



The World's Largest Open Access Agricultural & Applied Economics Digital Library

This document is discoverable and free to researchers across the globe due to the work of AgEcon Search.

Help ensure our sustainability.

Give to AgEcon Search

AgEcon Search

<http://ageconsearch.umn.edu>

aesearch@umn.edu

*Papers downloaded from **AgEcon Search** may be used for non-commercial purposes and personal study only. No other use, including posting to another Internet site, is permitted without permission from the copyright owner (not AgEcon Search), or as allowed under the provisions of Fair Use, U.S. Copyright Act, Title 17 U.S.C.*

No endorsement of AgEcon Search or its fundraising activities by the author(s) of the following work or their employer(s) is intended or implied.



Transportation Research Forum

Air Traffic Performance by Market Segments

Author(s): Dipasis Bhadra

Source: *Journal of the Transportation Research Forum*, Vol. 46, No. 2 (Summer 2007), pp. 47-62

Published by: Transportation Research Forum

Stable URL: <http://www.trforum.org/journal>

The Transportation Research Forum, founded in 1958, is an independent, nonprofit organization of transportation professionals who conduct, use, and benefit from research. Its purpose is to provide an impartial meeting ground for carriers, shippers, government officials, consultants, university researchers, suppliers, and others seeking exchange of information and ideas related to both passenger and freight transportation. More information on the Transportation Research Forum can be found on the Web at www.trforum.org.

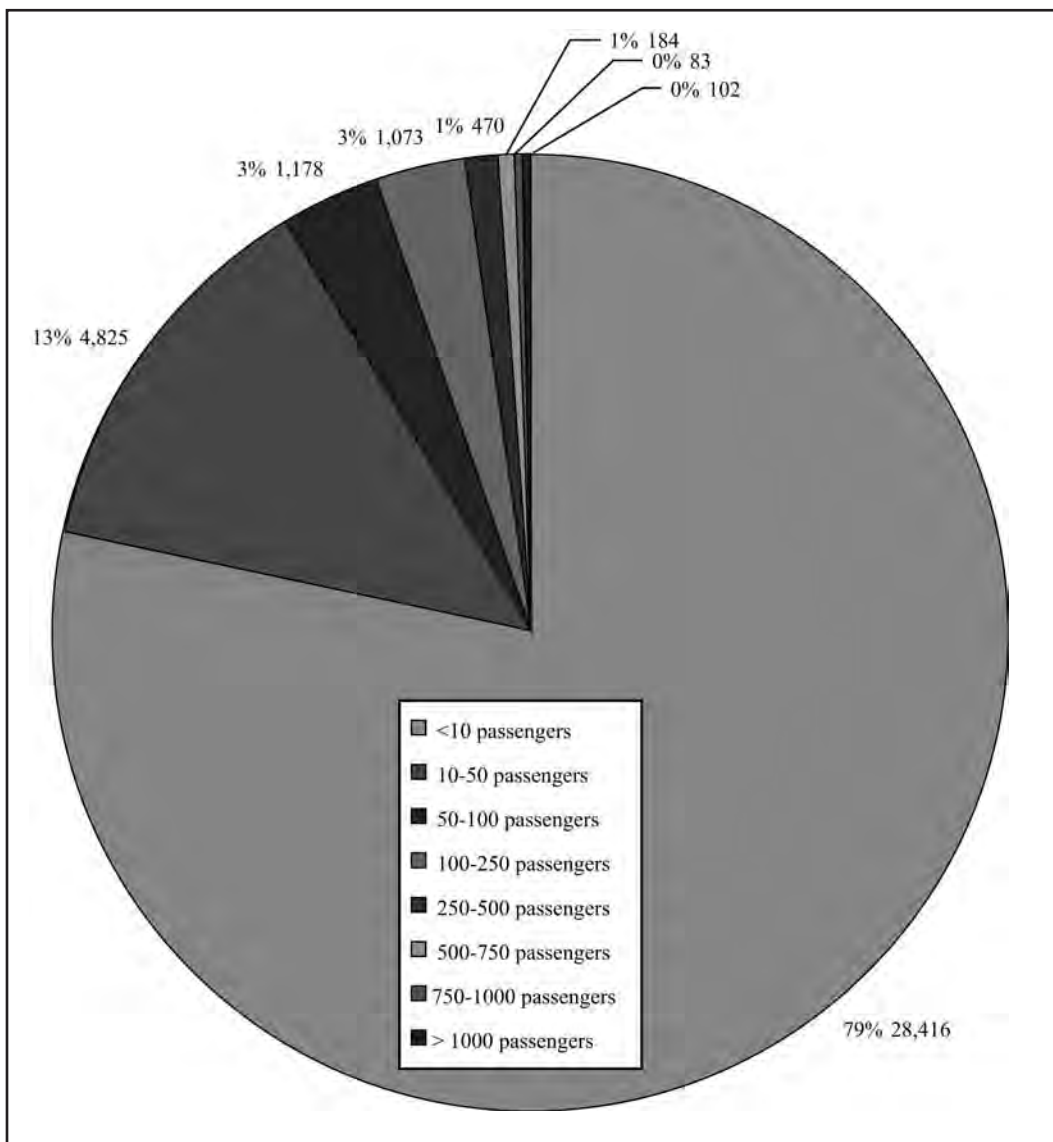
Air Traffic Performance by Market Segments

by Dipasis Bhadra¹

How is air traffic performance affected by type and location of markets? Is there any pattern to how air traffic performs with respect to the size and structure of markets, type of networks, and size of aircraft? In this paper, an empirical framework has been developed to examine the determinants of air traffic performance. Air traffic performance is defined as the ratio of airborne time to total ramp-to-ramp time. Using quarterly segment traffic data (i.e., T100 segment of Form 41) for the period 1995-2006, an econometric model is constructed to estimate and evaluate performance measures defined over market segments and networks. This econometric framework establishes and evaluates empirical linkages between performance measures and size of the markets, locations, distance, seasons of the year, and aircraft type over time. Statistical estimates indicate that size of market, type of aircraft, industry structure, and distance play important roles in influencing performance measures.

