AIRPORT SUBSTITUTION BY TRAVELERS: WHY DO WE HAVE TO DRIVE TO FLY?

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Abstract. This paper explores aspects of the determination of airline fares in selected medium-sized U.S. airports subject to competition from alternative airports within driving distance. Passengers in these markets often face substantial discounts at distant airports, in exchange for the time costs of driving there. Spatial linkages in airport competition are not well studied. A panel of 16 quarters is constructed in order to investigate models of spatial error correlation and spatial autoregression in overall fare levels in adjacent airports. We find that fare differentials between local and nearby alternative airports can lead to lower load factors and other indicators of poor performance in smaller local airports. Fare differentials at nearby airports often provide substantial incentives to travelers and are an important determinant of poor performance at medium-sized airports.

1. Introduction

A common allegation made in many airline markets involving small-to-medium airports is the lack of effective competition and apparent failure of the process of competitive entry to mitigate persistent high fares out of some local airports. A 1999 study by the Transportation Research Board suggests that fares are substantially higher in short-distance markets without low-fare competition, often at small-to-medium sized airports. Indeed, the problem can also occur in reverse; travelers in large cities such as Boston may sometimes obtain better options than at Logan Airport by flying out of Providence, R.I. This paper attempts to develop new evidence of the extent of this problem for a set of 65 such airports, by assessing how fare differentials across alternative airports affect performance.

Table 1 lists some examples of adjacent airport pairs in which the alternative airport choice is one of the largest twenty airports in the U.S.

[INSERT TABLE 1 HERE, Caption: Fare Differences at Alternative Airports for a fixed set of destinations from the Origin Airports]

To get a more representative picture of the mean airfares, the price index for a fixed bundle of tickets originating out of the smaller airport to its 50 most-frequently chosen destinations is calculated. The mean fare difference is then calculated, for the second quarter of 1998, as the difference between the (passenger-weighted index) mean airfare to these top destinations from each origin airport and the index of mean airfare from the alternative airport to the same destinations. As Table 1 shows, Providence, R.I. is an attractive alternative to Boston, saving about $78 on the typical itinerary, before including the economic costs of driving. In many instances, however, the biggest gains are found for travelers originating near small-to-medium airports, such as Melbourne Fl, where driving to Orlando yielded a gross gain of about $270. Passengers in smaller markets in particular often face substantial discounts at larger distant airports, in exchange for their time costs of driving there. In this study, we consider localities where the larger, nearby airport provides fare advantages as well as localities where the small nearby airport is cheaper.

Carriers originating from adjacent airports directly compete on common destinations when travelers find it attractive to drive to the alternative airport in return for lower fares. These arbitrage actions of travelers selecting among adjacent airports shape airline competition. Carriers set ticket prices optimally recognizing not only local travelers' demands, but also the demand induced from travelers who are willing to drive some distance to purchase a cheaper flight.

Spatial linkages in competition at small-to-medium sized airports are not well studied. For this study, a panel of 16 quarters is constructed in order to investigate, for the first time, temporal attraction of spatial fare differentials on performance in smaller airports and the subsequent adjustment in fare differentials following entry. Carriers may find that their costs are raised when travelers are drawn away from the local airport, reducing passenger volume and load factors. We find that fare differentials at alternative airports often reflect substantial incentives to travelers, but the siphoning of price-sensitive passengers through airport substitution leads to lower performance at the local airport in terms of load factors, passenger volume and revenue.

The layout of this paper is as follows: Section 2 summarizes the related literature. Section 3 describes the construction of a Laspeyres index across space, a weighted-average cost of a representative bundle of flights between the focal airport and the lowest-fare alternative. These weighted fare indexes proxy how substitutable two airports are and influence market competition and performance. Section 4 describes the data used, the assumptions made, and the covariates controlled for in our empirical analysis. Section 5 extends the empirical model to allow for spatial autocorrelation in the dependent variable and the error term when estimating the fare differential indexes. The empirical model of how fare differentials affect the performance and entry decisions of airlines operating at small-to-medium airports are described in Section 6. The empirical results for each of the models are reported in Section 7. Our conclusions follow in the last section.

