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The Economic Impacts of Air Traffic Congestion

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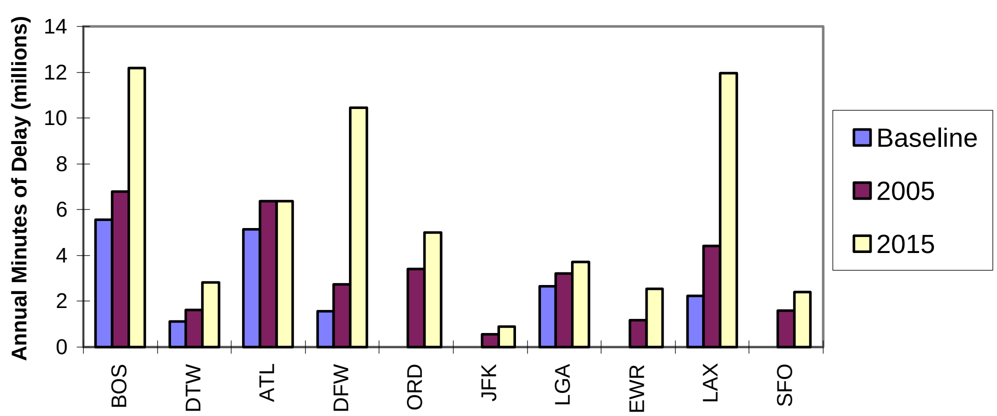
I. Introduction

Forecasts of future air travel demand predict significant increases in both passenger enplanements and aircraft operations. The 1997 Boeing Current Market Outlook predicts a 5.5 percent annual increase in worldwide revenue passenger miles (RPMs) by the year 2006, while the FAA Terminal Area Forecast estimates that total U.S. air carrier operations will increase by 2.5 percent during the same years. To support this travel growth, Boeing expects the worldwide aircraft fleet to rise by 7,330 aircraft.

Underlying all these predictions lies one crucial assumption: that the capacity of the airports and airspace system will expand to accommodate this demand. Yet recent studies by the Logistics Management Institute, American Airlines, and MITRE cast serious doubt on that assumption. Using typical assumptions for growth in operations, these studies predict increases in delay by the year 2005 that jeopardize the ability of airlines to operate the way they do today. The reason for this delay is that many of the largest airports in the U.S. are at, or very close to, maximum capacity and cannot accommodate much additional traffic under current air traffic procedures. For example, an LMI study for NASA predicts an increase of 78 million minutes of delay for U.S. air travel between 1996 and 2005, and another 33 million minutes by 2010. Figure 1 shows airport specific forecasts of delay for several of the busiest U.S. airports. The results predict severe capacity shortfalls, generating delays that would clearly reduce the predicted growth in air travel.

Figure 1. Airport Delay Forecasts



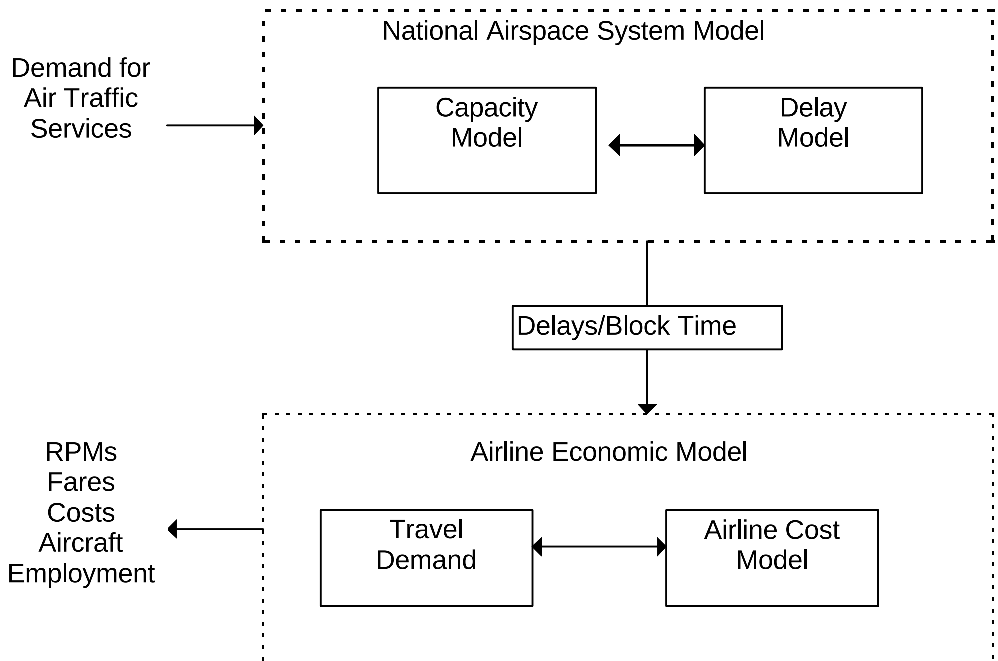
While the delay forecasts question the feasibility of the standard industry growth forecast, no published studies quantify the possible impact of air traffic capacity constraints on the economic future of the air transportation industry. This report develops a method for analyzing the interactions between air travel growth and system capacity, describes models that quantify those relationships, and presents preliminary results for the U.S. market. The basic idea is that delay imposes additional costs on air carriers that are passed on to consumers in the form of higher fares. Higher fares reduce the growth rate of travel demand.

The next section of this report describes the overall approach. Individual sections then follow that describe the individual models used to perform the analysis. The next section of the report generates the forecasts of air travel and aircraft fleet requirements for the unconstrained and constrained growth scenarios. The report concludes with a summary and suggestions for extending the analysis.

II. Technical Approach

Figure 2 summarizes our approach to analyze the interaction of travel demand and congestion effects. The approach requires four component models of the industry: a model of National Airspace System (NAS) capacity, a delay model, an air travel demand model, and a model of airline costs.

