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DEMAND FOR AIR TRAVEL IN THE UNITED STATES: BOTTOM-UP ECONOMETRIC ESTIMATION AND IMPLICATIONS FOR FORECASTS BY ORIGIN AND DESTINATION PAIRS

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ABSTRACT

In this paper, we examine the relationship between origin and destination (O&D) travel and local area characteristics. By combining data from the Bureau of Transportation Safety of the U.S. Department of Transportation (BTS/USDOT) on O&D travel with that of local area economic and demographic activities supplied by the Bureau of Economic Analysis of the Department of Commerce (BEA/DOC), we specify a semi-log linear demand relationship for O&D travel. The resultant dataset has more than 50,000 observations. Using a limited information maximum likelihood estimation procedure, we estimate demand for air travel in 11 market segments within the contiguous national airspace system (NAS), defined by non-stop distance traveled between O&D pairs. Our results confirm that local area income and demographyaffect travel positively for most of the markets. However, the levels of travel tend to peter out and eventually go down as the intensity of economic activities increases. We further find that shorter distance travel tends to be relatively more fare-inelastic than that for longer distances. Average fare tends to affect passenger travel negatively for all distances. Large hubs are important for passenger travel; so are the higher market share of established airlines and the presence of Southwest airlines in the O&D market. We then discuss approaches using our methodology for deriving bottom-up forecasts. These forecasts have distinct characteristics that make it more useful for analyzing flow features, such as passenger and aircraft flows within the NAS, determining and prioritizing infrastructure investment, and determining workload of Federal Aviation Administration (FAA) personnel at centers. Results from our forecasts can be easily complemented with those produced by the terminal area forecasts (TAF) and similar forecasts derived from top-down approaches.

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INTRODUCTION

Existing empirical research explains the rationale behind location choices of commercial air carriers, large hubs in particular, fairly well (Bhadra and Hechtman, 2002; see Button, Stough & Trice, 1999). Major and spoke airports that airlines choose to hub and serve depend largely on market demand and cost conditions. Hub-and-spoke networks have formed the basis for studies on industry structure (Brueckner, Dyer, & Spiller, 1992; Brueckner & Spiller, 1994; Oster & Strong, 2001; Rutner & Munday, 1996) and provided a foundation for policy prescriptions (USDOT,2001). While research probing into the structure of the industry has recognized the role and importance of local market conditions (Mumayiz & Pulling, 1992; Corsi, Dresner, & Windle, 1997), the methodologies for estimating air travel demand are still "top-down" approaches that employ little local information. As a result, aggregate knowledge is frequently at odds with those derived from micro data, e.g., T100 and 10% origin and destination (O&D) sample data from BTS/DOT. Due to a lack of use of local information, it is possible that trends that are being observed at the industry level—and are often expressed in representative company projections—may not coincide with that of top-down forecasts, and that of the (FAA), in particular. In other words, there is a potential inconsistency between what micro data may represent and what have been concluded from using macro data and a top-down structural approach.

While both the FAA (see, for example, FAA, 2003) and projections of the Regional Airline Association (RAA) seem to be in broad agreement concerning the overall trends for the future, there are some noticeable differences as well. For example, the growth rates of projected enplanements in regional jet market for the period of 2000-2010, according to the FAA and RAA, are, 5.5% and 5.0%, respectively, on an annual basis (see RAA, 2002). This is indeed a small difference. This difference, however, creates a bigger wedge in the future (2001-2010) when the initial numbers for the current year (2001) differ by 5 million, or more than 5% of the total (80 million by FAA and 85 million by RAA). Consequently, this leads to a major difference in estimating the number of aircraft in the future. By FAA's estimate, the number of regional aircraft [both regional jets (RJs) and turboprops] is expected to be 4,457 while RAA estimates it to be 4,777, a difference of 320 aircraft, or worth more than US $7 billion. This is a large number indeed! Other available estimates indicate that RAA's estimate is somewhat on the conservative side. For example, Bombardier (2001) estimates that the total delivered units in 2020 will be 8,345, almost twice what RAA projects for 2010; and almost four-times compared to what RAA estimated for the year 2001 or 2323 (see RAA, 2002). Some other differences arise from the details as well. For example, Bombardier and the industry as a whole anticipate that RJs will grow in size faster than what the FAA projects. Average size of an RJ aircraft has been projected by the FAA to become 48 seats in 2013, from its current size of 40, while Bombardier (2001) projects it to attain an average size of 61 by 2011. Similar differences, such as stage lengths, load factor, and the resultant revenue conditions can also be noticed between the FAA and the industry projections.

In this paper, we present a methodology that can be used to estimate and forecast O&D pairs for the entire national airspace system (NAS). By combining 10% O&D data with the data from respective cities from the BEA/DOC, we created a unique dataset that reveals important information regarding economic and demographic determinants for O&D travel. Despite its uniqueness, our analysis and data are somewhat limited and contain a few limitations. For example, our data demonstrate the final market as represented by city-pairs and thus is somewhat biased in its coverage. In addition, our dataset does not reveal the true itinerary for travelers. Finally, a calculated average one-way fare is reported in our dataset. While this is a good substitute, it does not allow us to understand the true impact of fares on those itineraries. Despite these limitations, our analysis is fairly indicative of O&D travel and thus can be used to derive forecasts of bottom-up travel by (O&D) city pairs.

The paper is organized as follows. Section II gives a brief background preceding our work and the context; Section III provides the analytical framework demonstrating the determinants of passenger demand for O&D air travel. Section IV provides the econometric framework together with description of the data and the process through which datasets have been combined. Section IV also provides detailed results together with explanations for each of the determinants. Section V explains the steps through which we can use the econometrically estimated framework to derive forecasts by O&D pairs. Section VI describes the process through which passengers can be mapped, both estimated and forecasts, into deriving optimal number of aircraft by O&D pairs. Section VII draws the implications of these forecasts, once derived, on measuring the workload pressures of the FAA. Section VIII concludes the paper by drawing policy implications and outlining future research. Finally, there are five appendices. Appendix A provides the definition of the demand model. Appendix B and C provide the standard air traffic hubbing map (i.e., FAA/USDOT) and commercial air carriers' hubbing map, respectively. Appendix D provides the current code-sharing partnerships between the commercial air carriers and regional air carriers. Appendix E provides a table detailing the concepts that have been used in the paper along with the contributions of this research over the existing work.

BACKGROUND

In a seminal workshop convened in 1989 by the Transportation Research Board (TRB), the FAA laid out the methodologies that have been in use for both short and long-term forecasting[1] including ways to study structural changes, such as effect of deregulation on the industry (Mayer, 1989). Noticing that large-scale structural micro-econometric modeling was neither possible nor desirable—due both lack of quality micro data and large fluctuations in activities following the deregulation—the FAA had made use of a macro-structural model combined with judgement and intuition in producing forecasts. The relative importance of modeling over intuition and judgement has always been a matter of contention in the forecasting community, FAA included. While using too much intuition may blur professional judgement on political grounds, using none may be equally problematic (Mayer, 1989). Use of a top-down macro econometric model may have made sense throughout the 1980s and perhaps in the beginning of the 1990s. However, relatively cleaner data—10% O&D sample data after 1995 in particular—and increasingly cheaper computations make structural econometric modeling at micro levels possible. The top-down structural econometric model, while easier to formulate and estimate, misses out interesting development at both sector levels (e.g., large jets versus RJs) and at the regions (e.g., those taking place in different metros). Sector changes, as well as changes in route choices, characterized the entire 1990s. Rapid growth in the industry led by the RJs and an explosion of routes carrying over half of a billion passengers a year throughout the NAS created a national air transportation infrastructure that had never been observed before. A top-down econometric framework is unable to describe and analyze complex and dynamic route networking, increasing complementarity between large carriers and RJs, and mounting substitutions of turbo-props by RJs, just to name some of the characteristics of the decade. Faced with increasingly restrictive labor rules created by scope clauses and observing relative cost efficiency of the RJs, many of the large carriers have found a natural ally in RJ carriers. Thus, code-sharing has become an important vehicle for seamless travel in the U.S. and abroad. Understandably, demand for air travel management (ATM) services, i.e., workload measures at towered airports, Air Route Traffic Control Centers (ARTCCs), and the need for other infrastructures, have become inherently dynamic and dependent on the evolving air transportation network. Forecasts based on a top-down approach, thus, essentially miss many of the intricate complexities of the NAS.

Notwithstanding the above, much is at stake in understanding the location choices at the local level. In the wake of deregulation of the industry, both industry watchers and policy-makers predicted competitive outcomes resulting in lower prices for air travelers. Many of the competitive outcomes have indeed come true, thanks to the 1978 Air Deregulation Act (ADA). However, spatial monopolization of markets by a few airlines remains a constant worry among policy-makers two decades later, casting doubt on the long-run future of competitive outcomes. Available empirical evidence shows that airlines indeed use their locational advantages commonly exhibited by hubbing to garner monopoly advantages. Predatory pricing to drive out potential competitors, manipulation of gates and physical facilities at the airports to narrow choices for the flying public, and consolidation of markets by mergers are some examples of these practices.

However, events following September 11, 2001, may have shaken this process somewhat. The Air Transportation Safety and System Stabilization Act of 2001, and insurance guarantees by the federal government, have gained wide industry support. Indirect pressures, on the other hand, on local and state governments to create a more favorable climate than would be otherwise required by competition or made available to competitors are also noticed in cities where airlines hub.