2. Literature Review

In order to analyze how fare differentials across alternative airports affect economic performance, one must understand two issues: 1) the source of the fare differentials and 2) the factors that drive carrier entry decisions and thus their expectations about the potential profitability. First, if alternative airports were perfect substitutes, then substitution by travelers would tend to equalize fares across the alternatives. Second, one can view economic performance issues from the vantage point of a potential entrant to understand the viability of service offerings in the context of existing competition among carriers. There is an extensive literature that examines each of these issues. Starting with the fare differential literature, Borenstein (1989) established that an airline's airport and route dominance determines the degree in which a carrier can mark-up over cost. Furthermore, their ability to mark-up does not extend to non-dominate carriers on that route. Borenstein and Rose (1994) observe fare differentials increasing on routes with more competition or lower flight density. Evans and Kessides (1994) attribute this variation in prices to multi-market contact, i.e., amount of overlapping network of flights by the carriers servicing that route. These findings suggest that the distribution of airfares available to entrants will differ across alternative airports.

The literature on carrier entry provides insights as well on how entrants decide on which routes to offer service. The first strand of this literature identifies factors that determine entry. Berry (1992), Brueckner et al. (1992), and Reiss and Spiller (1989) among others find that entry on a given route increases with a carrier's airport presence at the endpoints. Morrison and Winston (1990) determine that trunk carriers are less likely to enter routes with relatively high fares. These markets tend to be characterized by relatively high barriers to entry, relatively high costs of service, or aggressive response by incumbent firms to entry of a new carrier. Several papers focus solely on low cost carriers (LCC) entry decisions. Ito and Lee (2003a) ascertain that pre-market density - the average number of daily passengers transported on that route- is the most important market characteristic to induce nonstop entry by LCCs. Boguslaski, Ito, and Lee (2004) find evidence that Southwest's entry decisions have evolved over the years. Initially, Southwest entered medium-haul markets to service people who did not previously travel. By the second half of the 1990s, Southwest began to offer longer-haul service on routes previously avoided by major carriers.

The second strand of the entry literature examines incumbents' responses to these entry decisions. Dresner et al. (1996) and Morrison (2001) show that LCC's influence on airfares extend beyond a particular airport route they enter. Ito and Lee (2003b) find that incumbent hub-spoke carriers are fairly accommodating when LCCs begin to service their hubs. They rarely undercut entrants' average fares and usually only match their prices. Goolsbee and Syverson (2005) examine incumbent pricing behavior on routes where Southwest does not operate, but offer service at both endpoints. As expected, incumbents drop fares in anticipation of entry; the decline is the greatest for the more concentrated routes and higher priced business fares. Incumbents do not, however, cut fares on alternative routes, only on threatened routes where Southwest Airlines already operates at both endpoints. Finally, Windle and Dresner (1999), Whinston and Collins (1992), and Bamberger and Carlton (1999) are other studies that document incumbent fare responses to

LCC entry. While market power problems at large hub airports with a dominant carrier have been well studied by these papers, less attention has been shown to the price determination at smaller sized airports. An early study by the United States GAO (1996) documents regional differences in airfares at small-to-medium sized airports. Following deregulation, airfares in western states were generally found to be declining, while airfares in eastern states were generally increasing. The GAO attributes these differences to a greater frequency of entry by low-cost airlines in the western states. While lacking a formal model, the GAO suggests that low-cost carriers had avoided the eastern states during this earlier period because of "slower growth, airport congestion, and harsher weather" and because "one or two relatively high cost carriers have dominated the routes." Much has changed since 2000, however, because the east has become the area where most of the new LCC capacity is being deployed.[1]

Passengers' willingness to trade-off price and travel time is reported in Hartmann's (2000) study of consumer preferences for airline travel.[2] In this study, carriers set tickets prices to maximize market share regarding not only local travelers, but also those travelers who are willing to drive longer distance to purchase discounted fares. Using a discrete choice model, Hartmann estimates consumers' preferences for flying. Utility is defined as a function of flier and flight characteristics, e.g., flier income, ticket price, airport size, as well the distance and distance square traveled between the flier's MSA and the airport. This captures the trade-off fliers' face in their purchasing decisions, trading off cheaper flights for longer driving time to airports. The average flier is found to be willing to drive up to 8.6 miles to lower the ticket price by \$10.[3] Given that fliers are willing to drive some distance for cheaper flight options, it is hypothesized that airports do not

[1]See, for example, http://www.darinlee.net/data/lccnewcapacity.html.