Figure 2. Overview of Approach



The approach is straightforward, although challenging to execute. Using the standard industry forecasts of airport-specific demand, we estimate system delays in the future, based on assumptions of planned improvements in airport and airspace capacity. From the airline economic model, we estimate an unconstrained demand forecast using assumptions about changes in input costs and improvements in airline productivity. This unconstrained forecast yields predictions for industry output, fares, aircraft fleet requirements, and employment. We then modify this unconstrained forecast to incorporate the airline cost impacts of predicted delays from the NAS model to generate a revised forecast. By comparing the two forecasts, we quantify the potential effect of increased congestion on fares, output, aircraft sales, and industry employment. The next section describes the model used to estimate capacity and delay within the NAS. That is followed by a description of the airline industry economic model, and then the results of the study.

Estimating NAS Capacity and Delay

As shown in Figure 2, the first step in the analysis requires models of NAS capacity and aircraft delays. A recent model developed by LMI incorporates capacity and delay models in a structure that is convenient for analyzing system-wide delays in the NAS. This queuing network model of the NAS, called LMINET, provides an analytical solution (not a simulation) to estimating delays at airports and enroute sectors in the NAS. Through the airport and sector capacity models, parameters reflecting the impact of technologies and procedures can be modified to capture the effects of changes in the NAS. Through the extensive queuing model, a single run of LMINET quickly estimates the delay impacts of capacity and demand changes.

The following sections give more details on the capacity and delay models in LMINET. A complete description can be found in Reference [1].

A. Models of NAS Capacity

LMINET models flights among a set of airports by linking queuing network models of airports with sequences of queuing models of TRACON sectors and enroute sectors. Demands for air traffic services are driven by airline flight schedules and aircraft trajectories. The user may specify the sequences of sectors to represent various operating modes for the NAS. The sequences may, for example, correspond to optimal routes for the winds aloft of a specific day, or they may correspond to trajectories of flights as flown on a specific day, as determined from ETMS data.

The network is driven by a schedule of departures from its airports, and by a schedule of arrivals from outside the network. The OAG is one source of such schedules. Both airport and sector capacities may be affected by weather. Weather data are provided to LMINET as epoch-by-epoch values of meteorological conditions at each of the airports, and epoch-by-epoch values of a single weather parameter for each TRACON and enroute sector.

Service rates to the arrival and departure runways are determined by individual airport capacity models that generate arrival and departure capacities as functions of meteorological conditions (ceiling, visibility, wind speed, and wind direction) and arrival and departure demand. Several parameters characterizing a specific airport affect the airport capacity models, as shown in Table 1.

Table 1. Runway Capacity Parameters

Parameter
Mean communication time delay
Standard deviation of communication time delay
Length of common approach path
Distance-to-turn on departure
Fraction of operating aircraft that are type *i*
Mean arrival runway occupancy time of aircraft type *i*
Standard deviation of arrival runway occupancy time of aircraft type i
Mean departure runway occupancy time of *i*th aircraft type
Standard deviation of departure runway occupancy time of aircraft type *i*
Miles-in-trail separation minimum, aircraft of type *i* behind aircraft of type *j*
Approach speed of aircraft type *i*
Standard deviation in approach speed of aircraft type *i*
Wind variation experienced by aircraft of type *i*
Standard deviation of controller's information on position of aircraft *i*

With this set of parameters, the capacity impacts of varying weather conditions, technology and procedural changes, and demand scenarios can be quantified. In addition to the runway capacity parameters, LMINET's airport capacity models incorporate information on the configurations in which the airport is usually operated.

Presently, LMINET is implemented with 64 airports.[1] They account for over 80% of the air carrier operations for 1995, as reported in the Department of Transportation T-3 reports. The LMINET airports are a superset of the FAA's 57 pacing airports.

In the queueing model for the ARTCC and TRACON sectors of the NAS, the times between aircraft arrivals to each sector are assumed to have the Poisson distribution, and the time that an aircraft stays in a sector is assumed to be a random variable distributed according to an Erlang-3 distribution. A sector can simultaneously handle no more than N aircraft at a time, where the capacity N is determined by the sector's characteristics and the weather. We also assume that at most q aircraft will "wait," i. e., be delayed by speed changes or vectoring, to be served in a sector.

[1] The 64 airports are ABQ, ATL, AUS, BDL, BNA, BOS, BUR, BWI, CLE, CLT, CMH, CVG, DAL, DAY, DCA, DEN, DFW, DTW, ELP, EWR, FLL, GSO, HOU, HPN, IAD, IAH, IND, ISP, JFK, LAS, LAX, LGA, LGB, MCI, MCO, MDW, MEM, MIA, MKE, MSP, MSY, OAK, ONT, ORD, PBI, PDX, PHL, PHX, PIT, RDU, RNO, SAN, SAT, SDF, SEA, SFO, SJC, SLC, SMF, SNA, STL, SYR, TEB, and TPA.

The arrival demand to a sector is determined by the network flight schedule. The choice of the Erlang-3 distribution for the times-in-sector was made in view of ETMS data, and is explained in Reference [1]. We chose 18 as the maximum number of aircraft that a sector's controllers can handle at one time, to be consistent with Reference [3]. We base our choice of the maximum number of "waiting" aircraft on interviews with controllers at the Denver ARTCC.

Each airport's TRACON is modeled with two arrival sectors and one departure sector. The sectors are modeled as M/Ek/N/N+q queues. LMINET allocates arrivals to an airport so that each arrival TRACON sector sees roughly half of the arrivals in each epoch of operation. For the work reported here, an epoch is one hour long.

Like the TRACON sectors, enroute sectors are modeled as M/Ek/N/N+q queues.

- Adjusting LMINET to Model the NAS in 1996, 2005, and 2010

  Users may adjust several LMINET inputs: demand profiles, airport capacity models, sector capacity models, surface weather and weather aloft, routes between airports, and so on.