Factors governing the industry combined with factors that are essentially local are critical for the existence of airlines as a whole. All these point to the fact that local economics play, and will continue to play, significant roles in determining the fate of the emerging business models in the future. It appears that choosing the right business model(s) has become the key for survival of the entire industry, especially post 9/11 (Executive Flight, 2002; Costa, Harned & Lundquist, 2002). Finally, aircraft manufacturing, to a large extent, is also dependent on the patterns of networks emerging from the future of the dominant business models (Economist, 2002). For example, the steady rise of Southwest Airlines in the second half of the 1990s and its apparent reliance on spoke-to-spoke network have led many to suggest that the future of the air transportation network may very well be a diffused one compared to the current hub-and-spoke network that dominates the U.S. air travel.

AN ANALYTICAL FRAMEWORK OF WHAT DRIVES PASSENGER DEMAND IN THE NAS

It is essential, therefore, that we understand how demand for air travel is determined at the local levels. After all, the local economies and demographics, together with industry characteristics in the market routes, influence the way airlines meet travelers' demands and results in the route network that we observe in the NAS today.

The empirical literature stipulates that personal income and population—next to fare—are the key factors determining the demand for air travel (Battersby & Oczkowski, 2001; Corsi, Dresner, & Windle, 1997; Mumayiz & Pulling, 1992). It is reasonably certain that personal income, like gross domestic product (GDP), will affect air travel between O&D pairs positively. Instead of using aggregate GDP for the country or for the state as a whole, however, we propose to use local area personal income as it corresponds well to the local area air travel under this approach. In other words, we stipulate that local area air travel demand can be best estimated by local area income. Even though this specification alters the way we handle the demand for air travel under a macro-structural model, it builds on the central theoretical deduction that income—local area personal income as opposed to country's GDP—still drives air travel demand reported in O&D data.

A clear distinction should be made, however, between our approach and standard top-down approach including that of the FAA. First, demand, as represented by revenue passenger miles (RPMs), is determined econometrically by GDP, among other things, under FAA's approach. This estimated relationship is then allocated from the top down to the terminal areas, taking into consideration the historical shares of the airport, master plans, and expert opinion, to derive TAF. Hence it is a top-down approach. In contrast, our approach is based on econometric relationships that are estimated at a lower level [i.e., O&D travel between metro statistical areas (MSAs) as defined by the Office of Management and Budget (OMB)], and hence can be called a bottom-up approach. While TAF is primarily designed to serve as a terminal area planning tool, our approach is focussed on market routes and flows, i.e., passengers and aircraft, within.

Second, it is possible that other local factors, such as population, density, and interactions between economic and demographics may affect air travel. In order to account for these, we consider the following variables: population density (per square mile) of the origin MSA and the destination MSA(s), and the interactions between population and income representing the degree of economic strength of the (O&D). Effects of population, density, and interactions may not be as obvious, as it is for income. For instance, one can expect that as population increases, and the level of economic activities increase, O&D travel will increase establishing positive relationships with demand for air travel.[2] However, as the intensity of economic activities increase, so does the congestion and negative externalities. This is often experienced in the north-eastern corridor—where with the persistent increase in delays at airports and permanent changes in behavior of those who travel short distances may occur—establishing a negative linkage between the extent of economic activities and air travel. Therefore, it is possible that beyond a certain range, intensity of economic activities may actually affect the O&D travel negatively. Thus, we can not be certain, *a priori*, about the sign of the estimated coefficients for these variables.

Third, empirical literature has established that in situations when passengers have choices between airports that are large hubs and those which are not, i.e., medium, small hub airports, and airports without any hub status, passengers tend to choose large hubs (Button, Stough & Trice, 1999; Bhadra & Hechtman, 2002). This makes sense because large hubs represent more choices due to the predominance of hub-and-spoke networks in the US. Thus demand for air travel may be positively influenced by large hubs compared to those that are not. It is not surprising that major hub airports account for more than 75% of scheduled air travel, measured in terms of enplanements in the country (FAA, 2001). As with intensity of economic activities, the presence of large hubs may affect air travel negatively beyond its obvious positive ranges. Some of the large hubs are congested airports as well and perhaps demonstrate that they may have saturated the positive externalities that are often exhibited in large hubs. We account for this by creating a proxy variable categorizing O&D areas into large hubs and those which are not.

Fourth, the empirical literature in urban economics postulates that distance is bad in the sense that it reduces utility by reducing leisure which is good. Thus, as distance increases, it is expected that demand will go down. We may call this a *direct effect* of distance on passenger demand. Evidence on rising quality of services, including more leg-space and complete sleep travel for business class passengers in particular, offered by many airlines tend to suggest that there may be a negative relationship between air travel and utility, especially for longer haul travels. Passenger demand will go down as distance increases under these circumstances (Mills and Hamilton,1993). However, this may not be true when air travel is limited to shorter distances. Notice that on shorter trips, air travelers have more choices. Thus, in choosing air travel over other modes, a representative traveler makes a conscious decision by comparing the net marginal gain from traveling an extra mile by air as compared to an extra mile traveled by other modes. This process takes into account marginal utility from different travel options, and their prices. Utility can be expected to increase—so will the passenger demand—with an extra mile traveled as long as net returns from air travel exceed that of by other modes. We can call this the *substitution effect* of distance on passenger demand. One may expect to observe, therefore, a positive impact of distance on passenger demand for short-haul distances (and thus, stronger substitution effect);

while a negative impact otherwise (and thus, direct effect dominating substitution effect).

In addition to the above area characteristics, we have a host of industry characteristics that tend to differ from market to market defined by O&D distances. Fare is critical in determining the passenger demand. In order to account for that, we consider one-way fare for O&D travel. Data reported by the BTS are disaggregated by O&D pairs. Without the number of coupons and the prices charged for each leg of the journey (which are not available at this time), it is difficult to calculate more accurate fares and yield per mile. In the absence of more precise data, one-way fare may account well for O&D travel price. It is obvious that fare would affect the demand negatively.

Sixth, empirical literature cites evidence for and against the stipulation that airlines practice discriminatory pricing measures based upon market share (USDOT, 2001; Oster & Strong, 2001; GAO, 2001). While it is true that having a large market share may facilitate some power over pricing, market share of competitors may also deter such practices. Hence, we construct a ratio representing the share of the airline occupying the major market to that of those with lower market share. Therefore, if the market share of the major airline goes up, and/or the share of the minor airlines goes down, the ratio will increase, and hence may impact the demand for passengers through pricing. It appears to be still an open empirical question as to how market power may influence pricing and thus worth our while to test it in our dataset as well.

Seventh, the empirical literature shows that low cost carriers such as Southwest Airlines play an important role in determining the shape and structure of the market (Morrison, 2001). Southwest has traditionally captured market shares by offering low prices for less differentiated travel services, or what has become known as *spoke-to-spoke* services. Thus, the entry of Southwest in a market may have two impacts: first, a *substitution effect* of lower fares where air travelers switch from high-fare established route carriers to services to low-cost spoke-to-spoke services; and, second, a *complementarity effect* where lower prices of Southwest may actually induce more travelers into using air transportation as opposed to other modes, especially those in the short-haul markets (i.e., less than 1,500 miles of stage length). This latter effect may benefit both Southwest and other airlines thus establishing complementarity. While the competitive aspects of the Southwest effect have received much attention, the complementarity aspect[3] has received very little.[4] In order to capture the totality of the Southwest effect in determining passenger travel, we create a dummy variable representing Southwest's presence in markets where it is the primary carrier as well those where it has a minor share.

Finally, congestion and delays have serious consequences. Financial cost, scheduling complexities, and withdrawal of services leading to lack of competition are some of the consequences of airport delays and en-route congestion (Garvey, 2001). FAA data show that during the first nine months of 2000, delayed, canceled or diverted flights affected 119 million passengers. Initial analysis indicates that delays in 2000 cost the airlines an estimated $6.5 billion, up from $5.4 billion in 1999.[5] As FAA Administrator Jane Garvey pointed out, there are many conditions that cause delays: bad weather, inoperable runways, airport capacity limitations, aircraft equipment problems, airline maintenance and flight crew problems, and air traffic equipment outages (FAA, 1995). Studies show that bad weather is the primary cause for delays (more than 70%, (Jensen, Kuhn, Shavell, Spear, Taber, & White, 1999). Convective weather takes place during the late spring and summer months. During these periods, weather is often unpredictable, leading to serious en-route and airport delays. In order to mitigate this problem, the FAA initiated a collaborative partnership with the airline industry, known as the *spring-summer initiative*, that contributed into the Operational Evaluation Plan (OEP; FAA, 2002). To take into account the weather effect at particular times of the year, we consider a quarterly proxy, roughly approximating spring and summer weather, as a factor influencing passenger demand for air travel between O&D pairs.

Based on above discussion, the framework, therefore, can be stipulated as follows [for a complete list of variables used in this paper, please see Appendix A:

$$\mathbf{P_{ij}} = \text{F}\ (\text{f}_{\text{ij}};\ \text{PI}_{\text{ij}},\ \text{Density}_{\text{ij}},\ \text{Interactions}_{\text{ij}},\ \text{Distance}_{\text{ij}},\ \text{hub}_{\text{ij}},\ \text{Market Power}^{\text{D}}_{\text{ij}},\ \text{Market Power}^{\text{ND}}_{\text{ij}},\ \text{Southwest}_{\text{ij}},\ \text{season}) \qquad (1)$$

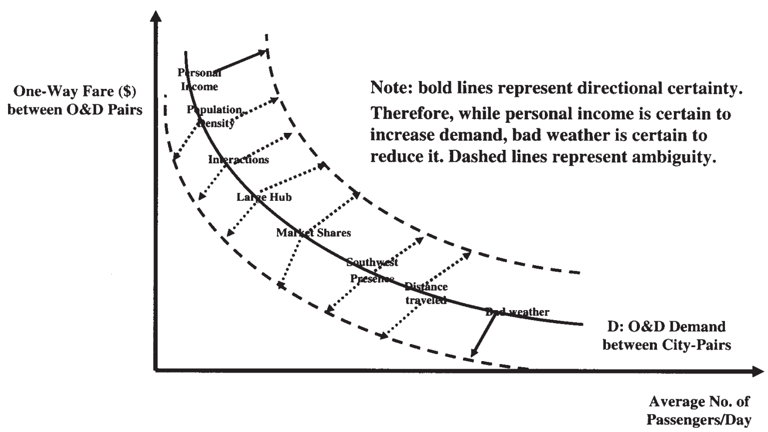
where i = origin city; j = destination city; P = average daily passengers; D and ND = dominant airlines and non-dominant airlines; f = one-way fare; PI = personal income; Density = population density per square mile; Interactions = intensity of economic activities as represented by interactions between population and income; Distance = distance traveled between O&D markets; Market Power = share of passenger demand by airlines in total O&D market; Southwest = presence (major or minor presence) of Southwest in the O&D market; and season = adverse spring and summer weather.