INTRODUCTION

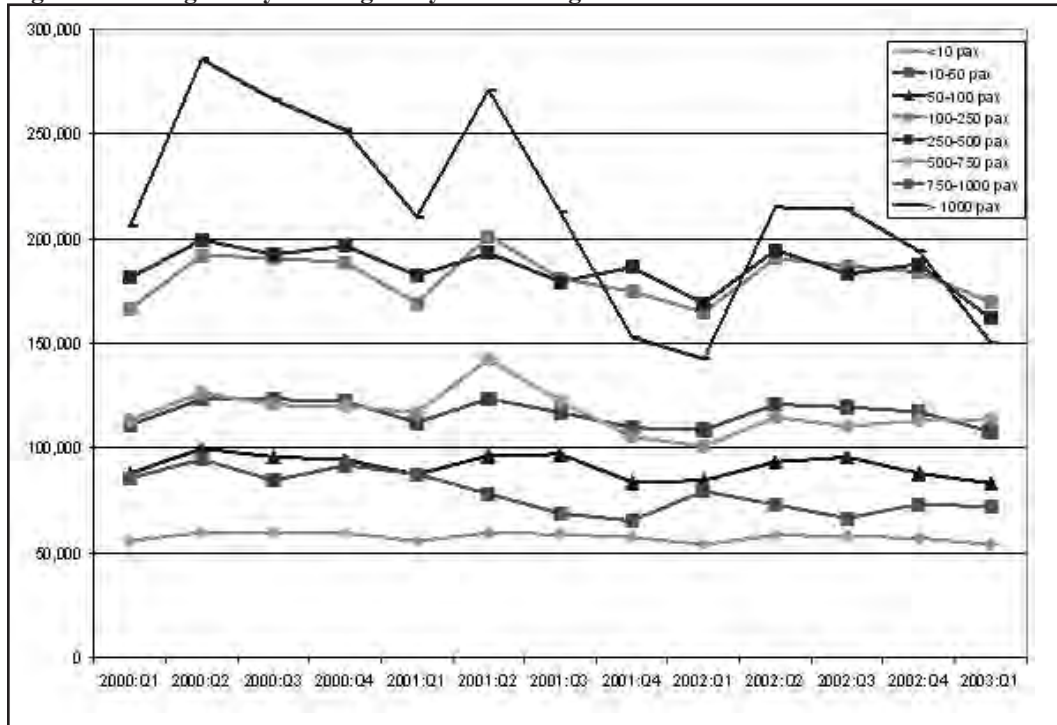
The National Airspace System (NAS) in the United States is structured primarily around a web of air transportation markets linked through a network of 519 commercial airports located in and around 369 metropolitan statistical areas (MSAs). The total number of origin-destination (O&D) markets in the NAS ranges somewhere between 36,000 – 40,000 pairs depending upon seasons and economic cycles. These markets are hierarchical; a smaller number of markets account for the largest number of passengers. For example, there were approximately 102 markets (0.3% of total) which had 1,000 or more passengers a day (i.e., “thick” markets), but these accounted for almost 17% of total passengers. On the other hand, there were over 28,000 markets (79% of total) with 10 passengers or less a day that accounted for only 6% of total passengers in 2003 (Figure 1).

Figure 1: Number of Markets by Market Segments

Source: DB1B (10%) database; Available at the www.bts.gov.

Note: % refers to share of the market segments in total; values next to % represent number of markets in the segment in 2003.

A majority of these markets (79%) are “thin” in size, (meaning they carry fewer than 10 passengers a day), followed by markets that carry 10–50 passengers a day (13%) (Figure 1). In comparison, “thicker” markets (i.e., 100 or more passengers a day) are relatively small, numbering somewhere between 1,900–2,200 during the period 2000–2003 with a relatively stable share of 5–6% of the total market. Interestingly, however, the share of the market in total passengers is asymmetrical. “Thick” markets carried somewhere between 66–90% of all passengers while “thin” markets carried only 16–18% of all passengers during the period 2000–2003 (Figure 2).

Figure 2: Average Daily Passengers by Market Segments

Note: Calculated from DB1B (10%) database; available at www.bts.gov.

Many of the thin markets are economically infeasible for commercial air service (GAO 2002 and Bhadra 2004). Lack of passenger volume makes them unattractive as stand-alone markets.² Hence, many of these markets are served as a point in the commercial air carriers' hub-and-spoke network.³ These spokes, or points, are critical for the viability of the hub-and-spoke network which evolved as the dominant form of the air transportation network following the deregulation of the industry in 1978.

Air travel in the U.S. has a hierarchical structure with a well-functioning hub-and-spoke network (Bhadra and Texter 2004). Air transportation between hubs (i.e., between the top 35 commercial airports, also known as the Operational Evolution Plan (OEP) airports⁴) handle almost 50% of total passengers followed by those between hub and spokes (i.e., travel between OEP and non-OEP airports) with a share of around 45% (www.bts.gov). In comparison, point-to-point (i.e., travel between non-OEP airports) travel had a share of around 5% of the total number of passengers; for details on these networks and numbers, see Bhadra and Texter (2004).

While the connectivity through a hub-and-spoke network has brought geographic proximity and economic prosperity to many of the small communities, it has brought some unavoidable consequences as well. Primary among them are the delays associated with air travel that is passed onto these small communities from those that they are connected with. It is well-known (FAA 2004) that delays in air transportation are heavily concentrated in airports that are primarily large hub airports. Large hubs are also connected to a larger number of spokes.⁵ Thus, as large hubs experience delays in air transportation, they cascade through the system onto the spokes. Hence, it is likely that the spoke airports that are connected to large hub airports through the hub-and-spoke system may bear a relatively larger proportion of these delays compared to those that are not. Furthermore, the larger the extent of these connections, the more intense the effect will be on the system. Hence, the delays at Chicago's O'Hare (ORD) are likely to impact the nation more severely than other airports⁶. It is also likely that the extent and intensity of these delays would be influenced by the

type of hubs. For example, if a hub is dominated by one carrier (i.e., a so-called “*fortress*” hub), the impact of delays on spokes may be different than if it was served by one or more carriers (Brueckner 2002; Mayer and Sinai 2003). The extent of delays at airports that are connected by a point-to-point network, as opposed to those connected by a hub-and-spoke system, is expected to be different as well.

Finally, much has been written (Coy 2005; Rupp, Owens, Plumly 2002) about airlines’ performance in the U.S. The U.S. DOT also tracks the airlines’ performance regularly (http://www.bts.gov/programs/airline_information/; retrieved July 5, 2006) by collecting and releasing data on on-time performance over time. While these data and much of the analyses provide broad overview of the performance and uniqueness of NAS, very little effort has been placed on understanding the systematic drivers of these performances. A NAS-wide analysis of the carriers’ performance over time and by the types of network does not exist at present.

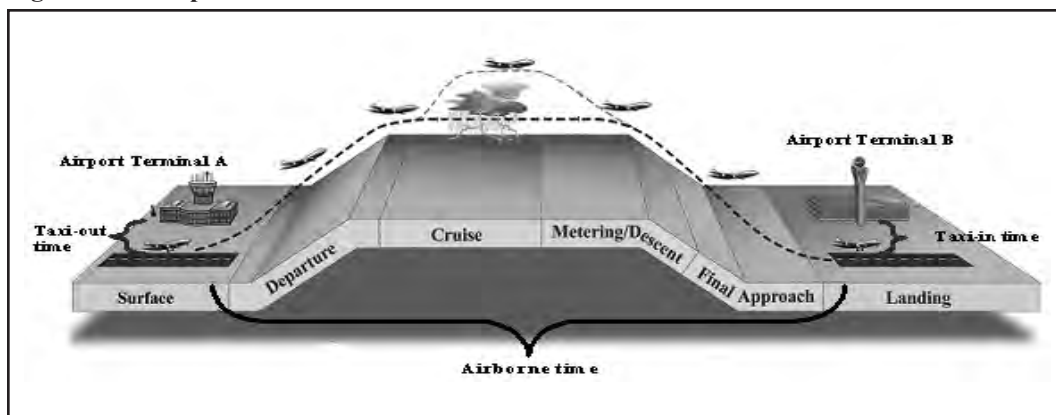
This paper is an attempt to understand the air traffic performance by market segments. In particular, we ask the following questions: How does the air traffic performance behave by type of market segment, and type of network? Can the performance patterns be explained by systematic factors, e.g., time of the year and/or by market factors such as volume and type of passengers and type of air carriers? To what extent do these patterns depend on type of aircraft serving these markets? The paper is organized as follows: the second section defines air traffic performance measures in the context of available literature and provides data with regard to performance trends over time and by different types of air carriers. The third section introduces the data and postulates the key empirical hypotheses. The fourth section discusses the empirical findings of the study. Finally, the last section offers some conclusions.