  We used the operations forecasts given in the "1996 Aviation Capacity Enhancement Plan and Airport Database," distributed on a compact disc by the FAA's Office of System Capacity, to model future demand for the airports in LMINET. The FAA's percent growth in operations value is for the fifteen year period of 1995-2010.

  We developed demand inputs to LMINET for 2010, by scaling up departures at each network airport by the FAA's forecasted annual airport growth rates, compounded for 14 years. We also increased the out-of-network arrivals at each airport by the same factor as the one used to scale up departures. We scaled up out-of-network arrivals to the sectors by 41%, as representative of the overall traffic growth expected from 1996 to 2010.

  To develop 2005 demands in this way is to assume that departures from a given airport will increase in the same ratio for all destinations. This is not likely to happen, but we have at present no satisfactory way to predict how the distributions of departures will change. To develop such predictions is beyond the resources of this task.

  Also—and, we believe, quite significantly—air carriers are not likely to retain present schedules if doing so would result in serious delays. Faced with substantial delays, carriers would probably exercise such options as opening new hubs, operating more city-to-city services and fewer hub-and-spoke routes, and/or changing schedules to smooth out peaks in scheduled departure rates. Here again, adequately modeling carriers' responses to significant changes in the NAS requires a substantial effort that could not be accommodated in the present task.

The airport capacity models require as inputs four parameters characterizing runway capacities as Pareto frontiers, for each of five meteorological conditions (VMC1, in which IFR flights may be concluded by VFR approaches; minimal VMC, the standard 1000-foot ceiling and 3 mile visibility; ILS Category I; ILS Category II; and ILS Category III.) We built these using the LMI Runway Capacity Model (described in Reference [2]).

- Modeling Annual Variations With Representative Days

  To make an estimate of yearly delay costs, we made weighted averages of delay costs for three representative days, April 8, June 12, and November 29 in 1996. A study of 30 years of weather data at 10 busy airports that the Institute made for NASA in 1995 showed that the airports experienced VMC more than 80% of the time. They had ILS Category I conditions roughly 10% of the time. Guided by this we chose weights of 0.8 for the June day, 0.13 for the April day, and 0.07 for the November day.

B. Results of Delay Analysis

We estimated delays for the 1996 baseline and the years 2005 and 2010, using the demand growth rates described in the previous section. The results show a total amount of delay in 2005 of 2.07 million hours. By 2010, this delay grows to 2.61 million hours. This represents roughly 10 percent of total block hours in 2010.

It is unlikely that airlines or travelers will ever directly observe these large delays. However, we believe it is useful to use these estimates to quantify what may be first-order impacts of air traffic congestion. While airlines are likely to make decisions to offset some of the delay increase, those decisions will probably shift costs to other parts of system, not eliminate those costs. We also expect that the gradual increase in scheduled block times over the past decade will continue, so that total block times will rise even if measured delay remains constant.

Using aircraft and airline cost models, the added cost of these delays (assuming they were actually incurred) is approximately $4.3 billion in 2005, and $7.8 billion in 2010. The increased block time, and their associated increases in direct operating costs (DOC), are input to the airline industry economic model to evaluate their impacts on travel demand, fares, and costs. The airline industry economic model is described in the next section.

III. Economic Analysis of the Supply and Demand for Air Travel Demand

The second part of this analysis requires models of airline industry demand and costs. The demand model is required so that delay and cost changes can be translated into changes in air travel and fares. The model of airline costs provides the intermediate mechanism for integrating airline operations and schedules, operating costs, and fares.

As part of our work supporting the NASA Advanced Subsonic Technology program, LMI developed an economic model of the airline industry that integrates industry-wide supply and demand factors. Called the Air Carrier Investment Model (ACIM), the model forecasts the demand for air travel under a variety of user-defined scenarios. From these demand forecasts, the user can estimate the derived demand for factors of production, such as the number of aircraft in the passenger airline fleets, or the number of airline workers. Since it is a parametric model linking airline costs with demand factors, different air travel demand forecasts over a 20-year period are generated when changes in input costs, such as labor and fuel, are entered into the model. For changes in the air traffic management system, factors affecting airline costs - such as delays - can be incorporated into the inputs to evaluate their impacts on airline output and fares.[2]

A. Derivation of the ACIM Functional Cost Module

The Functional Cost Module (FCM) of the ACIM is the key component for evaluating the impact of new technologies on the airline industry. The FCM uses an Activity Based Cost approach to explicitly calculate cost functions for different classes of airlines. The FCM utilizes a bottom-up approach in which airline costs are computed at the carrier level and aggregated to obtain industry costs. Thus, an important feature of the FCM is that productivity ratios, cost parameters, and even demand assumptions may differ among air carriers.

To estimate the demand for air travel, we analyzed 85 U.S. airports. Subsequently, we collected 10 years of annual traffic and pricing information from U.S. DOT Origin and Destination data for 26 airlines and identified a set of factors that influence a carrier's output. These observations were then used to developed an econometric model of demand for passenger service at the city-pair level of aggregation.

Applying concepts from activity-based-costing to the Form 41 traffic and financial operating data, we next constructed cost functions for each of the individual carriers or carrier groups. The cost functions are based upon six functional cost categories with flight equipment capital costs modeled in an especially detailed manner. This functional cost approach provides a high degree of accuracy in estimating air carrier costs.