The signs of the variables, following the logic laid out above, can be shown to have an impact on passenger demand in the following fashion:

$$\begin{array}{ll} \delta Q_{ij} / \delta f_{ij} < 0; & \delta Q_{ij} / \delta PI_{ij} > 0; \\ \delta Q_{ij} / \delta Density_{ij} = ? & \delta Q_{ij} / \delta Interactions_{ij} = ? \\ \delta Q_{ij} / \delta Distance_{ij} = ? & \delta Q_{ij} / \delta Market\ Power_{ij} = ? \\ \delta Q_{ij} / \delta Southwest_{ij} = ? & \delta Q_{ij} / \delta Seasons_{ij} = < 0 \\ \delta Q_{ij} / \delta Hub_{ij} = ? & \end{array} \quad (2)$$

The above discussion is summarized in the following diagram:

Figure 1. Determinants of Demand and their Effects



It is clear from the above exposition that beyond standard stipulations, such as on fare and personal income, we do not have clear *a priori* hypotheses on most of the variables. Therefore, it makes sense to estimate demand for air travel by O&D markets and derive useful information from estimated coefficients.

ECONOMETRIC ESTIMATION: DATA, METHODOLOGY AND RESULTS

Conceptually speaking, our econometric framework makes use of the same underlying economic logic presently employed in the top-down framework. That is, the passenger demand, as represented by revenue passenger miles (RPM), is a function of income as represented by gross domestic product of the country. All available approaches, based on our research and knowledge reveal that both the industry and FAA employ some variant of top-down approaches. This perhaps makes sense for the industry, given the typical short-term considerations and lack of resources. However, from a medium and long-term planning considerations, trend projections often arising from top-down approaches may not be an effective tool. More detailed approaches, such as examining the characteristics of O&D travel may become necessary for situations where aggregate results may be misleading. In addition, however, we postulate that the demand for O&D air travel is also determined by the level of population, spatial variables, airport characteristics, airline characteristics, and network characteristics in both origin and destinations.

Primary data for this analysis is based on the 10% O&D sample obtained from the BTS/DOT (USDOT, 2002). The 10% data of BTS/DOT is based on tickets ending with a '0' (or, tenth-coupon as it is commonly referred to) of all scheduled itineraries. Based on an average monthly travel of 45 million passengers, 4.5 million records are fairly substantial and statistically representative of scheduled travel. In addition, we use T-100 schedule data collected by the BTS. We combine the O&D travel data with local economic, demographic and spatial variables collected by the BEA. The combined dataset has a little over 50,000 records for eight quarters.[6]

Figure 2. Segmentation of national airspace system by equi-distance of 250 miles: An Example

Using this data, we segment the contiguous NAS into 12 equi-distance air travel markets in 250 mile increments (see Figure 2). The rationale behind this segmentation is to capture the inherent differences between markets that may be essentially different. For example, a 250-mile-radius market may be very different than a 1,000-mile-radius market. While the demand for travel in the first market may be different than for those who travel in the later market, as often expressed in choices available, and responsiveness to fares, it is also different from a fleet planner's perspective. A fleet planner may fly a standard turboprop in the former market, while an RJ may be a better choice for the latter market. Furthermore, travel below any radius below 250 miles is often uneconomical for air transportation, scheduled air transportation in particular. Other modes of transportation, e.g., automobile, make travel by air in areas less than a 250 mile radius less attractive as well. Based on these rationales and to capture the qualitative differences between the markets in the NAS, we came up with a 12-segment market for the entire NAS.

A BROAD OVERVIEW OF DATA: TRAFFIC AND FINANCIAL STATISTICS

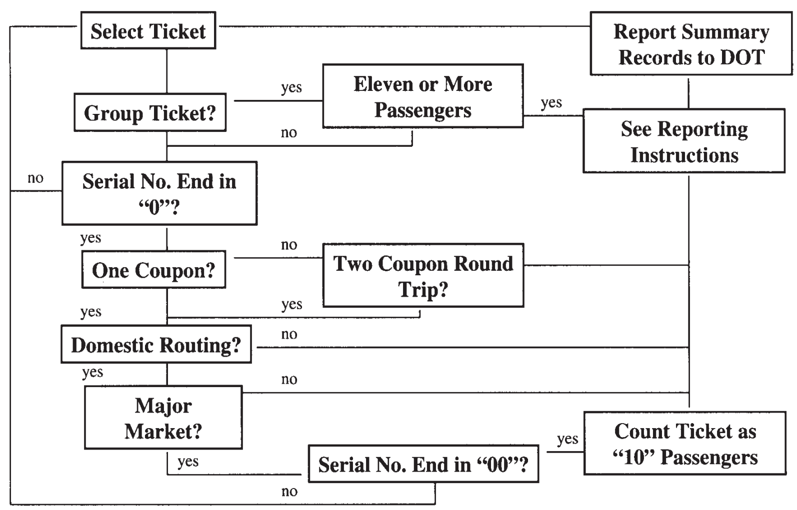
Economists have been using the 10% sample for O&D travel and Form 41 data for numerous studies, including that of determining the competitive structure of the industry, cost structure, pricing, and regulatory issues. See, for example, Brueckner (2001) for a comprehensive study on failed British Airways/American Airlines alliances; and Pitt and Norsworthy (1999) for a comprehensive study on the impact of productivity, technology, and deregulation on U.S. commercial airlines. Since these data play an important role in deriving conclusions on many important issues, it is useful to give a broad overview of what these two datasets truly capture.

BTS/DOT Ten Percent Sample of Tickets Lifted/Used: O&D Survey Data Records

The FAA requires large U.S. scheduled passenger air carriers to participate in an ongoing (O&D) survey of 10% of passengers carried through the system. It is called the 10% survey and often known as DB1A, the name of the BTS database. Foreign air carriers do not directly participate in the survey, although some of their data are captured in the survey since passengers who share a ticketed itinerary between a U.S. carrier and a foreign carrier may be sampled by the US carrier (see 14 CFR part 241; section 19-7).

Reporting on the fifteenth of May, August, November, and February for quarters of the calendar year a carrier responding to this survey examines the coupon itinerary for each flown ticket number ending in a zero. If the lifting carrier is the first reporting carrier on the itinerary (or has a codeshare relationship with same in that market) the operating carrier should include that ticket information in his O&D survey quarterly filing to the USDOT.

Figure 3. Flow Charts of O&D Reporting from Tickets



Source: Office of Airline Information, Department of Transportation (1999).

The data which is reported includes: a) the gross fare, including Federal Excise Tax (FET) and Passenger Facility Tax (PFC), on the ticket; b) the number of coupons on the ticket; c) the number of passengers on the ticket; and d) the coupon itinerary which includes: each airport of enplanement and deplanement, the operating and marketing carrier on each leg of travel, and the fare class on each leg of the passengers journey.

Prior to submission of the carriers O&D survey filing, the carrier is instructed to sort the reportable data into unique records (other than passenger count) and then summarize identical records together reporting the aggregate number of passengers. The DOT adds distances to each leg, calculated on the basis of great-circle distance, and a total distance for each ticket. They also determine what the passenger's probable destination was for each ticket. To accomplish this, the DOT examines the itinerary of travel, keeping track of the distance from the origin and the amount of circuity involved to determine a best guess as to where the passenger's directional break occurred (for details, see Database Products, Inc., 1999).

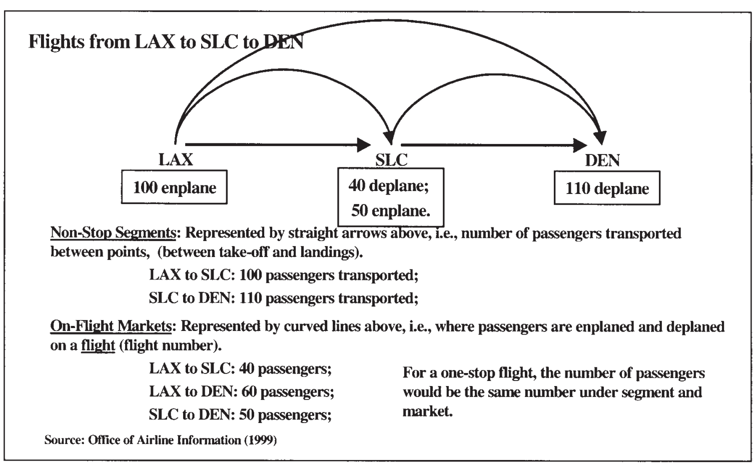
T100 Market and T100 Segment Schedules

T100 Segment is the Data Bank 28DS of Form 41 that provides traffic and capacity data of U.S. air carriers. The data are reported by U.S. air carriers operating non-stop between airports located within the boundaries of the U.S. and its territories. Information by aircraft type and service class for departures performed, available capacity and seats, passengers transported, freight and mail transported, scheduled departures, and aircraft hours ramp-to-ramp and airborne are provided. Data Bank 28DM of Form 41 or T100 market schedule, on the other hand, provides domestic market data of U.S. air traffic carriers. These data are often referred to as either Market or On-Flight Origin-Destination records. The data fields contain information on passengers, freight and/or mail enplaned at the origin airport of the flight, and deplaned at the destination airport of the flight (for more information see BTS/DOT, 1999).

