (total flight personnel) on the new Schedule P6.

Other labor-related expenses—such as personnel expenses, insurance and pension, and payroll taxes—were included as labor expenses. Since labor-related expenses are provided on functional lines rather than on employment class basis, they were allocated to each of the five employment groups on the basis of the expenditure share

expenditure shares are used to weight each subcomponent's contribution to the overall index number. See Caves, et al. (1982); Diewert (1976); and Good, et al. (1992) for details.

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of that class. After the 1987 Form 41 changes, these three expenditure categories are provided on Schedule P6 as line 10, 11, and 12, respectively.

The quarterly total head count of full-time equivalent personnel was found by averaging the monthly full-time personal plus one-half of the part-time employees over the relevant quarter.

In 1977, Schedule P10 was changed from a quarterly to an annual filing cycle. This meant that allocations of head counts into specific employment categories could not be done directly except for the fourth quarter of each calendar year. Instead, the distribution of head counts among the five labor groups was interpolated using the annual figures. The estimated head count in each group was found by multiplying the interpolated percentage by the calculated full-time equivalent head count for that quarter. In 1983, Schedule P10 was simplified. This simplification collapsed the handlers category into a smaller number of separate accounts, but did not change the overall structure of our procedure.

Using the expense and head count information from above, the expense per person quarter and the number of person quarters were calculated. The multilateral Tornqvist-Theil price and quantity indices for the labor input were then derived.

Energy

The objective of the energy input category is to capture aircraft fuel only. Fuel that is used for ground operations and electricity are both captured in the materials index. The energy input was developed by combining information on aircraft fuel gallons used with fuel expense data per period. Aircraft fuel cost in dollars comes from Schedule P5, account 5145.1. Gallons of aircraft fuel is listed in Schedule T2, account Z921.

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This input has undergone virtually no change because these accounts remained substantially unchanged over the 23-year span of our data set. Even though only one component exists, the multilateral Tornqvist-Theil index number procedure is used to provide normalization of the data.

Materials

The materials input is comprised of 69 separate expenditure accounts aggregated into 12 broad classes of materials or other inputs that did not fit into the labor, energy, or flight capital categories. Carrier-specific price or quantity deflators for these expenditure groups were unavailable. Instead, industry-wide price deflators were obtained from a variety of sources. These price deflators were normalized to 1.0 in the third quarter of 1972. The classification of these expenditure accounts are presented below along with the corresponding source for the price deflator.

In 1987, the modifications of Schedules P6 and P7 led to the elimination of hundreds of separate account categories. In most cases, this did not affect the ability to reconstruct the categories. The sources of information did change, however. Advertising expense, passenger food, and landing fees appear as line 22, line 6, and line 12 of the new Schedule P7, respectively. Expenses for aircraft maintenance materials, communications, insurance, outside services and outside maintenance and passenger and cargo commissions appear as line 17, line 23, line 24, line 25 + line 28, and line 26 + line 27 of the new Schedule P6. Ground equipment rental expense was line 31 of Schedule P6 minus account 5147 from Schedule P5. Amounts for other supplies and utilities appear aggregated together as line 19 of new Schedule P6. These amounts were apportioned to the supplies and utilities categories using the carrier's average proportion in these groups over the 1981 through 1986 periods. Ground equipment that is owned was unaffected by the 1987 accounting change.

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Flight Capital

The number of aircraft that a carrier operated from each different model of aircraft in the airline's fleet was collected from DOT Form 41, Schedule T2 (account Z820). Data on the technological characteristics for the approximately 60 types of aircraft in significant use over the period 1970 through 1992 were collected from *Jane's All the World's Aircraft* (1945 through 1982 editions).

First, for each quarter, the average number of aircraft in service was constructed by dividing the total number of aircraft days for all aircraft types by the number of days in the quarter. This provides a gross measure of the size of the fleet (number of aircraft).

In order to adjust this measure of flight capital, we also construct the average equipment size. This was measured with the highest density single-class seating configuration listed in *Jane's* for each aircraft type. The fleet wide average was weighted by the number of aircraft of each type assigned into service. In some cases, particularly with wide-bodied jets, the actual number of seats was substantially less than described by this configuration because of the use of first-class and business-class seating. Our purpose was to describe the physical size of the aircraft rather than how carriers chose to use or configure them.

We use the average number of months since the FAA's type-certification of aircraft designs as our measure of fleet vintage. Our assumption is that the technological innovation in an aircraft does not change after the design is type-certified. Consequently, our measure of technological age does not fully capture the deterioration in capital and increased maintenance costs caused by use. Our measure does capture retrofitting older designs with major innovations, if these innovations were significant enough to require recertification of the type.