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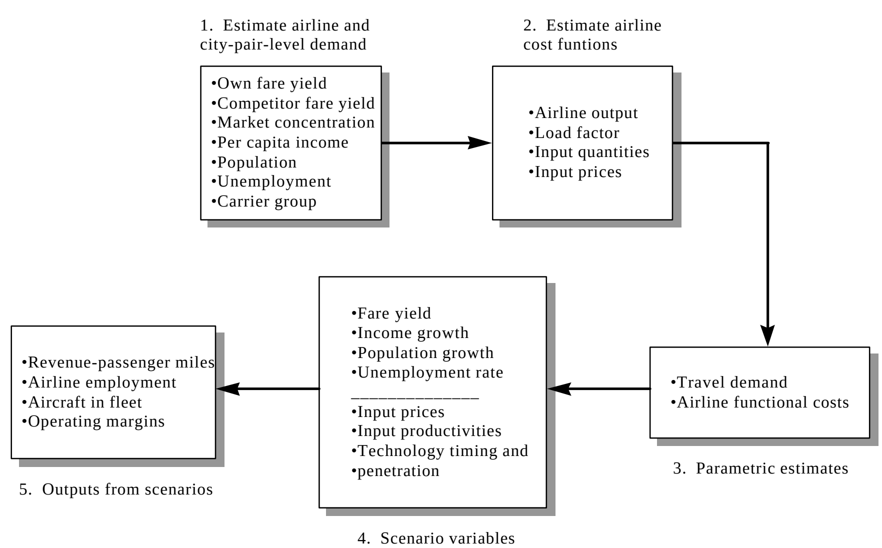
[2] Reference [5] contains a complete description of the Air Carrier Investment Model.

We then linked the carrier-specific demand models to the cost functions to determine an industry equilibrium. From the cost functions, we generated derived demand schedules for the factors of production, in particular aircraft fleets. The derived demand schedules are a function of the level of passenger service supplied, the airline load factor, and various aircraft productivity measures such as seats per aircraft.

Because it is so capital-intensive, the airline industry must earn positive operating profits in order to maintain and expand its aircraft fleet. Accordingly, we added a profit margin constraint to the model. When this option is activated, passenger fare yields are adjusted up or down to ensure that the target profit margins are met.

Figure 3 summarizes the operation of the Functional Cost Module. The model starts with the factors affecting the demand for scheduled passenger air travel at the airline and city-pair level. It then examines historical data on airline costs and the resulting industry supply curve. The objective of the demand analysis is to obtain parametric estimates for air travel demand, while the objective of the cost analysis is to obtain estimates of airline costs by functional cost category. These parametric estimates can then be combined with user-specified values of key supply and demand variables to generate industry-level forecasts of RPMs flown, airline employment, number of aircraft in the fleet, and operating profit margins under various scenarios.

Figure 3. Schematic of the ACIM Functional Cost Module



- Air Travel Demand

  The FCM analyzes air travel demand at the city-pair level of aggregation. This approach is rooted in the assumption that market competition between carriers is best characterized at this level. The approach offers the additional advantage of providing many observations with which to estimate the parameters of the model. However, special econometric techniques are required to manage a data set that includes both a time dimension and a cross-sectional dimension. We chose to employ a *fixed-effect* model to account for the cross-sectional variation in the data. Thus, our estimates are based upon changes in demand over time holding the cross-sectional variation constant.

For a particular route originating at city i and terminating at city j, carrier k will generate a certain level of passenger traffic. The U.S. DOT's Origin and Destination data record a 1 in 10 sample of all tickets. From these, the RPM service originating at time t on route i, j for carrier k was constructed.

Demand for a carrier's service between city pairs is driven by the carrier's passenger fare yield (measured by the average ticket price for travel between the cities divided by the nonstop mileage distance), the average yield of the carrier's competition on the route, the size and economic prosperity of the cities, the carriers market share for service between the cities, and the degree of market concentration. 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 1985 through the last calendar quarter of 1994. This approach yields a data set with nearly 2 million observations.

The demand function, in equation form, is

$$q_{t,i,j}^{k} = D_{t,i,j}^{k}(p_{t,i,j}^{k}, p_{t,i,j}^{c}, x_{t,i,j}), \qquad \text{[Eq. 1]}$$

where $q_{t,i,j}^{k}$ is the scheduled demand (in RPMs) originating at time t for travel between city i and city j on carrier k. $p_{t,i,j}^{k}$ is the average yield for service originating at time t for travel between city i and city j on carrier k. $p_{t,i,j}^{c}$ is the average yield for the other carriers generating traffic at time t between city i and city j. $x_{t,i,j}$ are the other demand characteristics at time t for city pair i, j. These include population and income measures and market competition characteristics. In addition, conventional treatments for firm and city-pair fixed effects were used. These effects capture those important characteristics of a particular city pair that are not easily measured, such as tourism effects. We used a log-log specification for Equation 1 so that the regression coefficients may be interpreted as elasticities.

Table 2 shows the demand variable estimates that were incorporated into the model. We allowed the own-price elasticity to vary by carrier group. All of the important forecast variables were found to be statistically significant at the

95 percent level of confidence.[3] The overall fit of the model is quite good with a multiple coefficient of determination (adjusted R-square) of 91.6 percent.

Table 2. Demand Forecast Variables

Variable	Name	Coefficient	T-ratio
Per capita income	LNPCI	2.0690	111.76
Population	LNPOP	0.2316	41.51
Competitors yield	LNYLDOT	0.1422	31.85
Own yield (major)	LNYLDOW×MAJOR	-1.1483	-473.76
Own yield (national)	LNYLDOW×NATIONAL	-1.0881	-139.78
Own yield (regional)	LNYLDOW×REGIONAL	-1.3856	-51.40
Own yield (shuttle)	LNYLDOW×SHUTTLE	-0.9526	-15.99
Own yield	LNYLDOW×NONSCHEDUL	-0.6395	-8.65

Because of the log-log specification, the estimated coefficients may be interpreted as elasticities. For example, the coefficient of 2.069 on LNPCI implies that a 1 percent change in per capita income will generate a 2.069 percent change in demand. The other coefficients have similar interpretations.

- Air Travel Supply

The second major component of the Functional Cost Module is designed to capture the costs of providing air travel services. The approach taken is to explicitly calculate costs in six functional cost categories using concepts from Activity Based Costing. Within each functional cost category, total costs are a function of output, underlying productivity, and per-unit input prices. The cost analysis was based on observations from DOT Form 41 data in conjunction with detailed aircraft fleet inventories from AvSoft's ACAS Fleet Information System.[4] The cost data follow the 26 U.S. passenger air carriers with annual observations from 1985 through 1995.