It is evident from above that there are some important differences between market and segment data. One such important difference is demonstrated by the passenger coverage in the T100 segment and market data. As Table 1 demonstrates, while the market data capture revenue passengers' enplanement and segment data capture revenue passengers' transported, confusion remains in interpretation between these two data. Figure 4 attempts to illustrate the difference between the two datasets.

Therefore, the essential differences between the two datasets are in number of stops (i.e., in segments) it made (as captured by on-flight

Figure 4. Segment and Market Data: How Are They Different?



Source: Office of Airline Information, Department of Transportation (1999).

Table 1. Data Description, Types of Records, and Form and Schedule Numbers

Code	*Description*	*Type of Record* *Segment*	*Market*	*Applicable Form 41 Schedule Number*
	Carrier, carrier entity code	S	M	T–100(f)1,2,3
	Reporting period date	S	M	T–100(f)1,2,3
	Origin airport code	S	M	T–100(f)3
	Destination airport code	S	M	T–100(f)
	Service class code	S	M	T–100(f)1,2,3
	Aircraft type code	S		T–100(f)1,2,3
110	Revenue passengers enplaned		M	T–100(f)1,3
111	Total psgrs. in market—first cabin		M	T–100
113	Total psgrs. in market—middle cabin		M	T–100
112	Total psgrs. in market—coach cabin		M	T–100
130	Revenue passengers transported	S		T–100(f)
131	Passengers transported—first cabin	S		T–100
133	Passengers transported—middle cabin	S		T–100
132	Passengers transported—coach cabin	S		T–100
140	Revenue passenger-miles			CFD* 1,2
210	Revenue cargo tons enplaned			CFD*
217	Enplaned freight		M	T–100(f),3
219	Enplaned mail		M	T–100 3
230	Revenue tons transported			CFD*
237	Transported freight	S		T–100(f)
239	Transported mail	S		T–100
240	Revenue ton-miles			CFD* 1,2
241	Revenue ton-miles passenger			CFD* 1
247	Revenue ton-miles freight			CFD* 1,2
249	Revenue ton-miles mail			CFD* 1,2
270	Available capacity payload	S		T–100
280	Available ton-miles			CFD* 1,2
310	Available seats, total	S		T–100
311	Available seats—first cabin	S		T–100
313	Available seats—middle cabin	S		T–100
312	Available seats—coach cabin	S		T–100
320	Available seat-miles			CFD* 1,2
410	Revenue aircraft miles flown			CFD* 1,2
430	Revenue aircraft miles scheduled			CFD* 1
501	Interairport distance			CFD* 2
510	Revenue aircraft departures performed	S		T–100(f)1,2,3
520	Revenue aircraft departures scheduled	S		T–100 3
610	Revenue aircraft hours (airborne)	S		T–100 1,2
630	Aircraft hours (ramp-to-ramp)	S		T–100 1,2
650	Total aircraft hours (airborne)			2
810	Aircraft days assigned to service-equip.			2
820	Aircraft days assigned to service-routes			2
921	Aircraft fuels issued (U.S. gallons)			2

*CFD = Computed by DOT from detail Schedule T–100 and T–100(f) data.
T–100 = Form 41 Schedule T–100 for U.S. air carriers
(f) = Form 41 Schedule T–100(f) for foreign air carriers
1– = Form 41 Schedule T–1; 2 = Schedule T–2; 3 = Schedule T–3
NOTE: Cabin data are reported only in Group III international operations; in all other instances, totals are reported in items 110, 130 and 310.

Source: 14 CFR Ch II (1-1-01 Edition), Pt. 241, Office of the Secretary, Department of Transportation, 2001.

markets segments), and consequently, the number of passengers it delivered to destination points.

Financial Statistics Data: Form 41 Reporting

The financial information required from large certificated air carriers is laid out in Part 241 of Title 14 of the Code of Federal Regulations (14 CFR), entitled, Uniform System of Accounts and Reports for Large Certificated Air Carriers. There are, broadly speaking, ten financial statistics that are required from the large carriers:

1. Inventory of Airframes and Aircraft Engines
2. Airframe and Aircraft Engine Acquisitions and Retirements
3. Balance Sheet
4. Aviation Fuel Costs in cents per gallon
5. Aviation Fuel Consumption
6. Operating Expenses by Functional Groupings
7. Operating Expenses by Objective Groupings
8. Aircraft Operating Costs by Aircraft Type
9. Employment Statistics by Labor Category
10. Income Statement

DATA

Our data come from multiple sources. We combine data on passenger movements by origin and destination areas with local area characteristics (e.g., income, population, and area), and industry characteristics (e.g., fares, market concentration, and presence of competitive airlines such as Southwest). Aviation statistics come from the BTS while the local area data come from the BEA and the U.S. Census Bureau. Some other characteristics, e.g., status of hubs and weather influence during spring and summer, have been given special attention as well.

We use USDOT-defined hubs based on aviation activities rather than those defined by commercial airlines' activities. See appendices A and B for maps describing the DOT definition and hubs defined by commercial operations. In order to associate BTS datasets with economic statistics released by the BEA, we used data within commercial geographic information systems (GIS) software. Using shapefiles—spreadsheets or database tables whose records contain a geographical component—issued by the BTS in its 2000 National Transportation Atlas Data (NTAD), we overlaid map layers showing U.S. air traffic hubs (BTS, 1999) and primary MSAs. Our map overlay is restricted to the MSAs and to airports that had one or more domestic enplanements in 1999 and are contained within these MSAs. The MSAs that we chose roughly correspond to the hubs listed in the BTS report entitled *Airport Activity Statistics of Certificated Air*

Carriers. We arrived at the list of MSAs by taking all the areas listed in the BTS report and breaking those areas into component MSAs. There were two hubs in the BTS report (Valparaiso, Islip, and Palm Springs) whose names are not found within the list of MSAs defined by the OMB. In these instances, we added to our list the MSAs in which these towns are located. Our list excludes MSAs outside of the 48 contiguous states. Our list also ignores consolidated metropolitan statistical areas (CMSAs), instead focusing on primary metropolitan statistical areas (PMSAs) and regular MSAs.

We combine the above data with that of local area personal income compiled by the BEA(n.d.). Our analysis takes into account MSA population and per capita personal income, grouped by MSA, for 1999 and 2000. The land area measurements used to calculate these densities were taken from the U.S. Census Bureau report *State and Metropolitan Area Data Book: 1997-98* (1998). By using MSA codes to join the airport information, population, per capita income, and population density tables, we built a data base that indexes these datasets by airport. Once these datasets were imported into a single spreadsheet, we calculated total enplanements and commercial services by MSA.

We also placed the airports and their corresponding MSAs into three groups: large hubs, medium hubs, and small hubs. The MSAs in which 1.00% or more of domestic enplanements took place are considered large hubs. There are 31 primary large hubs at present. Medium hubs are those at which at least 0.25% and fewer than 1.00% of passengers enplaned. There are 35 such primary hubs at present. Small hubs are those with greater than or equal to 0.05% and below 0.25 percent of domestic enplanements. There are 71 small hubs at present. Non-hubs were those that fell below 0.05% of domestic enplanements and defined in primary and non-primary categories. At present, there are 282 primary and 127 non-primary non-hubs (FAA, 2001). Unlike the BTS, we applied these definitions to both the hub MSAs and their component airports. Thus, we have data for both MSAs and airports.

Despite its uniqueness, the dataset we use for our analysis and demonstration is somewhat limited in comparison to the 10% O&D sample. The 10% sample is also much larger in magnitude. For example, the sample has more than 4.5 million records (i.e., 10% of more than 450 million total scheduled domestic O&D passengers) for the year 2000. Our dataset also contain a few limitations that we should mention at this point. First, the O&D travel indicated by the data here have been extracted from the original DB1A. BTS/DOT personnel then combine these data with other market information to come up with the information they report to the public. BTS/DOT does not report the actual airport-to-airport travel (as reported by 10% sample); rather, it is reported for the *final market* as represented by city-pairs. This is done, understandably, to protect market-specific information that airlines report in the 10% sample. Consequently, the data for markets in which proportionately more travel takes place (e.g., Atlanta) tends to be biased in its representation of those markets. Second and most importantly, this dataset does not reveal the true itinerary for travelers. As a result, information relating to network travel (i.e., hub-and-spoke travel) is lost. Passengers in this dataset travel between nonstop O&D pairs. Although this is likely for smaller distances, hub-and-spoke travel is a fundamental part of today's air travel. A quick calculation suggests that, on average, 25-30% of passengers use some sort of hub to reach their destination. Third, other information, such as fares that are uniquely associated with an itinerary is not revealed as well. In contrast, a calculated average one-way fare, based on the itinerary fares, is reported. While this is a relatively good substitute, it does not allow us to understand the true impact of fares on those itineraries. In order to solve these issues, we conduct a much larger study in our subsequent research where we build and test models, similar to the one presented in this paper, but based on more detailed 10% dataset instead of the one we report here for demonstration purposes.