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Finally, it is clear that the major innovation that took place during the 1960s and 1970s was the conversion to jet aircraft. While many carriers had largely adopted this innovation prior to the study period, it was by no means universal. Many of the local service airlines used turboprop aircraft as a significant portion of their fleets. We implement this aspect by measuring the proportion of aircraft in the fleet that are jet powered. The proportion of wide-bodied aircraft was also calculated.

Output

Our data set provides several measures of airline output and its associated characteristics. The most commonly used measure of carrier output is the revenue ton-mile. Our data set provides this measure as well as measures of revenue output that are disaggregated into scheduled and nonscheduled output. Nonscheduled output includes cargo and charter operations. We further provide measures of airline capacity. This again can be disaggregated into scheduled and nonscheduled operations. Revenue and traffic data were available from DOT Form 41. These data allowed us to construct price and quantity figures for seven different outputs produced by the typical airline. Again, the price per unit (passenger-mile or ton-mile) of the relevant service as constructed by dividing the revenue generated in the category by the physical amount of output in that category. These prices were normalized to 1.0 in the baseline period (the third quarter of 1972).

In cases where a carrier offered only one type of service (the convention was to call this "first class"), the service was redefined to be coach class. The reporting of revenue and traffic charter operations between cargo and passenger service was very sporadic. These two outputs were combined into a single category with passenger-miles converted to ton-miles, assuming an average weight of 200 pounds per passenger (including baggage). Changes in DOT Form 41 in 1985 led to the elimination of the

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distinction between express cargo and air freight. Consequently, these two categories were also collapsed.

Three different price and quantity index pairs are generated. The first is total revenue-output and uses the multilateral Tornqvist-Theil index number procedure on all the revenue-output categories. The second used the Tornqvist-Theil index number procedure on the two passenger categories. The third results from the use of the index number procedure on mail, cargo and charter services.

The capacity of flight operations is also provided in our data set. This describes the total amount of traffic generated, regardless of whether or not it was sold. While it is possible to distinguish between an unsold coach seat and an unsold first-class seat (they are of different sizes), such distinctions are not logically possible in the case of cargo operations (mail and cargo could be carried in the same location). Consequently, our measure of airline capacity includes only three broad categories: first-class seat-miles flown, coach seat-miles flown, and nonscheduled ton-miles flown.

With the change to T100 as the primary data base for airline traffic in 1990, carriers are no longer required to report available seat-miles, revenue seat-miles, or revenues by the level of passenger service. Instead, these amounts are aggregated with revenues supplied as account 3901 on Schedule P1 after 1990.

Again, the convention that passenger along with baggage is 200 pounds (one-tenth of a ten) is used to construct the nonscheduled ton-miles. Potential revenues that could be collected, if all services were sold, are constructed assuming that the prices for each of these categories remain the same as for output actual sold. In other words, the price for first-class revenue passenger-miles flown is imputed to first-class available seat-miles flown. Again, the Tornqvist-Theil index number procedure is used to generate price and quantity pairs for total capacity output, passenger capacity output, and nonscheduled capacity output.

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Two important measures of the carrier's network are also generated. The first is a passenger load factor. This is found by dividing revenue passenger-miles by available seat-miles. This measure is generally related to flight frequency with a lower number indication more frequent flights and consequently a higher level of service. Other definitions of load factor are possible, such as dividing the total passenger revenue collected by the total that would be collected were the planes flown full (derived from the passenger capacity output times passenger capacity price). If desired, these can easily be constructed using information in the data set. Stage length also provides an important measure of carrier output. Generally, the shorter the flight, the higher the proportion of ground services required per passenger-mile and the more circuitous the flight (a higher proportion of aircraft miles flown is needed to accommodate the needs of air traffic control). This generally results in a higher cost per mile for short flights than for longer flights. Average stage length is found by dividing total revenue aircraft miles flown by total revenue aircraft departures.

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Appendix B

European Data

Supply

Our supply data set consists of a panel of the eight air carriers from Europe that were used in Captain and Sickles (1997). A number of data series used therein were extrapolated between 1985–1990. Results presented here are based on a newly constructed and complete data set of 37 international airlines from 1976 to 1994. The construction of this data set is explained in Appendix C. These carriers and countries are followed with annual observations from 1976 through 1994.

In addition to the stage length and load factor constructed in the world data set, we construct a measure of network size. The number of route kilometers provides a measure of the total network size.