The immense size of the major carriers relative to the rest of the industry significantly increases the risk of inaccuracy from using the group mean to populate the parameters of the cost function. Therefore, we determined that a more accurate estimate of carrier costs would result from calculating functional costs at the individual airline level for the largest eight airlines. The

[3]The partial regression coefficients show the effects of changes in the independent variables (e.g., own fares, and competitors' fares) on the dependent variable (i.e., total demand for an air carrier's passenger service). The T-ratios show the degree to which the partial regression coefficients are statistically different from zero. For degrees of freedom over 30, a T-ratio of 1.96 provides 95 percent confidence that the partial regression coefficient is not zero.

[4] AvSoft Information Systems, Warwickshire England.

remaining airlines, however, are modeled by carrier group with the exception of the identified outliers, which are omitted.

Within each functional cost category, operating costs per ASM are determined by the interaction of a productivity parameter and a unit price for the corresponding input. In the fuel cost category, for example, the fuel costs per ASM are calculated as the ratio of fuel price per gallon (unit price) to the ASM per gallon of fuel (productivity parameter). In some cases, the productivity parameter may itself depend upon the interaction of other underlying productivity ratios. For example, ASM per gallon of fuel is actually determined as the product of ASM per block hour and block hours per gallon of fuel. One advantage of modeling productivity in this way is that per unit costs are not dependent upon an arbitrary choice of a cost driver. Figure 4 summarizes the cost calculations.

Figure 4. FCM Cost Calculations

$$\text{Fuel costs} = \text{ASM} \times \left(\frac{\text{fuel price / gallon}}{(\text{ASM / block hour}) / (\text{gallons / block hour})} \right)$$

$$\text{Flight personnel costs} = \text{ASM} \times \left(\frac{\text{flight personnel labor rate / block hour}}{\text{ASM / block hour}} \right)$$

$$\text{Maintenance costs} = \text{ASM} \times \left(\frac{(\text{maint. labor} + \text{maint. mat.}) / \text{block hour}}{\text{ASM / block hour}} \right)$$

$$\text{Flight equipment capital costs} = \text{ASM} \times \left(\frac{\text{capital costs / aircraft day}}{(\text{ASM / block hour})(\text{block hours / aircraft day})} \right)$$

$$\text{Ground property and equipment costs} = \text{ASM} \times \left(\frac{\text{GP\& E costs}}{\text{ASM}} \right)$$

$$\text{Indirect costs} = \text{ASM} \times \left(\frac{\text{indirect costs}}{\text{ASM}} \right)$$

Total costs within a functional category are then determined by the product of the cost per ASM and the number of ASMs flown. Some cost categories contain more than one cost element. Maintenance costs, for example, are comprised of both labor and materials components. In such cases, the total category costs are determined as the sum across all individual cost components. In the case of the indirect cost category, some elements, such as landing fees, are enumerated explicitly. Others, however, are grouped under a residual element termed “other indirect costs.”

With the exception of the capital costs, the baseline productivity and unit price parameters of the model are derived directly from the carrier-specific Form 41 observations. In the case of the smaller airlines, which are modeled by carrier group, the productivity and price parameters are determined by computing the weighted average across all carriers in the group.

- Integrating Air Travel Demand With Airline Costs

The joint model of supply and demand for commercial passenger air service specified in our study and the inferences about factor demands that are imbedded in our functional cost categories enable us to simulate the effects of emerging technologies. We can also forecast 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: first, we predict the change in RPMs on the basis of changes in the explanatory variables and the demand equation estimates. Next, we estimate airline revenues on the basis of forecast RPM growth and hypothesized changes in ticket prices. Then, we estimate changes in airline operating costs on the basis of forecast RPM growth, changes in load factor, changes in underlying productivity, and changes in input prices. We predict the aircraft inventory from the required ASMs and the underlying productivity of each carrier's aircraft. Similarly, we project total air carrier employment on the basis of block hours (for flight personnel), required ASM (for nonflight personnel), and the underlying productivity of each carrier's employees. Finally, to validate our baseline model, we compare forecasts from the Functional Cost Module with predicted changes in RPMs, aircraft fleet, and operating margins from other published forecasts.

For purposes 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 FCM predicts that, for major carriers, a 10 percent reduction in fares will increase RPMs by 10.061 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.

To predict changes in airline costs, the FCM begins with actual airline cost, productivity, and output parameters for calendar year 1995. Thus, with the exception of capital costs, the baseline 1995 numbers are identical to the carriers reported Form 41 observations. For subsequent years of the forecast, the parameters of the model change according to user-supplied assumptions regarding productivity growth and changes in input prices. To the extent that changes in productivity and input prices follow predictable trends, the cost calculations will remain accurate throughout the forecast period.

- Deriving Industry Equilibrium

  The flow of data within the FCM begins with the econometric estimates of air travel demand. The coefficients from the demand estimates together with user-supplied (or baseline) assumptions regarding annual demand variable changes determine a time series of RPMs flown by each of the individual carriers and carrier groups. Combining the RPM time series with the fare yield projections, the model obtains a revenue series. Then, for each carrier, the RPM series is supplemented with carrier-specific load factor observations to produce a time series of required ASM.

  Once the operating costs have been calculated for each functional cost category, the model aggregates across the carriers to obtain industry costs, revenues, and operating profit margins. If the user has indicated that fare yield changes are to be endogenously determined, the FCM then compares the projected operating profit margins with the target operating profit margins and adjusts the fare yield changes to satisfy the profit constraint.

- Aircraft Fleets and Airline Employment

  Estimating the aircraft fleet required to meet the forecasted travel demand is a straightforward calculation. The number of aircraft is a function of the ASM series and two aircraft productivity measures as shown by equation 4 where an aircraft year is defined as one aircraft in service for 1 year.

$$\textit{Number of aircraft} = \frac{\textit{ASM}}{\textit{(ASM/block hour)(Block hours/aircraft year)}} \qquad \text{[Eq. 2]}$$

  Changes in either of the aircraft productivity ratios will impact the number of aircraft in the fleet. For example, if the average size of aircraft is increasing, all else being constant, the ratio of ASM to block hours will increase and less aircraft will be required to service a given level of demand. The calculations are performed at the individual carrier level and aggregated to obtain the industry fleet.