PERFORMANCE CRITERIA IN THE LITERATURE⁷

Two measures that are often used in the literature to evaluate operational performance of aircraft, air carriers, and the airspace system in turn, are time from ramp-to-ramp⁸ and airborne time (see Bolzack et al. 1997 for standard definitions). Ramp-to-ramp time is computed from the moment an aircraft first moves under its own power for purposes of flight, until it comes to rest at the next point of landing. The airborne time is computed from the moment an aircraft leaves the ground until it touches the ground at the end of a flight stage. Thus,

$$\text{Ramp-to-ramp time} = \text{taxi-out time} + \text{airborne time} + \text{taxi-in time}$$

Figure 3: Description of Different Phases of Time in Air Travel

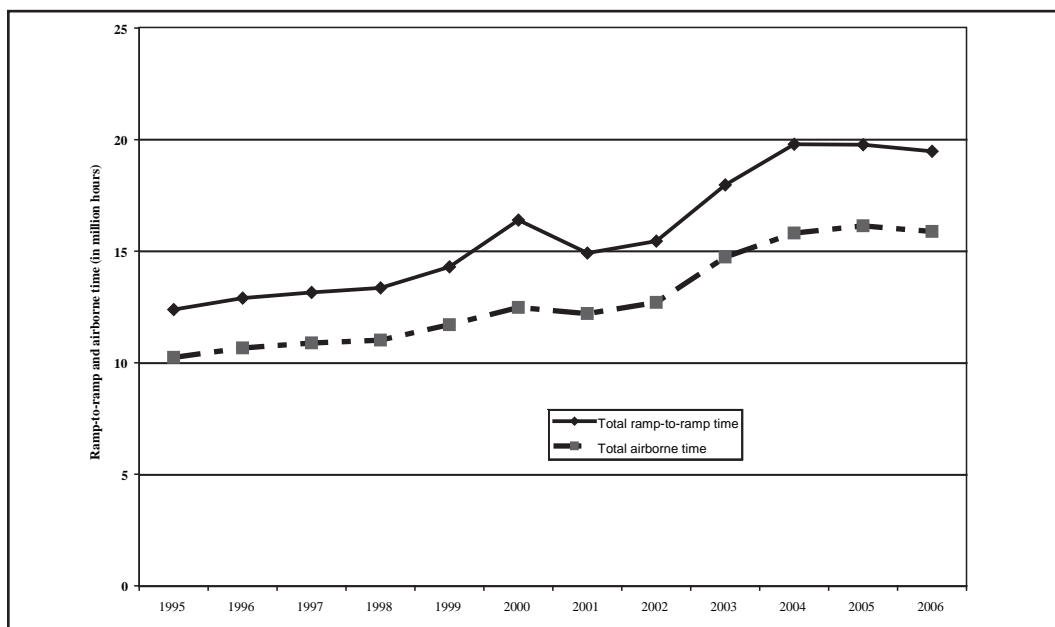


Poor performance can be classified into strict categories according to taxi out delays (e.g., those arising from queues, ground delays, and ground stops), airborne delays (e.g., those arising

from holding in the airspace due to bad weather or unavailability of landing space), and taxi in delays (i.e., queues and congestion at the airport, apron, and gate); see Auerbach and Koch (2007). For reasons of cost and safety, airborne holding does not happen frequently. Most delays occur on the ground, either at the taxi out or at the taxi in phases. Thus, the higher the ratio of airborne time to ramp-to-ramp time, the higher the efficiency of the flight. For this analysis, the performance criterion is thus defined as the ratio of airborne to ramp-to-ramp time, with lower and upper limits approaching 0 and 1.⁹

Figure 4 demonstrates that NAS utilization is increasing over time. The annual growth rate in the mid to late 1990s was approximately 3% for both ramp-to-ramp and airborne hours, tracking quite closely to each other. This was followed by an accelerated growth period (1999 – 2000) where the airborne hours grew at an annual growth rate of 6%, while ramp-to-ramp time grew at an annual rate of 11%. This imbalance likely contributed to the deterioration of air transportation performance. The period of 1999 to 2000 is widely known for high delays in air transportation (Coy 2005). Symmetrically, the downward adjustment in ramp-to-ramp hours, following Sept. 11, 2001 (9/11), was far more dramatic (-9%) than the downward adjustment in airborne hours (-2%). This suggests that a large part of the adjustment in NAS utilization may have come from adjusting for ground performance. Using on-time performance data of the large network carriers, Coy (2005) found that domestic operations of U.S. major airlines were far more reliable after 9/11 than it was the year before. While a large part of this improvement had come from reduction in number of flights, a disproportionate cut (61%) in short haul flights also increased operational efficiencies of the major carriers (Coy 2005).

Figure 4: Trends in Ramp-to-Ramp and Airborne Time



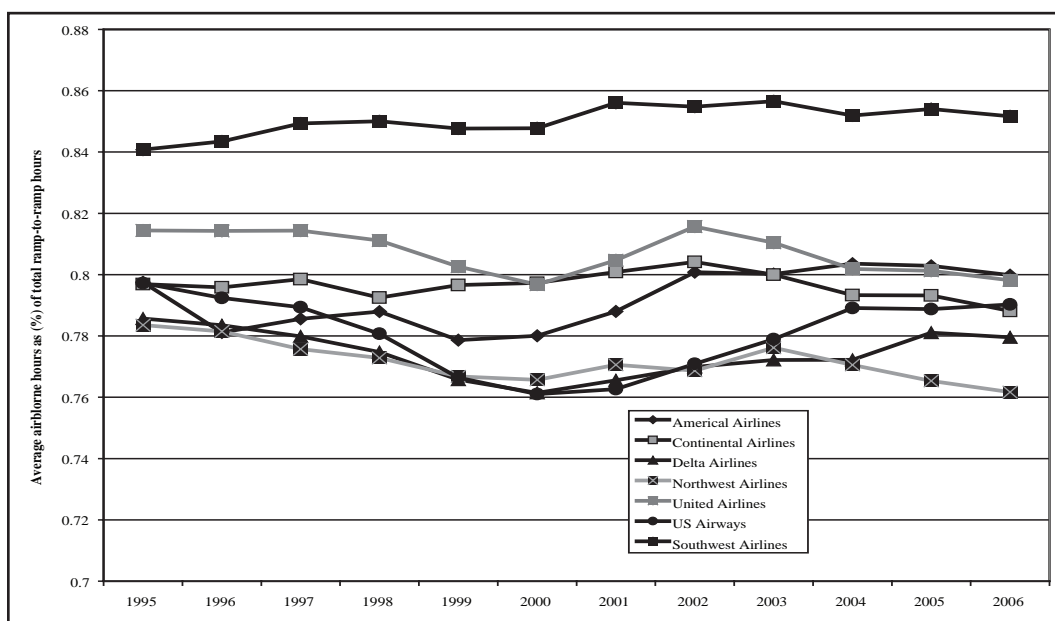
Source: Calculated from T100 segment database; available at www.bts.gov.

Another acceleration occurred during 2003-2004 where ramp-to-ramp time grew at an annual average growth rate of 13% and airborne hours tracked closely with approximately 12% growth rate. Comparable growth in airborne hours with ramp-to-ramp time represented more balanced air traffic performance unlike the period 1999-2000. The last two years (2005 and 2006) observed a slowdown in ramp-to-ramp and airborne times. Finally, there are some seasonal variations in the data when evaluated by quarters.