ECONOMETRIC FRAMEWORK FOR ESTIMATING O&D PASSENGER TRAFFIC

Following our analytical specification in equation (2), we specify the following equation for estimation in semi-logarithmic form:

$$\begin{aligned}\ln(\mathbf{P_{ij}}) = {} & \alpha + \beta * \ln(f_{ij}) + \chi * \ln(PI_{ij}) + \gamma * (\text{hub status}) \\ & + \delta * \ln(\text{Density}_{ij}) + \phi * \ln(\text{Interactions}_{ij}) \\ & + \varphi * \ln(\text{Distance}_{ij}) + \eta * \ln(\text{Market Power}^{D}_{ij}) \\ & + \iota * \ln(\text{Market Power}^{ND}_{ij}) + \kappa * (\text{Southwest}_{ij}) \\ & + \lambda * (\text{season}) + e_{ij} \qquad (3)\end{aligned}$$

We take the log of those independent variables for which logarithmic interpretations are meaningful. Thus, we leave out the hub status, Southwest presence and season as dummy variables. Second, log-linearity of the demand function implies that the underlying root function is of Cobb-Douglas (C-D) type. This may or may not be true. We make this assumption for two reasons: estimated coefficients of a C-D function have interesting interpretations and can be easily compared with a vast number of other studies for which similar functions have been estimated; and, these functions are computationally less expensive.[7] In a larger context, however, appropriateness of the functional form itself can be empirically tested.

Given that, i ≠ j and D ≠ ND, therefore, full specification of the above can be written as follows:

$$\begin{aligned}\ln(\mathbf{P_{ij}}) = {} & \alpha + \beta * \ln(f_{ij}) + \chi_i * \ln(PI_i) + \chi_j * \ln(PI_j) \\ & + \delta_i * \ln(Density_i) + \delta_j * \ln(Density_j) \\ & + \phi_i * \ln(Interactions_i) + \phi_j * \ln(Interactions_{ij}) \\ & + \eta * \ln(Market\ Power^D{}_{ij}) + \iota * \ln(Market\ Power^{ND}{}_{ij}) \\ & + \kappa^D * (Southwest_{ij}) + \kappa^{ND} * (Southwest_{ij}) \\ & + \gamma_i * (hub\ statusOrigin) + \gamma_j * (hub\ statusDestination) \\ & + \varphi * \ln(Distance_{ij}) + \rho * (season) + \varepsilon_{ij} \qquad (4)\end{aligned}$$

where ε_{ij} distributed normally.

It is evident that equation (4) resembles a demand function. However, it is well established in econometrics literature that equation (4) is part of a simultaneous equation system consisting of both supply and demand functions. Therefore, a straightforward estimation of equation (4) will produce biased and inconsistent estimates.

Generally speaking, an economic system typically consists of many interdependent variables and relationships among them. In estimating the equations of such systems, econometricians frequently encounter an obstacle known as the identification problem. It is known to be more pronounced when estimating one equation from the system.

The identification problem can be illustrated by describing the process by which fares and travel are simultaneously determined in the O&D market. To model this process in its entirety, we must develop a quantitative estimate of both the demand and supply functions in a system. Typically the data used to estimate these functions are past observations of price and output determined by the points of intersection between the demand and supply curves. Therefore, if, in the past, the supply curve has been shifting due to changes in production and cost conditions for example, while the demand curve has remained fixed, the resultant intersection points will trace out the demand function. On the other hand, if the demand curve has shifted due to changes in personal income, while the supply curve has remained the same, the intersection points will trace out the supply curve. The most likely outcome, however, is movement of both curves yielding a pattern of fare and quantity intersection points from which it will be difficult, without further information, to distinguish the demand curve from the supply curve or estimate the parameters of either. Fare and travel are determined by the solution of two simultaneous equations. Therefore, fare and travel are said to be jointly determined. This is a very common occurrence in economics. Under these circumstances, ordinary least squares estimators are biased and inconsistent (Greene, 2001).

Fortunately, several techniques have been developed for the estimation of the structural parameters of an *a priori* specified system of simultaneous stochastic equations. These include indirect least squares, two stage least squares, instrumental variables, three stage least squares, full information maximum likelihood, and limited information maximum likelihood.

STATISTICAL RESULTS: PASSENGER DEMAND AND ITS DETERMINANTS

We use SAS (version 8) for our estimations. In our estimation, we use limited information maximum-likelihood (LIML) estimation to estimate one equation from a system of equations. The LIML method results in consistent estimates that are exactly equal to two-stage least squares (2sls) estimates when an equation is exactly identified (see Greene, 2001 for formal proofs of these assertions). LIML can be viewed as least-variance ration estimators or as maximum likelihood estimators. LIML minimizes the ratio λ = (rvar_eq) / (rvar_sys), where rvar_eq is the residual variance associated with regressing the weighted endogenous variables on all predetermined variables appearing in that equation, i.e., all the right-hand side variables. The rvar_sys, on the other hand, is the residual variance associated with regressing weighted endogenous variables on all predetermined variables in the system. The k-class interpretation of LIML is that K = λ and thus stochastic, unlike that under ordinary least squares and 2sls where $0 < K < 1$.

Table 2. Model Summary

Market Hauls (in miles of non-stop distance) (1)	*N (no. of observations) in the Dataset*	*N (no. of observations) used in Estimation*	*(N in Est / N Data) (%)*	*Adj. R^2*	*F-Value*
<250: Short Haul1	2424	1785	74	0.57	170.53*
250-499: Short Haul2	8161	4601	56	0.51	346.92*
500-749: Short Haul3	9935	5685	57	0.41	287.69*
750-999: Short Haul4	8894	5396	61	0.42	289.44*
1000-1249: Short Haul5	6686	3981	60	0.35	155.47*
1250-1499: Medium Haul1	4252	2457	58	0.37	102.79*
1500-1749: Medium Haul2	3239	1934	60	0.50	139.35*
1750-1999: Medium Haul3	2983	1652	55	0.54	141.66*
2000-2249: Long Haul1	2184	1392	64	0.55	123.54*
2250-2499: Long Haul2	2160	1310	61	0.48	87.26*
2500-3000: Long Haul3	996	510	51	0.48	34.24*
Contiguous US NAS Total	**51914**	**30703**	**59%**		

'*': Significant at 99%.

Many of the interesting results from the estimations for the 11 markets[8] separated by non-stop distances of 250 miles for the first 2,500 miles and 500 miles for the segment of 3,000 miles have been summarized in tables 2 through 4. We use SYSLIN procedure from SAS that uses a Limited Information Maximum Likelihood (LIML) with K class estimation. K-class estimators are instrumental variable estimators where the first-stage predicted values take a special form: $Y^* = (1\text{-}k)Y + kY$ for a specified value of k. The probability limit of k must equal 1 for consistent parameter estimates.

Results are self-explanatory but some remarks are in order. As table 2 indicates, the estimation suffered quite a bit, on average it lost 40% due to larger specification and an incomplete dataset. Therefore, we could only use 30,703 observations (59%) from the complete dataset containing 51,914 observations.

As is also clear from the table 2, the overall model results, represented by Adj R^2 and F-Value, are quite significant. The fraction of the variance of the dependent variable, i.e., average daily passenger demand on a day, explained by the independent variables (R^2)[9] ranges between 35% to as high as 74%. For a small time series (2 years) pulled cross-section data, this is relatively good.

The F-statistic for the specified model tests the hypothesis that all the slope coefficients, excluding the intercept, in a regression equation are zero. Under the null hypothesis with normally distributed errors, this statistic has an F-distribution with k-1 numerator degrees of freedom and T-k denominator degrees of freedom. The p-value given next to the F-value, denoted Pr>F, is the marginal significance level of the F-test. In all our 11 models, the p-value is essentially zero. Therefore, we reject the null hypothesis that all of the regression coefficients are zero. Notice, however, that the F-test is a joint test of model suitability. Thus, even if all the t-statistics are insignificant, the F-statistic can be highly significant making the model's overall appropriateness.

Average One-Way Fare

Average one-way fare affects all market segments negatively, as expected. However, in some markets, the responsiveness of travelers to fare changes are relatively less responsiveness, i.e., inelastic, than others. For example, least inelastic market appears to be Short-Haul2 where non-stop distance is between 250-499 miles.[10]

Travel in the shorter haul markets may tend to be relatively less responsive to changes in fares for several reasons.[11] First and foremost is the structure of passengers. It is relatively well known that most of the passengers who travel shorter distances are business class passengers. They tend to pay a higher premium to purchase tickets at the last moment. Consequently, they have very little or no choice to respond to changes in the fares. Passengers who are more capable of responding to fare changes, i.e., leisure class, tend not to fly these shorter distances. This occurs even though other modes of transportation should make the demand curve flatter, and therefore, more elastic. An overall inelastic demand curve, therefore, suggests that travel is perhaps dominated by the business class passengers in the shorter-haul markets.