Demand

The demand data was collected for the European countries in the study. The demand data for Denmark, Sweden and Norway are used to create as single data series for Scandinavia by weighting by their respective GDPs. The GDP series was obtained from the *Main Economic Indicators*, a publication of the Economics and Statistics Department of the Organization for Economic Cooperation and Development (OECD). The GDP figures are reported in billions of dollars. The series on private consumption expenditure growth is taken from the publication *Historical Statistics*, which is published by the OECD. These data are an implicit price index with year-

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Table B.1 List of Countries and Financial Instruments Used to Find Short-Term Interest Rates

Country	Instrument
Belgium	Three Month Treasury Certificates
Denmark	Three Month Interbank Rate
France	Three Month Pibor
Germany	Three Month Fibor
Italy	Interbank Sight Deposits
Netherlands	Three Month Aibor
Norway	Three Month Nibor
Spain	Three Month Interbank Rate
Sweden	Three Month Treasury Discount Notes
United Kingdom	Three Month Interbank Loans

to-year percentage changes. The annual short-term interest rates are also taken from *Historical Statistics.* Table B.1 lists the financial instruments that are the basis for the series for the respective countries. The rail data is from *Jane's World Railways.* The rail price was calculated as the ratio of passenger and baggage revenue to passenger tone-kilometers. This is consistent with the price of air travel. The OECD International Energy Agency's publication *Energy Prices and Taxes* is the source for the gasoline price data. The gasoline prices include all taxes.

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Appendix C

World 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 percent of the scheduled passenger traffic in the world. The carriers and countries are presented in Table 4.1. These carriers are followed with annual observations from 1976 through 1994.

The primary sources for our data includes the Digest of Statistics for Commercial Air Carriers from the International Civil Aviation Organization and the Penn World Table [Mark 5.6] (Summers and Heston, 1994). There are frequent instances where these sources were not complete. Consequently, data was supplemented with other sources such as the International Air Transport Association's World Air Transport Statistics and Federal Express Aviation Service's Commercial Jet Fleets. Using these sources, we construct a set of four airline inputs: Labor, Energy, Materials, and Aircraft Fleet. In addition we construct several aggregate airline outputs along with characteristics of these outputs.

Materials

Our materials index is based on the financial data from ICAO. It uses total operating expenses minus the amounts spent on aircraft rental, depreciation, fuel and labor (from ICAO Fleet and Personnel). Because our data is in different currencies, with different bundles of goods and services that those currencies will purchase, we need to put amounts in common terms. Simply using exchange rates does not adequately

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make expenditures comparable across countries since exchange rates are heavily influenced by the narrower sets of goods that are imported and exported. Instead, we use purchasing power parities. Unlike our U.S. data set based on Form 41, we do not have much detail about detailed subcomponents. While expenses are broken up along functional lines (ticketing, passenger services, etc.), we generally do not have adequate information to remove other physical inputs (primarily labor) from these categories and do not have separate price indices for them, even in those cases where we are able. This leaves our materials index with a single subcomponent.

Labor

Inconsistencies in the definition of labor categories, differences in aggregation and missing data (primarily expenditure data) demand that our labor index is also constructed from a single subcomponent. 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.

Energy

Unlike the U.S. Form 41 data, we do not have independent, carrier specific measures of either quantities and prices or quantities and expenditures for aircraft fuel. This is particularly problematic since fuel prices vary widely around the world, primarily the result of tax differences. ICAO does compile 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 the fuel expenses by this price. For consistency, we use ICAO's prices even when we have carrier specific information

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available from other sources (such as U.S. DOT Form 41). The U.S. and ICAO prices compare fairly closely.

Flight Capital

Because of the importance of flying capital in our model, we describe this input in considerably more detail: providing several characteristics of the fleet in addition to its quantity and user price. We use an inventory of aircraft fleets 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. We considered several alternatives in constructing these user prices. We rejected the traditional approach of basing cost on book value since this is not responsive to changing demands for different types of aircraft at different points in time. For example, following deregulation in the US, the demand for small aircraft increased dramatically (along with their selling price) while wide bodied aircraft had a dramatic decrease in price. Our valuation 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. The primary liability of this approach is that it does not capture benefits (for example reduced maintenance) for newer rather than older aircraft within a particular type. This approach also poses some problems for aircraft that are not widely traded or for aircraft that are not jets. For aircraft that are not widely traded, we used the most comparable aircraft that was traded in order to get a market value. For the BAC/SUD Concorde, we used the Boeing 747–200. While the 747 is a much larger aircraft, because of its speed, the revenue generating capability of these two aircraft