Controlling for O&D segments and distances, the higher the ratio of airborne to ramp-to-ramp time (i.e., index value closer to one), the more efficient is the flight. That is, the higher the percentage of time in the air, *ceteris paribus*, the higher the overall productivity of the aircraft and, hence, the higher the positive impact on air carrier profitability. Technical aircraft superiority (i.e., climbing rate and cruising speed) also influences performance and may reduce air traffic delays; see Cavcar and Cavcar (2004) for an analysis on technical specifications of aircraft and their impact on air traffic delays.

The overall cost efficiencies of an air carrier arise from minimizing these delays, in part, by maintaining the overall performance throughout the system by optimizing the aircraft efficiency. An example of this accomplishment is cited (Rupp, Owens, Plumly 2002) by the experience of Southwest Airlines. Southwest Airlines, on average, has a faster turn-around time than any other air carrier and, hence, is likely to attain higher airborne time relative to ramp-to-ramp time (Figure 5). The performance characteristic of Southwest Airlines over the time series is consistent with that observed in route-specific analysis (Rupp, Owens, Plumly 2002). Figure 5 depicts this relative efficiency of Southwest Airlines over others.

Figure 5. Air Traffic Performance by Air Carriers



Source: Calculated from T100 segment database; available at www.bts.gov.

The evaluation of system performance using delay as the chief criterion has been often used to account for the economic losses (Bolczak et al. 1997). Eurocontrol (2000) estimates the annual losses stemming from air traffic control delays to be approximately 5.73 billion Euro (€). Dell’Olmo and Lulli (2003) estimates losses of \$2 billion from longer trajectories arising from flying fixed airway networks, and \$10 billion due to air traffic control actions generating deviations from optimal aircraft flight profiles. Clearly, delays have serious economic consequences; see also Auerbach and Koch (2007).

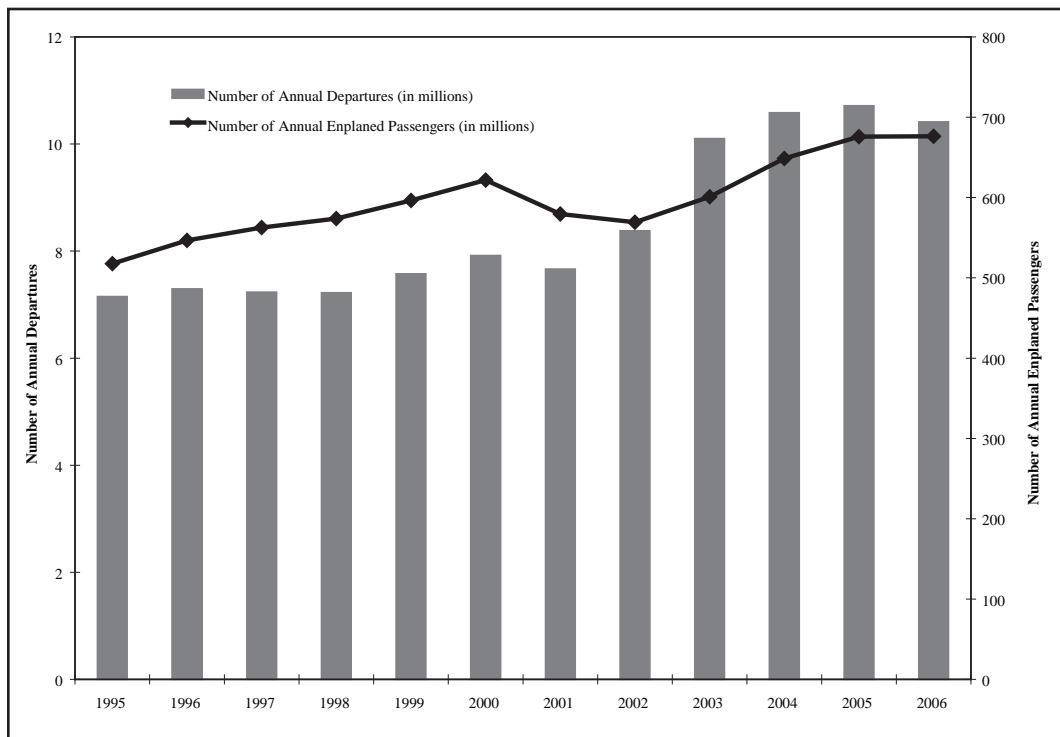
This analysis is unique in three respects from earlier work in this area. First, it offers a new metric for measuring air traffic performance that is broad and yet captures the essential dynamics. Second, it econometrically models the drivers of the air traffic performance and identifies key systematic factors. Third, the analysis employs a long term data series that is unique in its characteristics.

DATA AND RESEARCH QUESTIONS

Data for this exercise comes from the Bureau of Transportation Statistics/Department of Transportation's (BTS/DOT) T100 schedule (www.bts.gov).¹⁰ T100 is broken into two parts: T100 market segment (T100M), which covers all the O&D markets and the T100 segment (T100S) which provides data for market segments serving O&D markets. In particular, T100S is the Data Bank 28DS of Form 41 that provides segment traffic (i.e., the number of passengers and departures scheduled and performed) by scheduled air carriers, as well as data for freight, mail, service class, type of aircraft equipment, capacity (i.e., available capacity payload and available capacity seats), performance indicators (i.e., ramp-to-ramp elapsed time, airborne elapsed time), distance, month, and year. The data are reported by major air carriers operating between airports located within the boundaries of the U.S. and its territories (USDOT 2001). Figure 6 illustrates the magnitude of traffic, i.e., number of annual departures and enplaned passengers, for the time series 1995-2006.

For the empirical analysis, T100 domestic segment data for the period covering 1995: first quarter (Q1) – 2006: fourth quarter (Q4), or 48 continuous quarters has been used.

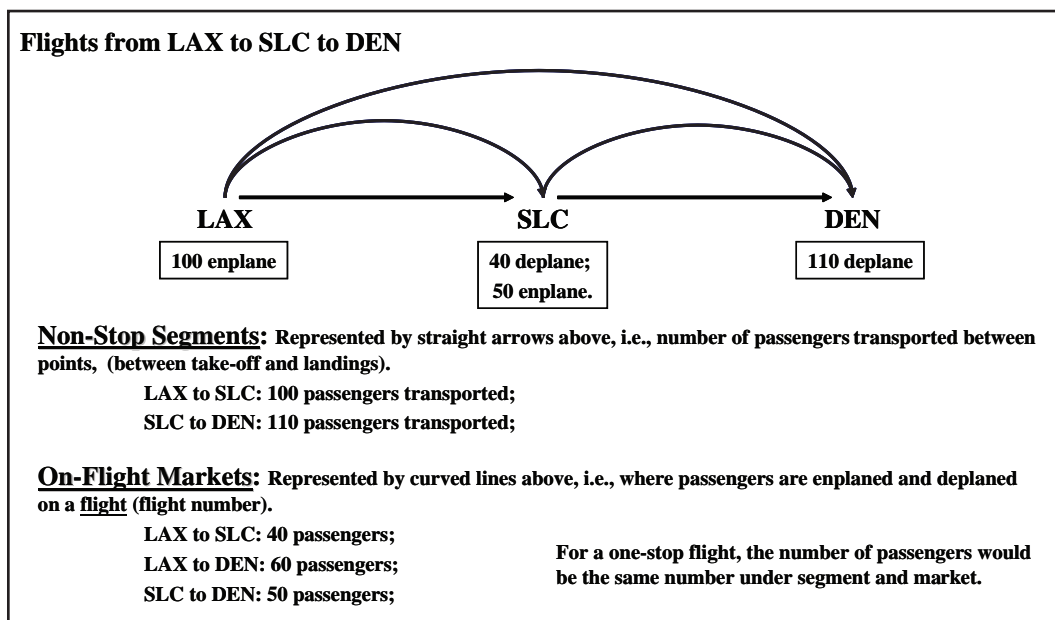
Figure 6: Domestic Segment Air Traffic



Source: Calculated from T100 segment database; available at www.bts.gov.