Judging from the results above, it appears that the short haul markets 4 & 5 have similar characteristics as do short haul markets 1, 2, and 3. On the other hand, all medium haul markets tend to share similar elasticity with long haul market 1 (i.e., 2000-2249 miles). It is not clear why long haul

Table 3. Fare Elasticities of Demand by Distances

Market Hauls (in miles of non-stop distance)	*Elasticity of Demand with respect to fares*	*t-value*	*Pr > | t|*
<250: Short Haul1	-0.66650	-11.16	<.0001
250-499: Short Haul2	-0.55762	-11.32	<.0001
500-749: Short Haul3	-0.73791	-15.35	<.0001
750-999: Short Haul4	-1.45383	-28.27	<.0001
1000-1249: Short Haul5	-1.81597	-29.63	<.0001
1250-1499: Medium Haul1	-0.85086	-11.55	<.0001
1500-1749: Medium Haul2	-1.07697	-10.22	<.0001
1750-1999: Medium Haul3	-0.84224	-8.28	<.0001
2000-2249: Long Haul1	-1.06010	-9.22	<.0001
2250-2499: Long Haul2	-1.38358	-9.64	<.0001
2500-3000: Long Haul3	-0.85995	-3.79	<.0001

Figure 5. Fare Elasticity of Air Travel in US

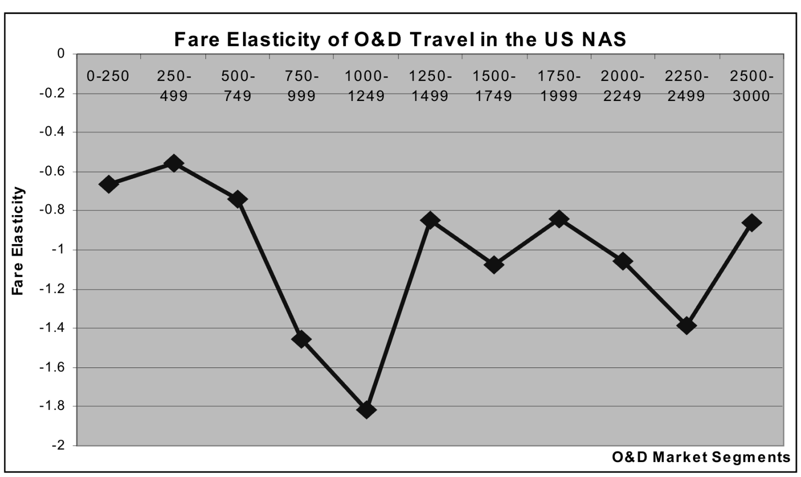


Table 4. Distance Elasticities of Demand by Market Hauls

Market Hauls (in miles of non-stop distance)	*Elasticity of Demand with respect to average distance (miles)*	*t-value*	*Pr > | t|*
<250: Short Haul1	1.5862	20.99	<.0001
250-499: Short Haul2	-0.44612	-6.16	<.0001
500-749: Short Haul3	-0.16116	-1.46	0.1432
750-999: Short Haul4	0.585804	3.56	<.0004
1000-1249: Short Haul5	0.162264	0.61	0.5417
1250-1499: Medium Haul1	-0.24265	-0.67	0.5054
1500-1749: Medium Haul2	0.052665	0.11	0.9155
1750-1999: Medium Haul3	0.587395	1.08	0.2803
2000-2249: Long Haul1	4.070675	5.89	<.0001
2250-2499: Long Haul2	0.491526	0.47	0.6399
2500-3000: Long Haul3	-0.84207	-0.47	0.6391

markets 2 and 3 appear to be so different in terms of their elasticity magnitudes.[12] We plan to examine the 10% data in more detail to probe the above results further.

Average Distance

We have postulated that the average distance between O&D pairs can have either negative or positive effects. As it turns out, average distance may have played any role in passenger demand for only 4 markets. It is interesting to note that while for the shortest distance, average distance affected the demand positively, for the markets right above it, it affects the demand negatively. These results indicate that our understanding, and therefore, the specification will have to be cast on a firmer ground than we have done here. While it appears that distance may play some roles in affecting passenger demand, its role is not as clear cut as some of the other variables.

Market Share

Market share index, the market share of larger airlines relative to those who have smaller shares, strongly affects the demand for O&D travel in all markets except the last two long-haul markets. The index is constructed by taking the share of larger airlines compared to those who have smaller market share. Thus, a rising index, i.e., due to an increasing share of already established airlines, or due to a decreasing share of smaller airlines, or a combination of both, may actually increase the passenger demand. Since we have already taken fare into consideration in our framework, this result may be indicative of the choices that are often associated with those increased shares. Generally speaking, larger airlines tend to operate in a hub-and-spoke network. Thus, an increasing market share may alternatively represent greater expansion of hub-and-spoke network. An increasing share may affect passenger demand via offering more choices. Those choices appear to be important for passengers who are flying within the 2249 miles distances.

Density: Origin and Destinations

Density is representative of economic activities. Thus, it is possible that the higher the density, the more the air travel there will be. However, beyond a certain range of density, negative externalities may set in and thus may affect the air travel negatively. Our results indicate that while the positive effects are still prominent, there are situations where densities have affected travel demand negatively.

Income: Origin and Destination

Unlike density, income (both O&D) tends to have a positive impact on travel decisions over almost all market segments. A negative relationship, if found, would imply that air travel is an inferior commodity. Given the state of the technology in alternative modes of transportation, it appears from our results that air travel is still income-elastic for most of the distances. One can identify, just like in the case of fare elasticity, income elasticity by looking at the estimated parameters of personal income for both O&D. Looking at those results, we find that air travel in the shortest market segments (i.e., 0-250 miles) is the most income-sensitive with respect to origin. Thus, as income increases 1% at the origin, travel increases by almost 3%, far higher than the reported national average. In contrast, air travel is least sensitive (around, one-half) to the origin income in the 1,750-1,999 miles market, among all those elasticities which are statistically significant. Destination income, on the other hand, is positive and elastic wherever they have been found to be statistically significant.

Interactions: Origin and Destination Economic Activities

For almost all the markets, other than the longest market distance market, economic interactions (between population and income in 1999) at origin tend to have a negative impact on demand for passengers. This is interesting since it tends to imply, together with results of density, that negative externalities may influence passenger demand at origin cities. Much of the discussion that centers ondelays, and how it tends to affect air travelers, seems to focus on those who are departing from origin airports. Thus, statistically relevant negative coefficients confirm the hypotheses that the higher the intensity of economic activities at origin cities, the less likely passengers will want to fly. For destination cities, results are mixed, and there are still positive benefits that affect the passenger demand.

Hub Status: Origin and Destination

Dummy variables representing the O&D cities, as defined by BTS/USDOT, capture the hub status. Hub dummies are equal to 1 if the cities are assigned large hub status, and equal to 0 if they have been assigned non-large hub status. Our results indicate that the size of hubs, at both O&D, is a critically important and positive factor determining passenger's travel decision. Thus, for all market distances, large hub status tends to affect air travel decisions positively. Highly statistically significant, these results point out, together with the results from market share, that air travel is still dominated by hub-and-spoke networks.

Southwest Effect: Major and Minor Presence

One of the important questions in recent times, especially after 9/11 and the economic recession of 2001-2002, has been the viability and long-run existence of the network structure of the major carriers. As the major carriers struggle through the period, Southwest Airlines and many other low-cost carriers, have continued their expansions in almost all markets. Starting from shorter haul distances, Southwest flies almost all the distances throughout the NAS. As noted earlier, Southwest's presence may have both substitution and complementary effects on air travel. To capture these effects, we have used two dummy variables: one representing when Southwest has the major market share; and, the other when Southwest has a minor presence in the market. Clearly, Southwest has a strong positive impact in the shorter haul markets. However, beyond the market of 1000 miles of non-stop distance, these effects are not so clear on the demand for passenger travel.

Spring-Summer Effect

Our dataset does not show any statistically meaningful relationships between the spring-summer dummy variable and passenger demand. One of the reasons is that passengers' decisions to fly are made, generally speaking, before weather's effects can be known. As a result, there may not be any relationship other than some observed spurious positive correlations in our results.

FROM ESTIMATED PASSENGER DEMAND TO FORECASTS OF PASSENGERS BETWEEN O&D PAIRS: THE PROCESS TO DERIVE RESULTS BY CENTERS

It is evident that the estimated equations from the 11 market segments can be used to forecast O&D passenger demand. It is obvious that there are some variables for which forecasted values are available, e.g., income, density, population, hub status, but for others, forecasts are not available. In particular, future fare information is not available; neither are available future values for market shares and Southwest presence.

The unavailability of this information poses limitations on the forecasts of passengers by O&D market. However, they also provide opportunities to derive a range of forecasts based on assumed values for the variables[13] for which forecasts are not available. At the core, however, we are still able to derive passenger forecasts by using the forecasts of local area personal income, demographics, and other characteristics.[14]

A FRAMEWORK FOR MAPPING PASSENGERS TO AIRCRAFT

To establish the statistical relationships between passenger demand and aircraft fleet choice, we use the following methodology.

First, we define the markets by stage lengths, i.e. short-haul (1,200 miles or less), medium-haul (*between 1,201 and 2,001 miles*) and longer hauls (2,001 or more miles). Second, we classify aircraft into different categories, i.e., piston (2 classes), helicopter & stol, turboprops (2 classes), and jet crafts (3 classes) from the disaggregated 59 types that had been observed (from the T100 segment of Form 41) to be in use during the 1990s. It is also possible to go into further desegregations, i.e., model types, if computational resources were not a constraint and users required such data.

Based on the data (T100 segment of Form 41), over 1.75 million records for 1991-2000, we determine answers to the following *qualitative question*: What is the *probability that one type of plane category* (from those 7 defined above) will be *chosen over others* given airline characteristics, market characteristics, number of passengers, proportion of non-passengers (i.e., mail, freight) to passengers, and other performance indicators, such as departures scheduled and performed, elapsed time ramp-to-ramp and airborne, market distance, year, and quarter.

Once we have estimated the qualitative model underlying this question, we then determine the probable types of aircraft by stage lengths (i.e., short, medium, and long) by using estimated coefficients and number of passengers, market distance, year, quarter, and airline characteristics which are also inputs to our passenger demand model.

Once the above mapping is complete, we use the forecast from the passenger demand model to generate the forecast of aircraft by O&D pairs. Figure 6 describes the process.