[2]Hsu and Wu (1997) analyze another trade-off, the trade-off between passenger travel costs and carrier operating costs in determining the optimal market size for airports.

[3]The results are based on a 10% sample of all flights at the top 138 airports between 1986 and 1996.

operate in isolation, but rather are linked. This linkage is to be expected given the complicated network of flights carriers operate. Russon and Riley (1993) find evidence that airport substitutability determines passenger flows in the short haul market. Dresner et al. (1996) observe that Southwest's presence on a route lowers prices on routes entered as well as on adjacent routes at nearby airports. Morrison (2001) quantifies the aggregate spillover effect of Southwest entry on ticket prices. He distinguishes between actual, adjacent, and potential entry by Southwest.

Finally, Ishii et al. (2006) find evidence that passengers substitute between alternative San Francisco airports based upon the total travel time from their home or office to their destination. While business travelers view the time lost to flight delays and driving to an airport as equivalent, airport choices by tourist fliers are more dependent on the travel time to alternative airports. Although the literature has examined how the existence of alternative airports depress passenger volume and ticket prices, it has yet to explore how the differentials in overall fare levels across airports influence the performance of the affected airports in an explicit spatial econometric framework.

We postulate an alternative hypothesis concerning the regional differences in fares. We examine how fare differentials across alternative airports affect performance adversely at small-to-medium sized airports. Using ticket price and quantity data from the U.S. Department of Transportation's Origin and Destination Survey, a panel of entry decisions for 16 quarters is constructed to investigate this link between performance and fare differentials.

3. The Implications of Airport Substitution for Competition and Performance

A key indicator of the attraction of a local airport for airline entry is manifested in the tendency of travelers to seek out lower fares in neighboring airports. To illustrate the approach taken here to identify if this is true, consider the situation facing travelers from Birmingham, Al,(BHM) two-and-a-half hours drive from

Atlanta, Ga (ATL). There are potential cost savings to Birmingham travelers who eschew the local airport and buy lower-priced tickets out of Atlanta, a larger nearby hub airport. [4]

To get an appropriate comparison of fare options **across the two airports**, we first analyze the travel destinations of Birmingham passengers, identifying the most frequent destinations for trips exceeding 500 miles and which are among the largest 50 American cities. We then construct a weighted average cost of flying out of Birmingham to this set of destinations, $FI_{BHM,t}$, weighted by the share of Birmingham passengers traveling to each destination. The weighted cost of this bundle of airline tickets to the same destinations starting from the alternative airport (Atlanta), $FI_{ATL,t}$, is also calculated and the average differential, between airports. In general, for any airport r and its best alternative airport k, $FD_{rt} = FI_{r,t-1} - FI_{k,t-1}$ denotes the lagged fare differential at airport r.

To get a better sense of what this measure implies, for the moment let us express the average fare differential in terms of *per hour of driving time*, although in the empirical models we do not make this adjustment. FD_{rt} is shown in Figure 1 for these airports over a period of 16 quarters (1996-1999). Thus, from Figure 1, one can see that Birmingham passengers on long trips are typically rewarded with savings of about $60-$80 per hour for the extra time spent driving to the Atlanta airport. [5]

[INSERT FIGURE 1 HERE, Caption: Airline fare differentials, per driving hour, Birmingham to Atlanta]

This large average fare differential provides substantial incentives for passengers with elastic demands and relatively low value of time to drive to Atlanta. It is not

[4]Fares out of Atlanta may be subject to market power distortions because it is a major hub and has a dominant carrier, Delta. (Borenstein, 1989). Nonetheless, ATL still provides pricing advantages relative to options available at BHM. As shown in Table 1, the mean fare index on the top 50 destinations out of BHM was $174 higher than the same bundle of itineraries out of ATL.