T100 data can be best explained in Figure 7 (USDOT 1992).

Figure 7: An Illustration of T100 Data

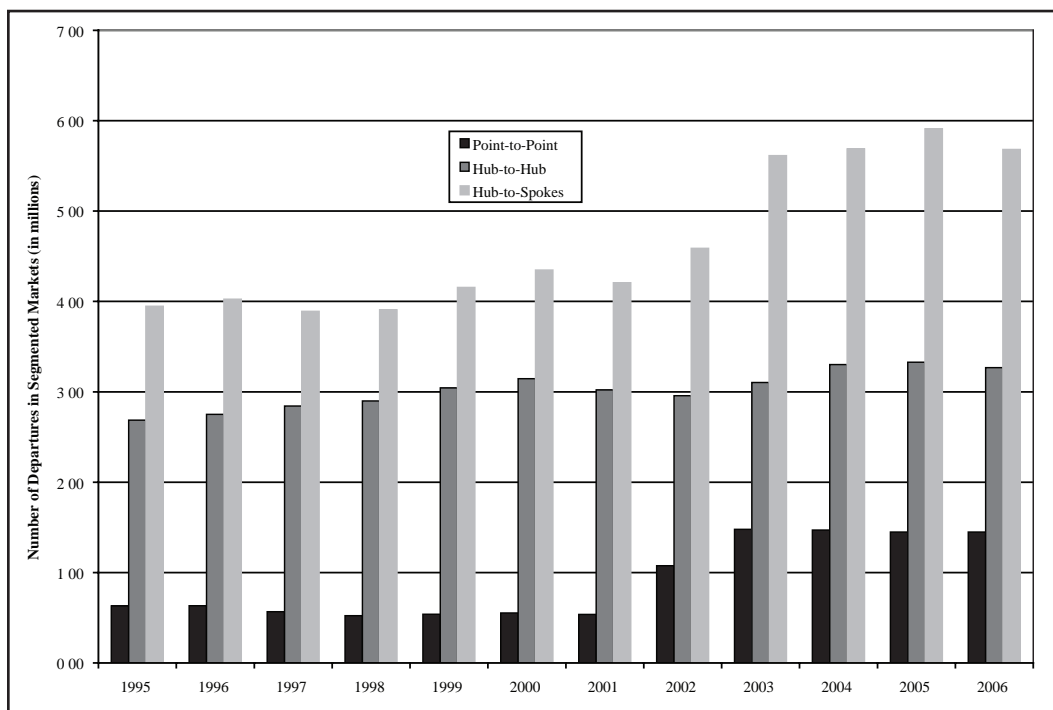


For a hypothetical flight between Los Angeles (LAX) to Salt Lake City (SLC) to Denver (DEN), non-stop segments data (T100S) accounts for the transfer passengers, in addition to O&D passengers. On-flight market segment data (T100M), on the other hand, accounts for the number of passengers that are traveling between O&D market pairs only. The T100M captures limited variables: number of passengers by O&D, freight, mail, carriers, distance, month, and year.

Each segment reported in T100S is unique, distinctly defined by air carrier and equipment type. Thus, the same LAX – SLC will be reported twice, for example, if a carrier flew the segment using two equipment types. This phenomenon increases as more carriers crowd in and fly more equipment types, i.e., the market becomes increasingly fragmented. Despite this fragmentation, the total number of segments can be aggregated over O&Ds to provide a logical basis for defining the network. For this analysis, point-to-point network is defined as traffic flow between non-OEP airports; hub-to-hub as traffic flow between OEP airports; and, hub-to-spokes as traffic flow between OEP airports and non-OEP airports (Bhadra and Texter 2004).

The complete time series of 1995-2006 contains 3,095,342 distinct records. Summing these distinct records over O&D segments, types of aircraft, reported carrier, year, and quarter yields 1,394,047 rolled up observations. There were 415,640 observations (i.e., number of rolled up segments) for the point-to-point network, 355,511 observations for the hub-to-hub network, and 622,876 observations for the hub-to-spoke network. These observations have been used for estimation of the econometric model. Number of departures in segmented markets is reported by year and by network in Figure 8.

Figure 8 demonstrates the pattern of traffic flow in the NAS. While traffic flow has been largely stable over the hub-to-hub network, there have been considerable changes in the point-to-point and hub-to-spokes network. Much of these changes represent the consequence of restructuring that took place during the last five years, following the tragic events of 9/11. However, these changes are slightly magnified by the changes in the data collection that were put in place by the USDOT in 2002 where all schedule carriers were required to report traffic under T100.

Figure 8: Number of Departures by Network

Source: Calculated from T100 segment database; available at www.bts.gov.

In order to estimate the performance index as defined earlier, the econometric model is specified as follows:¹¹

$$\text{index}^k = F(p_0, p_1(\text{dummy}), p_2(\text{mktsize}), p_3(\text{sumtotpax}), p_4(\text{Terrorism}), p_5(\text{Avgdistance}), p_6(\text{Avgdistancesquared}), p_{AA}(\text{American}), p_{CO}(\text{Continental}), p_{DL}(\text{Delta}), p_{NW}(\text{Northwest}), p_{WN}(\text{Southwest}), p_{US}(\text{USAir}), p_{UA}(\text{United}))$$

where index^k = performance measure = (airborne time/ramp-to-ramp time) and $k=0, 1, 2$ where 0 represents the point-to-point network segment, 1 represents the hub-to-hub network segment and 2 represents the hub-to-spoke network segment; dummy = seasonal dummy, where spring and summer = 1 and fall and winter = 0; mktsize = average available number of seats as a proxy for market size. Alternative to the mktsize specification, ACCategory dummy (1 being lowest, e.g., Cessnas and Pipers; and 6 being the largest, i.e., wide-bodies) was also used to capture the effect of aircraft size variations on performance; sumtotpax = sum of total segment passengers; Terrorism : a dummy variable capturing 9/11, i.e., time following Sept. 11, 2001; Avgdistance : average distance (in statute miles) between segment pairs; and $\text{Avgdistancesquared}$ is the squared average distance between segment pairs. Air traffic performance is expected to improve positively with distance (i.e., positive sign for first derivative or avgdistance), but such improvement slows with longer distance traveled (i.e., negative sign for second derivative or $\text{avgdistancesquared}$).

Mktsize is expected to influence performance differently for different networks, and hence, both positive and negative signs may result. For example, if the mktsize increases, controlling for total segment passengers, it is likely that the aircraft size will get bigger and thus performance may improve. Generally speaking, this is unlikely over a longer time period for airlines will soon

reoptimize the right aircraft size (or “rightsize”) for the segments. On the other hand, if *mktsize* increases, again controlling for segment passengers, it may also be likely that frequency may increase and hence number of departures. This may reduce the overall air traffic performance. This scenario is likely particularly for short haul routes where airlines serve business passengers and frequency is often valued (and appropriately priced) even at the cost of lower number of passengers (i.e., lower load factors).