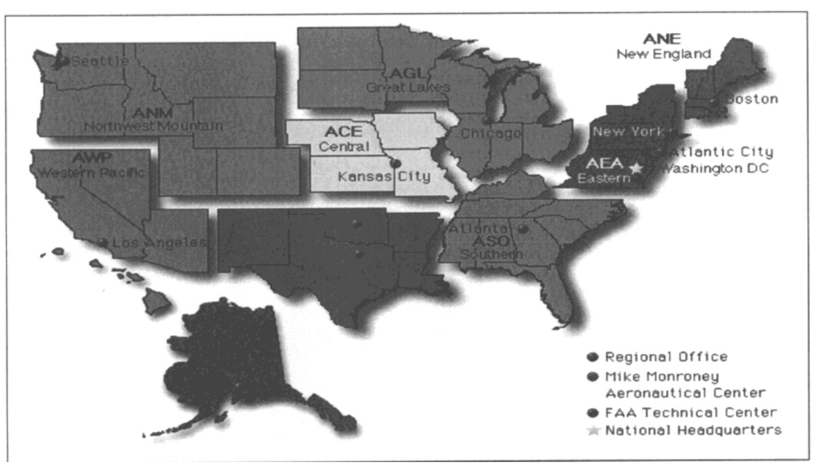
Figure 6. From Passenger Demand to Demand for Aircraft Operations by Market Segments: A Suggested Framework

WORKLOAD ISSUES: DEMAND BY FAA CENTERS OR ANY OTHER UNITS

This forecasting framework can be used to determining the workload at the FAA centers where workload is related to aircraft traffic.

At present, the NAS is divided into nine FAA regions (Figure 7). We merge our dataset with this information uniquely identifying both O&D travel with a center or centers. Thus, the entire contiguous NAS flow of travel can be associated with centers. The distribution of workload can be easily derived from the distribution of travel by centers.

Figure 7. FAA Centers



Source: http://www.faa.gov/ats/aaf/asr/locations/ctrsrgns.htm

CONCLUSIONS AND THE WORK AHEAD

Several conclusions emerge from this paper. First, it appears that slight modifications of econometric estimation and using micro data can result in substantial insights to O&D travel. For example, it is possible, as the present paper demonstrates, to determine city-pair travel and forecasts by using local area information. Local area information appears to be more relevant in determining local O&D travel than of national information such as gross domestic product. While the methodology does not depart from the basic economic premise, this paper demonstrates that local area data are far better indicators for local area travel than the national counterparts. Forecasts of O&D travel make use of the local area information, and hence, this methodology should be called a bottom-up approach, distinct from the traditional top-down approaches (see Appendix E).

The results from this work can be used to complement the work done by the TAF that is derived from top-down models. For example, it is well known among those who use the TAF that the distribution of hub structure within the NAS does not change over time. Thus, it is likely that there will be twice as many large hubs as small hubs in 15 years than it is now (i.e., 29 large hubs compared to 56 small hubs of today). Thus, a doubling of hubs, keeping with its relative distribution fixed, is a direct result of doubling of passengers in the NAS. This is likely to change under our suggested methodology because hub status itself can be endogenously determined. Second, it is also well known that the TAF is meant to serve as a planning tool, especially for airport planning. It was not designed to capture the *traffic flow* within the NAS. While the TAF has been stretched to fit this need including its most recent use in OEP, the TAF is better suited for longer-term planning. Our methodology, on the other hand, is based on the traffic flow between O&D cities and thus is designed to answer those questions which are related to dynamic flows. These include, but are not limited to, determining the workload distribution based on the forecasts of passenger and aircraft flow between O&D by centers; determining and prioritizing multi-modal infrastructure investments such as those under OEP; determining and prioritizing multi-modal investments within a broader framework; understanding the role of RJs in the national air space; understanding the role of changing industry characteristics, and so on.

Results from this econometric estimation provide some detailed insights into O&D travel as well. First, based on our results in this paper, now we are able to distinguish between different distance markets. Clearly, travel of 2,000-2,250 miles is distinctly different than shorter distances, such as that of less than 500 miles. Elasticity measures show that travels of shorter distances is relatively more inelastic than previously known. Second, our results also indicate that travel between O&D city pairs, distinguished by miles traveled, is relatively income-elastic and that elasticity changes with distance. This is true for both O&D. We also find that economic activities tend to have negative impact beyond a certain range as represented by the interactions of income and population. Third, our results indicate that market dominance by major airlines tend to have a positive impact on number of passengers traveled between O&D pairs, perhaps representing the effects of choice more than anything else. Many of these airlines also operate hub-and-spoke networks and thus higher dominance may provide more destination choices for passengers. However, such effects may not be conclusive as shown by the effects of Southwest in the markets. The presence of Southwest, both as a major or minor player, tends to have a positive impact on passenger demand.

Clearly, these are interesting results. However, like in any other research, our study is somewhat restricted by the data as reported above. Thus, any policy discussion should await results from our larger work. Nonetheless, this paper demonstrates that much can be learned from studying the O&D traffic. Furthermore, the paper demonstrates that it is possible, and perhaps desirable, to devise O&D-based market traffic forecasts. While the TAF will continue to play an important role in longer-range planning, our methodology could be used for studies works that relate to the network flow aspects of the NAS.

ENDNOTES

1. For a more recent discussion on aviation demand forecasting methodologies see TRB, 2002.

2. Standard derivation of this assertion comes from the economics literature where individual or household utility is specified to be dependent on consumption of goods - travel being one such good - which in turn depends on levels of income, number of people in a household, and other factors. More formally, $U = f[\,t(y; N, p, s; \phi); z)$ where U is an index of utility, t is levels of travel as a function of disposable income (y), number of people in a household (N), average fare (p), season (s) and a vector of other factors (ϕ). Composite commodity, z, is assumed to capture effects of all other factors influencing U. Assuming some simple restrictions on functional properties of f, we can easily derive demand functions for t^* and z^*. We show travel demand relationships graphically in Figure 1.

3. In a recent article, Morrison (2001) states that Southwest's low fares were directly responsible for $3.4 billion of savings to air passengers. In addition, $9.5 billion was saved due to the effect that actual, adjacent, and potential competition from Southwest had on other carriers' fares. Author finds that these savings ($12.9 billion) amount to 20 per cent of the domestic scheduled passengers' revenue in 1998. This is the first comprehensive, and perhaps the only quantitative estimation, of *Southwest effect* that I am aware of.

4. It is important to note here that Southwest had a little over 6% of the total market share in 2000. The large three, United, American, and Delta combined had a market share slightly over 50% (ATA, 2002).

5. There is a bill (#H.R. 1407) entitled *The Airline Delay Reduction Act* pending whereby the House Subcommittee on Aviation was to review requests for provision of antitrust immunity to the airlines to allow them to discuss ways to reduce delays and to consider other possible solutions to the airline delay problem. In order to address these issues, the Committee held a hearing on April 26th last year [see http://www.house.gov/transportation/aviation/04-26-01/04-26-01memo.html for details].

6. Choice of eight quarters is purely arbitrary for this demonstration. This dataset is somewhat restrictive because BTS/DOT guards some information to protect airlines' proprietary interests. At the time we were putting this dataset together, data for three years, 1998-2000 was available. We decided to drop 1998 because O&D travel was mistakenly identified by airport-pairs, and not city-pairs as reported in later years. Furthermore, we wanted to create a representative sample for this time-series pulled cross-section dataset without getting into serious computational difficulties for our limited purpose. Given our ultimate need for a bottom-up econometric estimation and forecasting framework, eight quarters observations for more than 50,000 observations appear to be substantial for the industry as well as for our purpose. A more detailed model using complete 10% data, along with its other apparatus reported later in this paper, exist at MITRE/CAASD.

7. Initial estimations with the larger 10% sample indicate that the larger the datasets, relatively longer time it takes to run estimations. While a large part is simply that it is computationally time-consuming, another part of the problem may be purely infrastructural, i.e., matching records through object database connections (ODBC) and working with SAS.

8. We combine the last two markets, i.e., 2500-2749; and, 2750-3000 together. The last market haul, 2750-3000, did not have enough data and thus combining it with the segments before that made sense.

9. One problem with using R^2 as a measure of goodness of fit is that it never decreases with the additions of regressors. Therefore, one can always obtain a high R^2 by including as many independent regressors as there are sample observations. Obviously, that would not make any sense! The adjusted R^2 penalizes the R^2 for the addition of regressors which do not contribute to the explanatory power of the model, and therefore, can be called a weighted measure.

10. One of the advantages of using a C-D specification is that the estimated coefficients of the log-linear model are elasticities. However, this is not true for other specifications, such as constant elasticity of substitution and translog functions.

11. See Battersby and Oczkowski (2001) for a study on Australian domestic market; and Vakil and Russon (1996) for short haul markets. For a comprehensive review of empirical results on air travel demand, see http://www.fin.gc.ca/consultresp/Airtravel/airtravStdy_3e.html. See also Brons *et. al* (2001) for comparative international experiences.

12. Available empirical estimates are not distance specific. Published studies document fare elasticities to range between –3.2 to 0.2 [see Brons *et. al* (2001) for original studies and accompanying explanations].

13. This process parallels what is known as policy simulations. For example, it is clear that (assumed) declining fare in the future would be representative of stronger industry competitiveness. While an increase in market share by majors and/or a decline of shares by minors would reduce the competition. Assuming those scenarios (i.e., competitive outcomes emanating from different sources), we would be able to derive forecasts of passengers for the future.

14. There are quite a few nationally well-known forecasting companies available. After BEA stopped forecasting these variables a few years ago, industry forecasters had traditionally depended on these companies for local area forecasts. For our study here and for the larger study, we use DRI/WEFA forecasts for the MSA level local area forecasts.