[5]The line drawn in the figure and in those that follow is a Loess line plot, a nonparametric smoothing technique attributed to Cleveland and discussed in Härdle(1990) and implemented in Axum 6.0 software.

difficult to see how the presence of fare differentials might siphon travelers from local airports to distant ones. If this pattern occurs more generally than BHM to ATL, it raises the question as to why fares are high in small-to-medium size airports, relative to large airports or hubs. First, if fares at the alternative airport are competitively determined, but the local airport is imperfectly competitive, fares may reflect market power. This explanation begs the question of why local market power could persist, since the local carriers should view fares at the distant airport as a limit price that they could effectively negate by pricing low enough to retain the local travelers. In addition, high fare differential should be a strong attraction for new carriers offering service out of the local airport. Indeed, the Birmingham airport depicted in Figure 1 saw entry in the form of a substantial expansion of routes served by Southwest Airlines beginning in the eleventh quarter (Q3 1998). It appears that this development had a dampening effect on fare differentials for that airport. One would expect, moreover, that decreases in fare levels and fare differentials following entry would be accompanied by an expansion in carrier performance indicators such as local passenger volume and revenues as well. This would be an interesting test of the market-expanding effect of entry, in contrast to other industries where the business-stealing effect predominates.

Local carriers' failure to respond to fare discounts prevailing in the alternative airport can adversely affect their costs of providing air service. Local carriers have an incentive to avoid this problem. Allowing travelers to be siphoned away from the local airport may make the scale of operations too small to achieve minimum efficient scale with the residual population. Nevertheless, differences in the cost of service at the local airport may explain some portion of the observed fare differentials. For example, costs of round trip fares to a given destination may be naturally higher at the local airport if service entails an additional connecting flight in the itinerary, compared to direct flights available out of the alternate, large hub. Thus, even in a zero profit competitive equilibrium, fare differentials can exist in which local patrons receive the added convenience of a "door-to-door" round trip by paying a premium to cover the higher costs.

Fare differentials like the example described above may not alone capture the potential profitability of a local market to potential carriers. It would be useful to control in the model for other determinants that cause fares to diverge in pairs of nearby airports. For instance, higher fare differentials are likely to prevail in northern states during winter season because the danger of driving in winter weather would deter the kind airport substitution envisioned here. Moreover, it is unclear whether fare differentials are high enough to justify the inconvenience of adding an extra driving leg to a trip.

In communities with high-income demographics, it is reasonable that the normal income elasticity effects will limit the number of passengers willing to accept additional inconveniences to obtain low or modest levels of cost savings. Moreover, empirical fare differential estimates such as $FD_{r,t}$ may be downward biased measures of the true time cost savings. If one drives to a large, nearby airport, there may be additional savings in terms of total time in transit in the air transport corridor. For example, the large hub may offer direct service that avoids waiting time en route, thus offsetting some of the driving time.

A more complete assessment would factor in parking costs and potential alternatives like limousines[6] that may be important. Parking fees could be an appreciable factor at congested airports. For the current study, many of these variables are not available in the data and will be proxied by the use of airport-specific fixed effects.

Timing issues are difficult to predict in this context. These issues include assumptions about how long is the delay in responses by passengers to changes in fare differentials, as well as the timing of adjustments that carriers might make to

[6]For example, Van Galder, Inc. operates an economical service between Chicago O'Hare and Madison, Wisconsin. The one-way trip takes three hours instead of the estimated two hours of driving, but may be a preferred choice for some travelers out of Madison.

local traffic loads. A key assumption will be that there are substantial, unmeasured fixed determinants of the airlines' performance at an airport. These may include the adjustment of flight schedules and aircraft deployment, information costs, and a variety of location-specific entry costs, such as the rental of counter space, baggage handling, and landing gates. Consequently, we expect to observe a period of time in which high fare differentials have persistent effects on performance. Thus, in any given quarter, measures of performance, such as load factors and passenger volumes, will depend on lagged average fare differentials and other demand and supply side determinants.