  In estimating air carrier employment, we made a distinction between flight personnel and nonflight personnel. Our reasoning was that the level of flight personnel employment was most directly influenced by the number of block hours flown, whereas the level of nonflight personnel employment was most directly influenced by the ASM flown. The calculations are given by equations 5 and 6.

$$\textit{Flight personnel employment} = \frac{\textit{ASM}}{\textit{(ASM/block hour)(Block hours/employee)}} \qquad \text{[Eq. 3]}$$

$$\textit{Nonflight personnel employment} = \frac{ASM}{(ASM/employee)} \qquad \text{[Eq. 4]}$$

The last step in the economic analysis is to use the estimated aircraft sales as inputs to an input-output model of the U.S. economy. This generates estimates of employment and shipments in supplier industries throughout the economy, such as avionics, engine manufacturing, and engineering services.

IV. Forecast Results

To generate an unconstrained air travel forecast we constructed a baseline scenario using forecasts of input prices and productivity changes from several industry forecasts. Reference [4] describes the principal variables and their input values. Most of the variable inputs are in annual percentage growth rates over the entire 20-year forecast period. Some variables vary by airline or airline group. This allows for differences in productivity growth among airlines. Table 3 compares the baseline FCM forecast to FAA and Boeing predictions. While there are some differences, as expected, the three forecasts are reasonably close, with the FCM predictions generally in the middle.

Table 3. Baseline Forecast Values

Forecast feature	FAA 1997	Boeing 1993	FCM
Absolute 1995 RPMs (billions)	543.6	578.6	526.1
Absolute 2005 RPMs (billions)	876.1	888.5	850.3
Absolute 2015 RPMs (billions)		1358.4	1304.8
RPM growth rates (%)	4.680	4.513	4.646
Total aircraft 1995	4100	3890	3836
Total aircraft 2005	5871	5332	5309
Fleet growth rates (%)	3.650	3.200	3.295
Fare yield change (%) (96-00)	-1.970		-2.085
Fare yield change (%) (01-10)	-0.802		-1.042

Note: The 1993 edition of the Boeing Current Market Outlook was used since it is the last year in which U.S. carriers are treated separately.

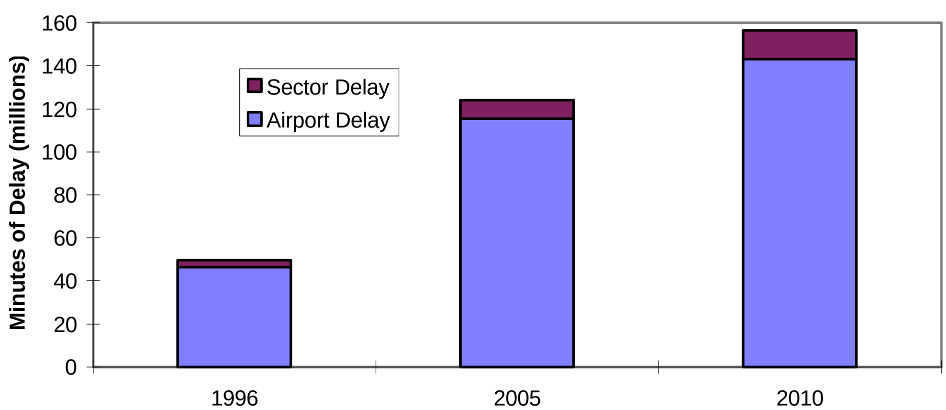
While all the variables affect the baseline scenario, only a few will change when congestion effects are included. The key variables that we modify to estimate the cost and travel demand impacts from delays are: aircraft miles/block hour, block hours/aircraft day, and ASM/block hour.

Table 4. ACIM Input Parameter Values		
Baseline feature	Baseline	Constrained
Aircraft miles/block hour	0.253	-0.93
Block hours/aircraft day	0.00	1.18
ASM/block hour	1.06	-0.13

Note: Parameter values are annual percentage changes.

The driver of the forecast results is the increase in delay arising from the failure of capacity to meet the growth in demand. From 1996 to 2005, our analysis grows traffic by 24 percent, but delays more than double. This increases airline operating costs through higher fuel and crew expenses, and reduced aircraft utilization. Figure 4 summarizes the delay forecasts. Airport delay includes arrival and departure delay, plus gate holds. Sector delays are incurred at en route sectors.

Figure 4. NAS Delay Forecasts



Incorporating these increased costs into the airline economic model requires several assumptions about the likely airline response to the increase in congestion. We assume that fuel and labor costs increase proportionally with the increase in delay, as scheduled block times get longer and less predictable.

Modeling the impact of greater delay on aircraft productivity is more difficult. One approach would be to treat the increase in scheduled time as a reduction in aircraft productivity, since for a given amount of time the aircraft would carry fewer passengers. In order to fly the same schedule, the airline would then have to purchase more aircraft. We developed an alternative approach that assumes that airlines would stretch their schedules out during the day, while simultaneously increasing the number of daily aircraft hours. Operationally, this appears as an increase in aircraft productivity (more aircraft hours per day), although the total output as measured by miles flown or RPMs is constant. Put differently, aircraft utilization increases when measured by block hours per day, but the airlines obtain no increase in output from the block hour increase because it does not enable them to carry more passengers.

Using these assumptions, the revised forecast indicates that from 1995 to 2010 the real cost per ASM will increase about seven percent, from 8.0 to 8.5 cents per ASM, over the baseline uncongested forecast. With a price elasticity of about -1.0, total industry revenues and costs are virtually unchanged, although total output is reduced by six percent over the baseline.