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APPENDIX A
Definition of Variables for Demand Modeling

$$\begin{aligned}\ln (P_{ij}) = {} & \alpha + \beta * \ln(f_{ij}) + \chi_i * \ln(PI_i) + \chi_j * \ln(PI_j) \\ & + \delta_i * \ln(Density_i) + \delta_j * \ln(Density_j) \\ & + \phi_i * \ln(Interactions_i) + \phi_j * \ln(Interactions_{ij}) \\ & + \eta * \ln(Market\ Power^{D}_{ij}) + \iota * \ln(Market\ Power^{ND}_{ij}) \\ & + \kappa^{D} * (Southwest_{\ ij})^{\ D} + \kappa^{ND} * (Southwest_{\ ij})^{\ ND} \\ & + \gamma_i * (hub\ statusOrigin) + \gamma_j * (hub\ statusDestination) \\ & + \varphi * \ln(Distance_{ij}) + \rho * (season) + \varepsilon_{ij}\end{aligned}$$

f_{ij} : one-way average fare between i (origin) and j (destination) Metropolitan Statistical Areas (MSAs);
$PI_{I,\ j}$: per capita personal income at i and j;
$Density_{I,\ j}$: Density (per sq mile) at i-th/j-th MSAs;
$Interactions_{I,\ j}$: multiplicative interactions between population and income as a measure of degrees of economic activities at ith and jth MSAs;
Market $Power^{D}_{ij}$: market power (%) of dominant airlines at the i-jth market; share of airlines (%) is defined (%) share in total number of enplanement;
Market $Power^{ND}_{ij}$: market power (%) of non-dominant airlines at the i-jth market;
Southwest $_{ij}{}^{D}$: presence of Southwest Airlines as major airlines (% share is higher than the nearest competitor); 0 = no (presence); 1 = yes (presence);
Southwest $_{ij}{}^{ND}$: presence of Southwest Airlines as minor airlines; 0 = no; 1 = yes;
hub statusOrigin : hub status of Origin MSAs defined by DOT/BTS: 0 = large hubs; 1 = non-large hubs (medium, small, and non-hubs);
hub statusDestination : hub status of Destination MSAs defined by DOT/BTS: 0 = large hubs; 1 = non-large hubs (medium, small, and non-hubs);

Table A1. Enplanements for Hub Type 2000

Hub classification	*Percent of total enplaned passengers*	*Number of enplaned passengers*
Large (L)	1.00 or more	6,106,287 or more
Medium (M)	0.25 to 0.999	1,526,571 to 6,106,287
Small (S)	0.05 to 0.249	305,314 to 1,526,571
Nonhub (N)	Less than 0.05	Less than 305,314

Adapted from Federal Aviation Administration (2001). Enplanements for Hub Type 2000. Retrieved May 28, 2003, from http://www.faa.gov/arp/Planning/hubtype.htm

$Distance_{ij}$: distance (miles) between I-jth market;
Season : spring, summer, Fall and winter; equivalent to 1st, (2nd, 3rd), and (4th) quarters respectively;
ε_{ij} : is distributed normally with mean = 0 and a constant variance.
ln = natural log.

APPENDIX B
Air Traffic Hubs

Note: Large hubs = 31; medium hubs = 35; and, small hubs = 71.

Adapted from Bureau of Transportation Safety (BTS) (1999). *Airport Activity Statistics of Certificated Air Carriers Summary Tables: Twelve Months Ending December 31, 1999*. Retrieved May 28, 2003, from http://www.bts.gov/publications/airport_activity_statistics_of_certified_air_carriers/1999/air_traffic_hubs.html

APPENDIX C
Hubbing by Commercial Airlines

Airline Hub Cities: American, Southwest & Northwest	
Airline Hub Cities: United, US Airways & Delta	
Airline Hub Cities: Alaska, Continental and America West	

Source: http://airtravel.about.com

APPENDIX D
Regional Airline Code-Sharing Partnerships as of April 2002

Airline	*Partner(s)*	*Primary Hub(s)*
Alaska Airlines	Era Aviation	ANC
	Horizon Airlines	BOI/GEG/PDX/SEA
	Peninsula Airways	ANC
Aloha Airlines	**Aloha Islandair**	HNL
America West Airlines	Big Sky Airlines	DEN/DFW/GEG
	Chautauqua Airlines	CMH
	Continental Express Airlines	CLE/EWR/IAH
	Mesa Airlines	LAS/PHX
American Airlines	**American Eagle Airlines**	BOS/DFW/JFK/LAX/LGA/MIA/ORD
	Chautauqua Airlines	STL
	Corporate Express Airlines	STL
	Executive Airlines	SJU
	Trans States Airlines	STL
American Trans Air	**Chicago Express Airlines**	MDW
Continental Airlines	Commutair	ALB
	Continental Express Airlines	CLE/EWR/IAH
	Express Airlines	DTW/MEM/MSP
	Gulfstream Int'l Airlines	FLL/MIA/TPA
	Horizon Airlines	PDX/SEA
	Mesaba Airlines	DTW/MEM/MSP
Delta Air Lines	American Eagle Airlines	LAX
	Atlantic Coast Airlines	BOS/CVG/JFK/LGA
	Atlantic Southeast Airlines	ATL/DFW/JFK/ORL
	Comair	ATL/BOS/CVG/DFW/JFK/LGA/ORL
	SkyWest Airlines	DFW/SLC
Frontier Airlines	Great Lakes Aviation	DEN
	Mesa Airlines	DEN
Hawaiian Airlines	Horizon Airlines	PDX/SEA
Midwest Express Airlines	Air Midwest	MCI
	American Eagle Airlines	DFW/LAX
	Astral Aviation/Skyway Airlines	MCI/MKE
Northwest Airlines	American Eagle Airlines	LAX
	Big Sky Airlines	BIL/BIS/GEG
	Continental Express Airlines	CLE/EWR/IAH
	Express Airlines	DTW/MEM/MSP
	Gulfstream Int'l Airlines	FLL/MIA/TPA
	Horizon Airlines	PDX/SEA
	Mesaba Airlines	DTW/MEM/MSP

Airline	*Partner(s)*	*Primary Hub(s)*
United Airlines	Air Wisconsin	DEN/ORD
	Atlantic Coast Airlines	IAD/ORD
	Great Lakes Aviation	DEN/ORD
	Gulfstream Int'l Airlines	MIA
	SkyWest Airlines	LAX/PDX/SFO/SEA
US Airways	Air Midwest	CLT/MCI/PHL/PIT/TPA
	Allegheny Airlines	BOS/DCA/LGA/PHL/PIT
	CCAIR	CLT
	Chautauqua Airlines	BOS/LGA/PHL/PIT
	Colgan Airways	BOS/LGA/PIT
	Mesa Airlines	CLT/DCA/PHL/PIT
	Piedmont Airlines	CLT/DCA/LGA/PHL/PIT/TPA
	PSA Airlines	CLT/DCA/PHL/PIT
	Shuttle America	LGA/PHL/PIT
	Trans States Airlines	PIT

Note: Carriers indicated by boldface are fully-owned by the Major/National Airline.
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APPENDIX E
Concepts, Explanations and Contributions of our Research

Market & Industry Characteristics	Explanations	Existing work	Our Research & Its Contributions
Fare Elasticities	This standard economic concept measures responsiveness of air travelers in changes in fares	All present empirical work, including that of FAA's, does not incorporate market-specific effects. Instead, a NAS-wide number is used to capture traveler's sensitivity to fare changes.	Market-specific effects have been modeled. Effects of policy changes (affecting fare, schedules, and access) can be looked, at and quantitatively estimated, by market pairs & segments.
Income Elasticities	This is essential for measuring air traveler's long-tem physical movements, including that of other economic decisions, e.g., choice of mode.	Economy-wide flow concept of income, such as gross domestic product (GDP), is used. This is not capable to explain regional disparities and imbalances in the NAS.	Market-specific effects have been modeled. In addition to explaining effects from policy changes, market-differentiated measures are important tools for explaining the present and future disparities and imbalances in the NAS.
Distance Elasticities	This measures traveler's sensitivity to changes in distances within a pre-defined market segment.	None of the present framework incorporates this measure.	Distance within the well-defined market segments have been modeled. These empirically estimated values will play important roles in determining traveler's choice (for airport, for example).
Seasonality	Seasonal changes in air travel are well-known. This measures the quantitative impact of spring, summer, fall, and winter.	Most of the passenger flow data are adjusted for to take the seasonality out to measure the real value.	Effects of seasonality have been modeled clearly to capture the seasonal changes that characterize air travel.
Low-cost carriers, aka Southwest Airlines	This measures the quantitative impact of Southwest Airlines in particular O&D markets.	Some earlier empirical work have attempted to model Southwest by both accounting for direct and indirect impact of Southwest entry. Most of the government (DOT, DOJ) measures the effects as part of anti-trust procedures	Presence of Southwest Airlines, both as major and minor airlines in O&D markets, have been modeled. Therefore, we can estimate - for example - benefits of Southwest on passenger flows, fares, and the value of a particular market.
Industry concentrations & market powers	Similar to Southwest, this measures effects of market powers on O&D markets.	At present, government (DOT,DOJ) addresses these issues as part of anti-trust procedures.	Market powers of airlines have been modeled in our framework. Thus, cost and benefit of such concentrations can be easily measured for a particular market.
Local economies, & demographics	Local economies and demographics play important roles in determining choice of markets, modes, etc.	There is no general framework incorporating these info. FAA includes these info through qualitative canvassing of master plans of airports.	Our model specifically model local information. Local economic and demographic factors are believed to be the primary drivers for air transportation.