4. Empirical Analysis

The current study uses price and quantity data from the Origin and Destination Survey and other data from the Domestic T100 Segment data administered by the Department of Transportation (DOT). The Origin and Destination data contain a 10 percent sample of domestic air passenger fares with pertinent information about the passenger's itinerary, carrier and airports. The first step in our analysis is to select a sample of airports meeting certain criteria. First, the airports are located in areas designated "medium or small air traffic hubs".[7] The DOT constructs geographic areas into "air traffic hubs" based on the percentage of U.S. passengers enplaned within. These areas may contain several airports. Large hubs encompass one percent or more of U.S. enplaned revenue passengers, or at least 5.9 million passengers in the local area. The medium or small airports record at least 1.5 million and 294 thousand enplaned revenue passengers, respectively. These latter airports would rank below the top 50 in size. Second, to be included, airports must have a nearby alternative airport, larger than itself and within 200 miles driving

[7]Although the FAA uses the terminology large, small and medium sized "hub", those distinctions somewhat confusing and misleading. If hubs are taken to be airports where passengers make connections (DFW, ATL, ORD, etc.), the FAA's notion of a "small-to-medium hub" includes airports where in fact no connections take place. We will refer to the latter as simply"small-to-medium airports."

distance from it. Given these criteria, there are 65 focal airports in the final sample. A complete list of airports is shown in Table 7 at the end of the paper.

The construction of the fare differentials in this sample also require a number of operational assumptions. First, noting that business and first class travelers would be less likely to be price sensitive regarding alternative airport opportunities, we limit our sample to economy-class fares.[8] Moreover, we find that the distribution of fares is such that the average fares are generally higher and more dispersed than median fares. An example is shown in Figure 2 for the two alternative airports for Des Moines (DSM), Omaha (OMA) and Kansas City (MCI).

Third, we find that for our focal airports, there are up to four alternative airports falling within the (admittedly arbitrary) 200 miles distance adopted here.[9] Thus, our initial analysis pairs up the focal airport with the alternative airport providing the best reported fare differential in the data. For the example above, if it appears that Omaha yields a higher return as an alternative, it is chosen for our empirical analysis. To be precise, in determining which airport is the best alternative, we impute a full cost measure of the bundle of flight destinations from the focal market by adding a travel time cost to the calculated cost of the bundle at each alternative. The value of time is assumed to be 30 dollars per hour. The best alternative is chosen as the airport that minimizes the full cost of the bundle, fare plus travel costs.

[INSERT FIGURE 2 HERE, Caption: Mean and median fare differentials between Des Moines Airport and its two alternatives, Omaha (OMA) and Kansas City (MCI)]

[8]The fares used in the empirical analysis to follow are not separated into "restricted" versus "non-restricted" fares, although there may be some advantages to consider separating them in the analysis. An exception is made for Southwest Airlines, since the data for this carrier reports all tickets as first class.

[9]Morrison (2001) found that defining markets including alternative airport origins or destinations using a 75 mile radius (as opposed to a 25, 50, 100, and 125 mile radius) had the best fit. Given that we are focusing solely on small-to-medium sized airports where consumers may drive farther distances to alternative airports, we believe it was best to increase the radius. Furthermore, extending the market radius to 200 will introduce little error to our estimation given that we identify the best alternative airport based on the lowest FD plus travel costs.

4.1. **Measuring entry.** It is interesting to examine episodes of new carrier entry into these smaller airports, since perhaps these occurrences are competitive responses to profit opportunities reflected in the fare differentials. Pure entry, the beginning of service by a carrier not currently operating at an airport, occurs relatively infrequently during the sample period for our selected localities. We focus on the share of total airport passenger revenues rather than the market shares on particular routes. Multi-market entry via route expansions is the usual pattern of airlines. Evidence of multiple, coordinated route expansions may be measured by the extent of routes serviced from the origin. For example, Southwest Airlines supposedly made a big expansion in its flight offerings out of Birmingham during this period. We look at Wall Street Journal articles to find evidence of route expansion episodes and search the data to verify that there were threshold changes in the airport market share of a major carrier, i.e. a share less than 1 percent rising in a single quarter to a level of more than 3 percent which is sustained in at least three successive quarters. Between 1996 and 1999, we identify 25 instances in which a major carrier entered a new airport or a national/regional carrier entered and achieved a substantial market share (3% or more) of overall passenger revenue.[10]

While there are too few events to do an extensive empirical analysis of the entry process, we hypothesize that fare differentials will decrease at airports following the introduction of new carrier entry. To illustrate with one pair of airports, Figure 3 gives the plot of changes in fare differentials between Manchester, NH and Boston, MA. The focal airport at Manchester (MHT) experiences entry in the 10th quarter, and this was followed by a rapid and substantial elimination of the differential in subsequent quarters.