The primary impact we measure is the change in air travel as measured by RPMs. From that output change, we calculate the change in inputs required to meet the revised output requirement. We measure the impacts on three industries - airlines, aircraft manufacturing, and all other industries. For each, we measure the value of lost output and the change in employment (measured by workyears).

Table 5. Summary of Forecasts

	1995	2005 Baseline	2005 Constrained	2010 Baseline	2010 Constrained
Cost/ASM (cents)	9.33	8.42	8.80	7.99	8.55
Yield (cents)	12.86	10.98	11.47	10.54	11.15
RPMs (billions)	526	848	814	1,049	986
Aircraft	3,836	5,305	5,093	6,211	5,831

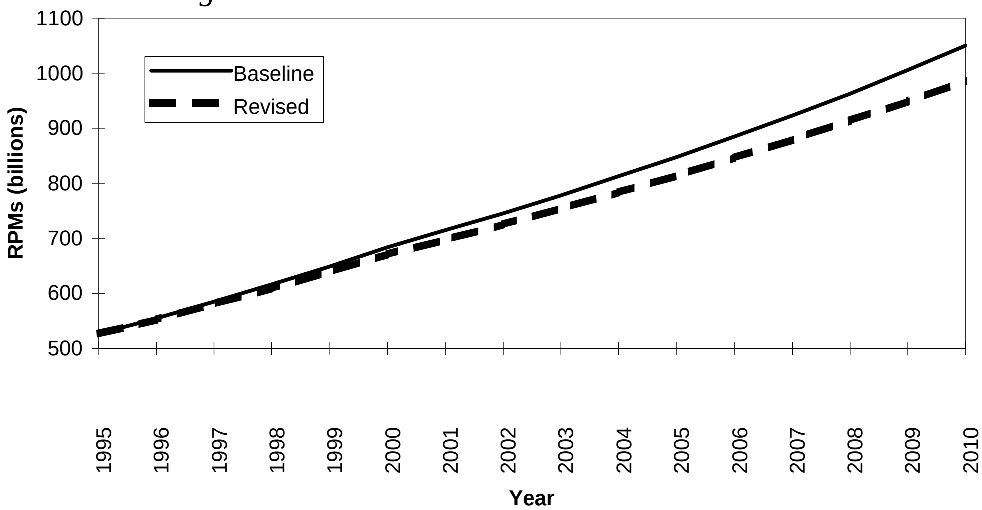
Note: All cost and revenue statistics are in constant 1995 dollars.

Figure 5 shows the baseline and revised forecasts of RPMs from 1995 through 2010. The baseline forecast projects a 99 percent increase in RPMs by 2010; the revised forecast also grows rapidly, although at a lesser 87 percent rate. By 2010, the revised forecast predicts that growing congestion will reduce RPMs traveled by 63.3 billion, or six percent. To place this amount in perspective, the reduced RPMs in 2010 are nearly twice the 34.9 billion average annual increase in RPMs during the forecast period. The six percent reduction far exceeds the annual compound growth rate of 4.7 percent.

As expected, the reduced RPMs in the revised forecast decreases the demand for aircraft. As shown in Table 5, the required fleet inventory to meet 2010 demand is lower by 380 aircraft in the revised forecast. These aircraft are valued at $20 billion at constant 1995 acquisition costs.

Table 6 summarizes the economic impacts of the constrained forecasts. In addition to the RPM and aircraft changes discussed above, the employment effects are noteworthy. For the airline workforce, there are two offsetting effects. Due to lengthier flight times, labor productivity of flight and cabin crews decreases, which implies that more workers are needed to maintain output. However, the reduction in total output decreases the demand for non-flight labor. This impact more than offsets the increase in flight crew, with the net result that cumulative workyears fall by about 32 thousand during the forecast period. In 2010, total airline employment is lower by about six thousand workers.

Figure 5. Baseline and Revised RPM Forecasts



The aircraft manufacturing industry also experiences a significant reduction in employment. By 2010, the reduction in U.S. aircraft production is predicted to reduce cumulative workyears of employment by 56 thousand. The ripple impacts on supplier industries is even greater, estimated at 149 thousand workyears.

As noted in Table 6, the cumulative reduction in RPMs of about 414 billion represents a lost output of $46 billion, priced at the average yield for the two forecasts. In comparison, total airline revenue in 1995 was $76 billion. Expressed differently, those 414 billion RPMs represent 5.6 million flight segments priced out of the travel market because of the higher costs generated by increased travel delays. In 2010 alone, the reduction of RPMs of 63 billion is expected to reduce the number of passenger trips by nearly one million.

Table 6. Summary of Economic Impacts

Economic Impact	Impact
Cumulative Change In RPMs (billions)	-414
Change in U.S. Airline Aircraft Fleet in 2010	-380
Cumulative Change in Airline Employment (Workyears)	-32,235
Cumulative Change in Airline Operating Cost ($ billions)	$53
Value of Lost Airline Output ($ billions)	$46
Value of Reduced U.S. Aircraft Production	$16
Cumulative Change in Aircraft Manufacturing Employment (Workyears)	-55,942
Change in Non-Aircraft Production ($ billions)	-18
Change in Non-aircraft and Non-airline Employment (Workyears)	-149,493

V. Conclusion

This initial effort to evaluate the possible economic impacts of increased air traffic congestion on the air transportation industry yields several important conclusions. First, it shows how analysts can use estimates of delay to calculate other measure other variables of interest to policy makers and airline operators: changes in fares and costs, industry output, and broader measures of economic impact such as aircraft production and employment. Analysts have striven in recent years to develop alternatives to traditional delay analysis to identify variables that are often of greater interest to decision makers. By developing a method for expanding the delay estimates to measure impacts on variables such as RPMs travel and cost per ASM, we hope to make the results of capacity and delay analysis more concrete to key industry decision makers.

The analysis is far from final. Many of the important feedback effects that will be engendered by increased congestion are not addressed in this study. Tactical and strategic airline responses to congestion are not analyzed directly, although its is obvious that such significant changes in the operating environment will generate important airline responses.