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is roughly comparable. Soviet equipment also posed some problems. Most airlines do not consider this equipment very desirable and its market value is considered to be fairly low. We value it as comparable to the oldest Western equipment of a comparable size. For example, we value the Tupelov Tu–154 at the same rate as the Boeing B727–100 and the Tu–134 as the same as a BAC–111. We value the Ilyushin Il–62 the same as a Douglas DC–8–10. Avmark also provides some limited information about turboprop aircraft. We divided turboprop aircraft into six categories (YS–11, Lockheed Electra, Lockheed Hercules, Fairchild F–227, Fokker 27, and Saab 340) and allocated different types to these categories based on age and size (for example, we allocated the Fokker 50 into the Saab 340 category since they are both relatively new design commuter aircraft. We allocated the HS–748 to the YS–11 category since they are both 1960s design 50 passenger aircraft). We had a final residual type of aircraft that could not conveniently be categorized this way. Some carriers, Swissair, for example, operate a small fleet of single engine aircraft. Others operate one or two helicopters. We valued single engine piston aircraft at 100,000 and helicopters at 400,000. These residual aircraft are so small (in terms of the number of seats of capacity) that our cost per seat user price is insensitive to whatever decisions we make about their valuation.

Because we value aircraft in half time condition, we assume their remaining useful life is 14 years and use a 1.5 declining balance method to calculate economic depreciation. We considered several alternatives in constructing the interest portion of the rental price: using local and US real interest rates and using fixed depreciation rates versus rates based on changes in the valuation of the asset. We rejected an approach that used country specific interest rates. It was not possible to find comparable interest and inflation rates across different countries. In some cases, Pakistan specifically, real interest rates were always negative and nominal rates did not change

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over the entire sample period. Under the assumption that marginal decisions about fleet size were based on the international leasing market, and the leasing market was dominated by U.S. carriers and U.S. prices, we used rates based on Moody's Baa rate for 6 month commercial paper. An alternative to using our depreciation method described above, is to construct the depreciation portion by viewing an aircraft as both a financial and economic asset. Under this approach, the cost of holding and using the aircraft would be the difference in market value at the end of the year compared to the beginning of the year plus the nominal interest rate. We ultimately rejected this approach because it lead to several instances where the capital price fluctuated dramatically near periods when the price for a particular aircraft was depressed due to random events (such as the DC–10 grounding in 1979, or the bankruptcy of a carrier leading to lots of a particular aircraft flooding the market). 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.

Data on these technological characteristics were collected for individual aircraft types from *Jane's s All the World's Aircraft* (1945–1996 editions). We used the average number of months since first flight of aircraft designs as our measure of the technological age of the fleet. Our assumption is that the technological innovation in an aircraft does not change significantly after the design is first flown. While it would have been desirable to use certification date of equipment (as in our U.S. data set), not all equipment types are FAA certified. Our measure of technological age does not fully capture the deterioration in capital and increased maintenance costs caused by use. Our measure does capture retrofitting older designs with major innovations, if these innovations were significant enough to lead to a new aircraft designation (e.g., a Convair 580 is a retrofitted Convair 240 with new turboprop engines and wing mod-

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ifications. A DC–8–72 is a retrofit of a previous version with new engines). Average equipment size was measured with the highest density seating configuration listed in Jane's for each aircraft type. This assumption was necessary for consistency. Over time, the number of seats in a particular aircraft type has increased by decreasing seat pitch. Even within a particular carrier's fleet, the number of seats varied, sometimes significantly, yet we were not able to identify the total number of seats. Further, for aircraft used in combination service, the actual number of seats would seriously understate the aircraft's true capacity and revenue generating capability. Since our purpose was to consistently describe the bulk transport capability of the fleet, we used this single maximum value regardless of the actual seating configuration. This average across the fleet was weighted by the average number of aircraft of each type assigned into service. In some cases, particularly with wide-bodied jets, the actual number of seats was substantially less than described by this configuration.