Sumtotpax may result in a positive or negative effect on performance depending upon the types of network. For hub-to-hub network, a portion of the passengers are connecting while the others are origin to destination passengers. Depending upon the nature of the passenger mix, the higher the portion of the connecting passengers, the more likely it will cause lower air traffic performance due to scheduling requirements, repositioning of flights, and other operational requirements. Since only a handful of the airports of the hub-to-hub network (as defined in this analysis) are truly operational (i.e., connections are higher than the O&D segments), we expect the *sumtotpax* in hub-to-hub network to have a positive influence (or weak negative) on air traffic performance, i.e., more passengers leading to a better performance. A similar logic applies to the point-to-point network for one would expect relatively better performance as segment passengers increase. However, one can not use the same logic for a hub-to-spoke network for increased passengers may often lead to higher demands on the networks for many of these spokes. Hence, increased passenger load may reduce air traffic performance.

Categorical dummies for airlines presence in the market segments have been specified to capture airline-specific impact on performance. Thus, *American* is a dummy variable representing American Airlines’ presence in the market segments and similarly for other airlines. Notice here that six network carriers are used (American Airlines, Continental Airlines, Delta Airlines, Northwest Airlines, US Airways, and United Airlines) and the most dominant low-cost carrier, Southwest Airlines in this analysis.

Given the discussion earlier, the following research questions are addressed:

- How is performance affected by the time of the year? Do busy seasons affect air traffic performance?
- How does the size of the market affect performance?
- How has performance adjusted following the events of 9/11?
- Does performance get better as longer distances are traveled?
- How does the size of the aircraft, either represented by types of aircraft or by number of seats, affect performance?
- How do network carriers compare among themselves, and how do they compare against Southwest Airlines in performance?

EMPIRICAL RESULTS

Time series data (1995:Q1 – 2006:Q4) is combined with a cross-section of elements (e.g., by segments and by network) for the empirical analysis. When time series data are used in regression analysis, it is well known (Pindyck and Rubinfeld 1991) that the error term is often not independent through time. Instead, the errors are serially correlated or what is commonly called autocorrelated. Under these circumstances, the efficiency of ordinary least-squares (OLS) parameter estimates is adversely affected and standard error estimates are usually biased.

When a series is correlated to its past error trends, then auto-regressive procedures can be applied. Depending on the number of lags, auto-regressive models with lag p , i.e., $AR(p)$ can be applied. The commonly used autoregressive error model corrects for serial correlation in time series models. This procedure can fit autoregressive error models of any order and can fit a subset of autoregressive models as well. In order to correct for serial autocorrelation, the *AUTOREG* procedure from SAS

(Version 9.1) was used to estimate the model. Using this procedure, it was found that $AR(p) = 4$, i.e., autoregressive models with four quarter lags, adequately corrects serial correlations.

Table 1 provides the maximum likelihood estimates of performance. The specification for the index^K model appears to have good statistical properties for two of the three networks. Overall statistical results for hub-to-hub and hub-to-spoke networks are fairly good and have desirable properties. The model's explanatory power for the point-to-point network segment is somewhat poor (i.e., independent factors do not explain the variations in the index^{K=0} well). However, when we ran the maximum likelihood estimation, other properties, i.e., root mean squared errors, and Durbin-Watson statistics, improved considerably over the OLS methods for all networks, including that of the point-to-point network.

Relatively speaking, the specification performs well for the hub-to-hub network followed by hub-to-spoke and the point-to-point networks. Interestingly, busy seasons tend to deteriorate air traffic performance for hub-to-hub and hub-to-spoke networks while performance improves for the point-to-point network. Interestingly, Southwest presence improves the air traffic performances, while other carriers tend to affect it negatively. Furthermore, average number of available seats and sum of segment passengers do not perform well for hub-to-hub and hub-to-spoke networks.

Table 1: Maximum Likelihood Estimates of Performance

Model Variables	Description of Variables	Point-to-point	Hub-to-hub	Hub-to-spoke
		Index = k = 0	Index = k = 1	Index = k = 2
		Estimated Model*	Estimated Model**	Estimated Model**
Intercept	Intercept	0.73622	0.63371	0.66601
Dummy1	season dummy spring and summer=1 fall and winter=0	0.005294701	-0.007344349	-0.002347535
Mktsize	Average number of available seats	-0.000008896	0.000000103	-0.000000062
sumtotpax	Sum of segment passengers	0.000004078	0.000000066	-0.000000008
Terrorism	9/11 dummy (>=2001 Q3=1 else=0)	0.048636	-0.011211	-0.018743
Avgdistance	average distance between segment pair	0.000218718	0.000276052	0.000295944
Avgdistancesq	square of average distance	-0.00000005760	-0.000000006	-0.000000007
American	American Airlines dummy	-0.060368	-0.028869	-0.046006
Continental	Continental Airlines dummy	-0.044152	-0.021953	-0.041138
Delta	Delta Airlines dummy	-0.066722	-0.021838	-0.038161
Northwest	Northwest Airlines dummy	-0.069937	-0.013836	-0.032426
Southwest	Southwest Airlines dummy	0.010867	0.049707	0.036893
USAir	USAir dummy	-0.038961	0.00303	-0.007853
United	United Airlines dummy	-0.057129	-0.010329	-0.030032
AR1	AR term with one quarter lag	-0.16138	-0.13728	-0.1816
AR2	AR term with term with two quarters lag	-0.089969	-0.094541	-0.057035
AR3	AR term with term with three quarters lag	-0.089547	-0.070691	-0.070105
AR4	AR term with term with four quarters lag	-0.081329	-0.05678	-0.031282
Total R-Square		0.108	0.4611	0.3663
Durbin-Watson		2.0844	2.004	1.9949
No. of Observations		415,650	355,511	622,876

**: all coefficients are significant at > 99% levels of significance;

***: all coefficients are significant at > 99% levels of significance, except Mktsize and sumtotpax.

Mktsize and sumtotpax are not statistically significant for hub-to-hub and hub-to-spoke networks.

Given the results in Table 1, we refit the estimating equation by substituting available seats with ACcategory. Different types of aircraft tend to have impact on air travel performance due to the diversity in technical requirements of aircrafts (e.g., cruise speed, ascent and descent). Table 2 provides the results of this refitted equation.

Like in the model presented in Table 1, the refitted equation has similar statistical properties. Examining the statistical estimates of the seasonal effect across different networks, it is observed that at busier times of the year (i.e., spring and summer), performance deteriorates for the hub-to-spoke network segment. The performance is worse for the hub-to-hub network segment compared

to the hub-to-spokes network segment as captured by the value of coefficient estimates (i.e., -0.007 and -0.002, respectively).

In comparison, busy time appears to improve air traffic performance in the point-to-point network segment. This result may indicate a prevalence of unused capacity in the point-to-point network compared to those under the hub-and-spoke (i.e., both hub-to-hub and hub-to-spokes) network segments. It may also coincide with the fact that airports that essentially form the hub-and-spoke network are disproportionately located in the areas of the NAS that are worst affected by weather during spring and summer (Wright 2004).