There are several factors that our analysis does not address. Perhaps the most significant omission is that we do not include any possible demand reduction impact from the longer scheduled time, or from moving flights to less desirable time periods. While clearly important, such impacts are difficult to quantify. For this exploratory study, we focused solely on the straightforward first-order impacts that we could measure using available models. Consequently, we view these results as conservative estimates of the costs of congestion.

We also did not attempt to analyze possible airline responses to increased congestion. Likely responses would be to accommodate demand growth through more point-to-point service, or with larger aircraft. Airlines could also open additional hubs.

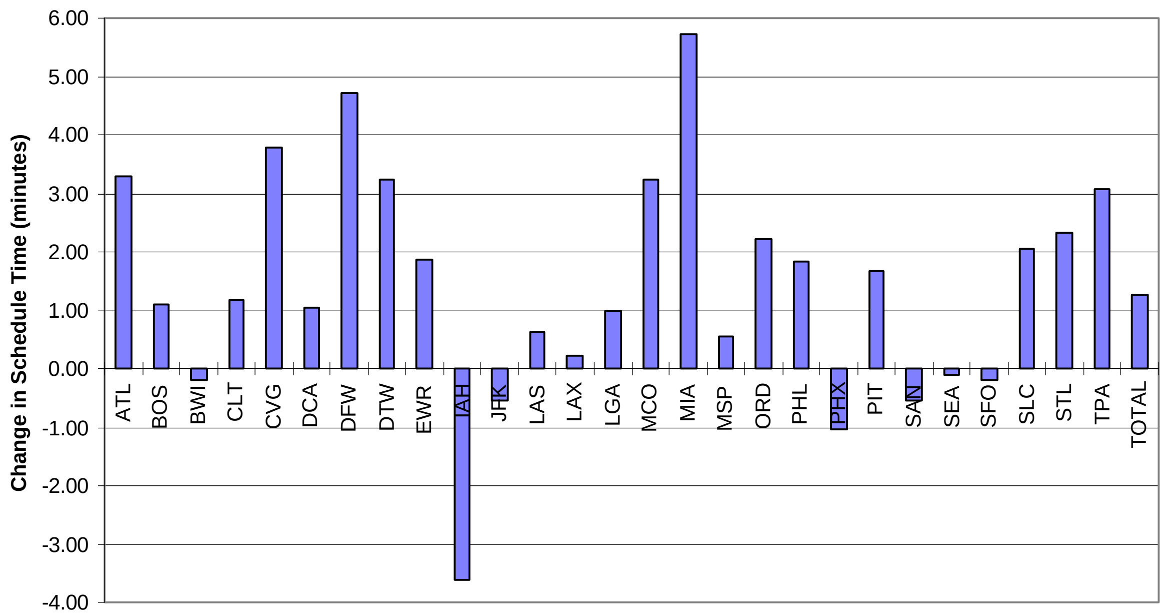
It is possible to argue that the delay forecasts we use to estimate the economic impacts are unrealistic, since analysts have previously forecasted delay increases that did not materialize. We have two responses to this claim. First, official delay measures do not provide accurate indications of congestion over time. As delays increase, airlines respond by modifying schedules, moving or eliminating flights, and other actions to reduce the delay costs. All these actions reduce reported delays, but only by shifting airline and traveler costs elsewhere in the system.

Second, we argue that delays have increased over time, but they have been disguised by increases in scheduled block times. One study reports that the ratio of block hours to air hours increased from 1.16 in 1981 to 1.21 in 1994 [5]. This gives a rough indication of the worsening trend in air traffic congestion.

Using more recent data on airline schedules, we estimated how schedules have changed in recent years. Based on the published OAG for April 1993 and April 1997, we found that scheduled block time for flights among the 29 hub airports in the U.S. increased by 1.25 minutes over this four year period. If we exclude the spacious new Denver airport, which opened in 1995, the average increase climbs to 1.61 minutes. The large impact of the new Denver airport indicates the significant impact of capacity improvements, and their ripple effects through the system.

The aggregate data mask some more significant effects at individual airports. At Atlanta Hartsfield International Airport (ATL), for example, scheduled times for departures increased 3.28 minutes. The increase at DFW was even greater, at 4.71 minutes. (These numbers for ATL and DFW exclude flights to and from DEN.) The cost to airlines and travelers of such increases is substantial. At DFW, for example, with about 450,000 scheduled departures in 1997, a cost of $40/block minute implies a cost increase of about $85 million over the four years in direct operating costs alone.

Figure 5. Trends in Scheduled Flight Time (April 1993 to April 1997)



The potential lost revenue from operational constraints and reduced aircraft and personnel productivity are likely to be at least as large as the direct cost increases. Using the DFW schedule increases as an example, if the airlines operating there could use those 4.71 minutes per flight to generate revenue, the result would be about $160 million.[5] While it is highly unlikely that all of that time could be used productively, at least some percentage could be used to carry passengers and generate revenue.

[5] Based on 450,000 departures per year, an average flight time of 142 minutes, and $10,661 in revenue per flight.

Another consideration, discussed by Captain Chew of American Airlines [6], is that as airports become more congested, the airline ability to respond to demand changes is reduced. Limited landing slots reduce airline opportunity to react to demand and revenue shifts. At the extreme, more airports become slot-constrained, if not directly regulated, and travelers end up paying more for restricted choices.

When evaluated from the perspective of changes in airline schedules over only a relatively short 4-year period, the forecasted increases in travel times and airline costs predicted by our models appear plausible. Focusing solely on reported delay against scheduled times misses the more important issue of how the lack of capacity, and its associated congestion, increase the costs and time for air travel.

This study examined only the impact on the U.S. of air traffic congestion. Similar, and in some cases worse, congestion has occurred in Europe. The rapid growth of air travel in Asia promises to create more congestion in that region. Consequently, the quantitative findings of this study are truly conservative.

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