We also constructed the percentage of aircraft in several categories: turboprop, jet, and a subgroup of jets: wide bodied jet (determined by having two aisles in the main cabin). To the extent that turboprop and jet aircraft percentages do not sum to one, it indicates the presence of either piston or rotary wing aircraft. These categories roughly provide measures of the potential productivity of capital as well as its heterogeneity. As more wide bodied aircraft are used, resources for flight crews, passenger and aircraft handlers, landing slots, etc. do not increase proportionately. The percent of turboprops also provide a measure of aircraft speed. This type of aircraft flies at approximately one third of the speed of jet equipment. Consequently, providing service of these types of equipment requires proportionately more flight crew resources than with jets. Our data provide for two separate categories of airline output: scheduled passenger output, non-scheduled, cargo and incidental output. This second category includes revenues that are attributable to airline related activities, but that are not

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the physical transport of passengers and cargo. An example would be maintenance performed for other airlines. For some carriers, this can be a significant component of revenue (and user of resources). For others, this category is virtually zero.

Output

Our scheduled passenger output is measured in revenue tonne 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 our scheduled and nonscheduled 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 constructed 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.

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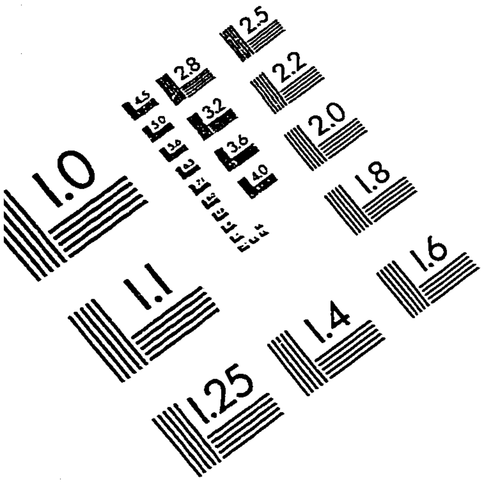
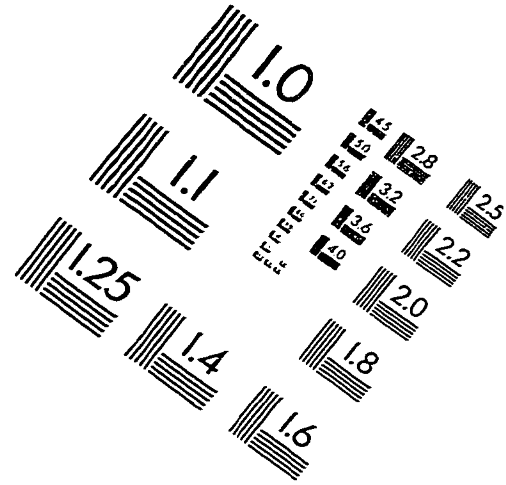
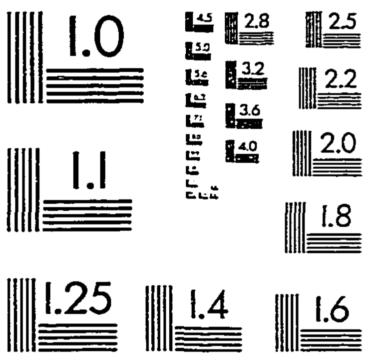
IMAGE EVALUATION TEST TARGET (QA-3)







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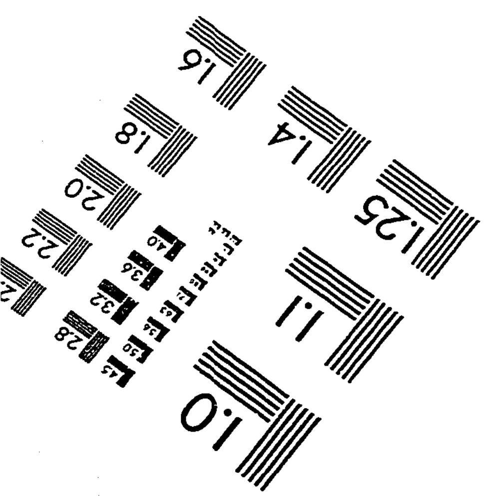

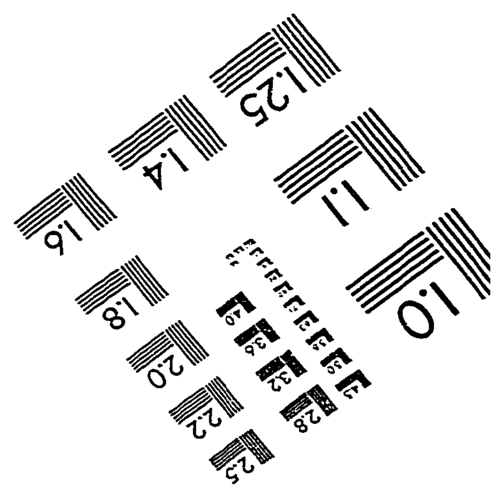

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