Table 2: Maximum Likelihood Estimates of Performance: An Alternative Specification

Model Variables	Description of Variables	Point-to-point	Hub-to-hub	Hub-to-spoke
		Index = k = 0	Index = k = 1	Index = k = 2
		Estimated Model*	Estimated Model*	Estimated Model*
Intercept	Intercept	0.80291	0.68432	0.71481
Dummy1	season dummy spring and summer=1 fall and winter=0	0.001968635	-0.007501503	-0.002723645
ACCcategory	A/C Category dummy	-0.03076	-0.013205	-0.017036
sumtotpax	Sum of total segment passengers	-0.000000205	0.000000085	-0.000000091
Terrorism	9/11 dummy (>=2001 Q3=1 else=0)	0.03164	-0.010317	-0.015198
Avgdistance	average distance between segment pair	0.000285382	0.000281517	0.000312383
Avgdistancesq	square of average distance	-0.000000007	-0.000000006	-0.000000007
American	American Airlines dummy	-0.03901	-0.022532	-0.03396
Continental	Continental Airlines dummy	-0.018645	-0.020517	-0.03023
Delta	Delta Airlines dummy	-0.026333	-0.011632	-0.018554
Northwest	Northwest Airlines dummy	-0.032551	-0.007556	-0.016582
Southwest	Southwest Airlines dummy	0.043068	0.050774	0.04713
USAir	USAir dummy	-0.011098	0.005599	0.003859
United	United Airlines dummy	-0.02073	-0.002926	-0.013576
AR1	AR term with one quarter lag	-0.1319	-0.13288	-0.17518
AR2	AR term with term with two quarters lag	-0.069794	-0.093187	-0.054807
AR3	AR term with term with three quarters lag	-0.066137	-0.070341	-0.068721
AR4	AR term with term with four quarters lag	-0.057118	-0.056904	-0.030801
Total R-Square		0.1367	0.4674	0.3766
Durbin-Watson		2.0797	2.004	1.9951
No. of Observations		415,650	355,511	622,876

*: all coefficients are significant at > 99% levels of significance.

Market size as represented by the sum of total segment passengers affects networks differently. The larger the size of the market, the better the air traffic performance under the hub-to-hub network segments. For an increase in million enplaned passengers, for example, air traffic performance is expected to increase by almost 1/10th of a point. In comparison, the point-to-point and the hub-to-spokes perform poorly as market size gets bigger. For an increase in million enplaned passengers, air traffic performance under point-to-point network is expected to experience a decline in performance in the magnitude of 1/5th of a point while a similar increase in passengers will reduce air traffic performance by 1/10th of a point under hub-to-spoke network. These results indicate that there may be significant positive externalities for market expansion within the hub-to-hub network segment than other types of networks. An increase in passengers may induce congestion and increase negative externalities in the hub-to-spoke and point-to-point networks.

The events following 9/11 seem to have affected networks very differently. For example, while the air traffic performance has markedly improved for the point-to-point network segment, it deteriorated for both the hub-to-spokes and hub-to-hub network segments. Absolute magnitudes of the negative effects indicate that the performance has deteriorated relatively more for the hub-to-spoke network than hub-to-hub following the events of 9/11 (-0.015 vs. -0.010).

The longer the distances between segment pairs, the more likely it is for air traffic performance to improve. In particular, for a 1000 mile increase in distance, air traffic performance is expected

to increase linearly by approximately $1/3^{\text{rd}}$ of a point. Notice, however, that the improvement diminishes (i.e., parameter estimates for squared distances are negative) with longer distances. This result is intuitively obvious, since with longer distances, airborne time relative to ramp-to-ramp time increases and, hence, the performance improves. It is obvious that with longer distances both labor and non-labor costs are less per passenger mile improving cost performance as well.

It is interesting to note that the presence of network carriers, in general, have a negative impact on air traffic performance, irrespective of types of network. The magnitude of the estimated parameters, however, reveals that network carriers operating in the hub-to-hub network have a relatively less negative impact on air traffic performance in relation to their operations in other two networks. US Airways seems to have much less negative impact on air traffic performance than other network carriers across different networks.

On the contrary, the presence of Southwest Airlines in segment pairs improves air traffic performances for all networks. Interestingly, the extent and magnitude of this improvement is highest when Southwest Airlines is present in hub-to-hub networks¹² followed by the other two networks. This finding is interesting due to the fact that Southwest has focused its efforts mostly in flying point-to-point routes in the past. The higher performance of Southwest Airlines under hub-to-hub and hub-to-spokes network segments indicates that network carriers may have to worry about quality of services in these markets in addition to traditional fare competition of Southwest Airlines.

Statistical results indicate that the size of the aircraft affects air traffic performance negatively, irrespective of the types of networks. That is, the larger the size of the aircraft, the greater the reduction in air traffic performance. Furthermore, the aircraft size affects the point-to-point network disproportionately more than it does to other two networks. This is likely due to the fact that larger aircrafts in point-to-point networks are subject to the vagaries of numerous other types of aircraft influencing the overall air traffic performance. It is no surprise that Southwest Airlines uses only one type of aircraft (Boeing 737) which may also influence its performance.

Finally, the lagged autoregressive process indicates that past errors (i.e., four lags¹³) can explain the incidence of air traffic performance fairly well.

CONCLUSIONS AND FURTHER RESEARCH

In this paper, an empirical framework was developed to examine the determinants of air traffic performance. The performance measure was defined as the ratio of airborne time to total ramp-to-ramp time (index^k). Using segment data from the traffic files of Form 41 during the period 1995–2006 and defining three different network segments (point-to-point, hub-to-hub, and hub-to-spokes), an econometric model was specified to identify the determinants of air traffic performance. Empirical results indicate that the specified model for the index^k has a reasonable fit.

The results for the index^k model indicate that the sets of explanatory variables explain the air traffic performance particularly well for hub-to-hub and hub-to-spoke networks. Results indicate that busy times of the year affect air traffic performance negatively for two variants of the hub-to-spoke network segments (i.e., hub-to-hub and hub-to-spoke) and positively for the point-to-point network segment. Second, market size tends to positively influence performance for the hub-to-hub networks while it negatively influences hub-to-spoke and point-to-point network segments. Third, while the incidence of terrorism has enhanced the air traffic performance for the point-to-point network segment, it affected the hub-to-spoke network segments negatively. Fourth, distance seems to improve performance but at a slower rate as distance rises. Fifth, while the presence of network carriers reduces performance, operations by Southwest Airlines improve it for all networks. Finally, the larger the size of aircraft, the poorer the performance in all networks.

These results have interesting policy implications. For example, the results demonstrate that hub-and-spoke networks may need long-term policy priorities in solving air traffic performance issues that characterizes busy periods. Second, there may exist some unused capacity within the

hub-to-hub system of airports. Hence, careful attention should be given to distinguish airports within the hub-to-hub network while planning for future airport capacity. Finally, careful attention should also be given to the size of aircraft and its impact on air traffic performance.

Endnotes

1. Author is a Principal Economist. Paper presented at the 4th Annual Technical Forum of the ATIO/AIAA, Chicago, IL, during September 20-23, 2004. I would like to thank the participants for their useful suggestions and comments. I would also like to thank two anonymous referees of this *Journal* and the Editor for their comments and suggestions that led to substantial improvement. All remaining errors are mine. Correspondences can be made to: dbhadra@mitre.org.
2. An acceptable “rule-of-thumb” for commercial feasibility requires daily O&D passengers of 75–100 a day. This may require 1 – 2 services a day using either turbo-prop or regional jet (RJ) service.
3. Strictly speaking, hub-and-spoke networks can be defined to include hub-to-hub and hub-to-spoke travels. In comparison, a point-to-point network consists of travel between two non-hub airports (for more details on these definitions and an econometric-time series model, see Bhadra and Texter (2004).
4. OEP is a major FAA initiative to meet emerging air transportation needs for the next 10 years. For more details see http://www.faa.gov/about/office_org/headquarters_offices/ato/publications/oep/version1/; retrieved July 5, 2006.
5. For example, Chicago’s O’Hare International Airport (ORD) connects to 174 airports (both hub and spokes) compared to Dallas Fort-Worth International Airport (DFW) 164, John F. Kennedy International Airport (JFK) 146, and Denver Stapleton Airport (DEN) 133 destinations. In comparison, fewer connections are offered at relatively smaller airports: Philadelphia International Airport (PHL) has 112 connections, while Baltimore-Washington International Airport (BWI) and Chicago’s Midway Airport (MDW) offered 74 and 63 connections, respectively, for a representative first week of August 2004 using the data from the official airline guide (www.oag.com). While the number of departures, and thus passenger flows, are relatively more in the thicker markets, smaller or thinner markets are linked to the system through the complex scheduling that places dominance to the larger hubs and their links to other thick markets.
6. In the month of August 2004, the Federal Aviation Administration (FAA) brought together all carriers serving ORD to voluntarily accept capacity limits in peak hour operations. This was the third attempt during the year 2003-2004 to solve the excessive delay problems at ORD. In describing the problem, the FAA Administrator stated “As Chicago goes, so goes the system” because when ORD gets congested, controllers delay takeoffs at other airports to give ORD time to clear out its backlog (see “O’Hare Delays Hold Up Whole System; FAA Wants it Fixed”, Associated Press report at <http://www.tennessean.com/business/archives/04/08/55430005.shtml>; retrieved 8/5/2004).
7. Data for the analysis come from T100 segment files of Form 41. For data and definitions, see also T100 traffic segment data that are filed by scheduled air carriers (<http://www.transtats.bts.gov/> for more details).

8. For evaluating operational efficiency, an aircraft's movement is tracked from the moment it moves on its own power. However, airlines often have control over ramps leading onto taxi-in and out phases, thus impacting the efficiency. In order to account for that effect, distinctions are made sometimes between gate-to-gate and ramp-to-ramp. Furthermore, these differences are systematic for larger airports and insignificant for smaller airports. For our analysis, we do not make distinctions between these two measures.
9. It is evident that the ratio can never attain either value of one or zero at the limit, since taxiing in and out will always be positive fractions of total ramp-to-ramp time.
10. T100 is the transportation schedule of Form 41 data that every commercial scheduled airline is required to submit to the DOT every quarter. For more details, see <http://www.transtats.bts.gov> and use the aviation data link for T100 domestic data segments in Form 41 traffic file.
11. The empirical model is not derived from a theoretical framework since in this case there is no optimizing economic agent.
12. In addition to its primary focus on servicing relatively larger metropolitan areas through secondary airports, Southwest also flies from airports that are designated as hub airports (e.g., Baltimore-Washington (BWI), Phoenix (PHX), Cleveland (CLE), and Detroit (DTW)).
13. Four lags were chosen because the resultant autoregressive model corrected serial autocorrelations.

References

Air Transport Association. See <http://www.airlines.org/public/home/default1.asp>, 2004.

Associated Press, "O'Hare Delays Hold Up Whole System: FAA Wants it Fixed", report at <http://www.tennessean.com/business/archives/04/08/55430005.shtml>; retrieved 8/5/2004.

Auerbach, S. and B. Koch. "Cooperative Approaches to Managing Air Traffic Efficiently-The Airline Perspective." *Journal of Air Transport Management* 13 (1), (2007): 37-44.

Bhadra, D. "Air Travel in Small Communities: An Econometric Framework and Results." *Journal of the Transportation Research Forum* 43 (1), (2004): 19-37.

Bhadra, D. and P. Texter. "Airline Networks: An Econometric Framework to Analyze Domestic US Air Travel." *Journal of Transportation and Statistics* 7 (1), (2004): 87-102.

Brueckner, J. "Airport Congestion When Carriers Have Market Powers." *The American Economic Review* 92 (5), (2002): 1357-1375.

General Accounting Office. *Commercial Aviation: Air Service Trends at Small Communities Since October 2000*. Report to Congressional Requesters, GAO Report No. GAO-02-432, Washington, D.C., 2002.

Bolczak, C. N., J.H. Hoffman, A.J. Jensen, and W.W. Trigeiro. "National Airspace System Performance Measurement: Overview. MITRE Technical Report (no. MTR97W0000035), McLean, Virginia: The MITRE Corporation, 1997.

Cavcar, A. and M. Cavcar. "Impact of Aircraft Performance Characteristics on Air Traffic Delays." *Turkish Journal of Engineering and Environmental Science* 28, (2004): 13-23.

Coy, S. "Management of Airline Arrival Performance Before and After September 11, 2001 in U.S. Domestic Markets." *Journal of Air Transport Management* 11 (4), (2005): 219-230.

Dell'Olmo, P. and G. Lulli. "A New Hierarchical Architecture for Air Traffic Management: Optimization of Airway Capacity in a Free Flight Scenario." *European Journal of Operational Research* 144 (1), (2003): 179-183.

Eurocontrol. *Aircraft Performance Summary Tables for the Base of Aircraft Data (BADA)*. Revision 3.3., EEC Note No. 18/20, Bretigny sur Orge, 2000.

FAA. *Capacity Needs in the National Airspace System: An Analysis of Airport and Metropolitan Area Demand and Operational Capacity in the Future*. Washington, D.C.: U.S. Department of Transportation, Federal Aviation Administration, 2004.

Mayer, C. and T. Sinai. "Network Effects, Congestion Externalities, and Air Traffic Delays: Or Why Not All Delays Are Evil." *American Economic Review* 93 (4), (2003): 1194-1215.

Official Airline Guide. www.oag.com, 2007.

Pindyck, R.S. and D. L. Rubinfeld. *Econometric Models and Economic Forecasts*, 3rd Edition. McGraw-Hill, Inc., New York, 1991.

Rupp, N., D. Owens, and N.W. Plumly. "Does Competition Influence Airline On-Time Performance?" Working paper, Department of Economics, East Carolina University, 2002.

SAS/ETS Software. *Applications Guide 2: Econometric Modeling, Simulation, and Forecasting*. Version 6, First Edition, SAS Institute, 1993.

U.S. Department of Transportation. *Code of Federal Regulations*. Ch II (1-1-01 Edition), Pt. 241, Washington, D.C.: Office of the Secretary, U.S. Department of Transportation, 2001.

U.S. Department of Transportation. *O&D Survey Reporting Regulations for Large Air Carriers: Code of Federal Regulations Part 241, Section 19-.7*. Washington, D.C.: Office of the Secretary, U.S. Department of Transportation, 1992.

Wright, K. "Aviation System Performance During the Summer Convective Weather Season." *Journal of the Transportation Research Forum* 45 (3), (2006): 77-92.

Dipasis Bhadra is a principal economist with the MITRE Corporation's Center for Advanced Aviation System Development (CAASD), a federally funded research and development corporation. At CAASD, Dipasis works in areas of quantitative modeling of air transportation systems including econometric modeling of passenger and aircraft flows, forecasting, and business case analysis for the federal sponsor, the Federal Aviation Administration (FAA). In addition, Dipasis has worked on civil aviation systems for China, Egypt, Asia-Pacific, and most recently, India, and Afghanistan. With a Ph. D. in economics (1991) from the University of Connecticut, Dipasis also teaches introductory economics at a local community college, and holds professional positions in the Transportation Research Forum (TRF), Transportation Research Board (TRB), and American Institute of Aeronautics and Astronautics (AIAA).