[10]There are several instances in our data where a carrier expands its route offerings at an airport and becomes a "beefed-up" competitor. During the period 1996-1999, Southwest and Northwest Airlines are especially active in expanding their route offerings at a number of cities included in our sample. We also calculate the number of destinations serviced by carriers at each focal airport as an alternative basis for identifying this route-expansion form of entry. The method is intractable, however, because of the complexity of the service networks affected by expansion via indirect connections.

[INSERT FIGURE 3 HERE, Caption: Effect of Entry on Fare Differentials at Manchester (MHT) relative to Boston (BOS)]

4.2. **Market Structure, Demographic and Control Variables.** The variables used in our empirical analysis are defined in Table 2 and the summary statistics are shown in Table 3.

[INSERT TABLE 2 HERE, Caption: Variable Definitions]

[INSERT TABLE 3 HERE, Caption: Summary Statistics]

Local market structures at the medium-to-small airports display a high degree of variation in market shares because of the presence of numerous, small commuter lines and the incidental presence of charter flights by major carriers outside the market. We calculate the presence at the airport of a major carrier by including only those that achieve a market share of 3 percent or higher in a given quarter. This variable is used for carrier-specific fixed effects and to identify the presence of a low cost carrier at the airport, *low cost*.

The variation in market shares suggests that structure may be best captured with the Herfindahl index calculated from revenues reported by every carrier with tickets originating at the local airport. Note that reported revenues are an estimate of actual revenues; they are constructed from the 10 percent Origin and Destination sample. It is not known whether biases may be introduced by non-randomness in the reporting. For example, all major carriers have established affiliations with regional and local airlines to service routes to and from smaller airports for them. We construct the Herfindahl index, *HHI*, while noting that, for commuter/regional carriers that are affiliated with others, all revenues for the carrier are attributed to the major carrier (if present in the market) in the affiliation. Additional control variables include an index of the price of jet fuel, *jet fuel*,[11] an index of gasoline

[11]Note that the average price paid for jet fuel is a function of long-term contracts, spot market prices, and point of sale (i.e., from which airport purchased). There are difficult timing issues involved in determining what relevant cost (the price of fuel today or the contracted price from a year ago) is affecting fares. Unfortunately, the jet fuel price index is the best publicly available data to proxy airline fuel expenses.

prices,*gas prices*, the logarithm of a quarterly population estimate for the metropolitan statistical area, *pop*, and an estimate of the personal income per capita in the MSA, *income*.[12] Finally, time-specific fixed effects are constructed for the panel models.

5. The Econometric analysis of Spatial Correlation in Fare Indexes

We begin with estimates of a fare index model that allows for spatial correlation and spatial autoregressive errors between each local airport and its nearby alternative. Traditional panel data models that allow temporal and cross-sectional fixed effects may be extended to include spatial correlation in the dependent variable or errors. A model allowing spatial autocorrelation in the dependent variable, the Spatial Autoregressive (SAR) model may be written as:

$$FI_t = \rho W FI_t + \alpha + \delta_t + X_t\beta + \varepsilon_t \tag{1}$$

where FI_t denotes the R×1 vector of observations on the dependent variable, the fare index, for each of the R airports at time period t, X_t denotes the R×k matrix of observations of k regressors for each of the R airports at period t, and ε_t denotes the R×1 vector of errors at time t. The R×R matrix W is the spatial contiguity matrix that indicates the correspondence between focal and alternative airport pairs in this study. The coefficient ρ is the spatial correlation coefficient. The R×1 vector α contains the airport-specific fixed effects, and the scalar δ is the temporal fixed effect.

A similar model allowing spatial error correlation, the Spatial Error Model (SEM), may be written as:

$$FI_t = \alpha + \delta_t + X_t\beta + \eta_t \tag{2}$$

where

$$\eta_t = \rho W \eta_t + \varepsilon_t \tag{3}$$

[12]Income data are linear extapolations from data available at the REIS website at http://www.ciesin.org/datasets/reis/reis-home.html.

As with the SAR model, the matrix W is the spatial contiguity matrix and ρ is the spatial correlation coefficient. In both models, ε_t is assumed to have zero mean and covariance matrix $\sigma^2 I_R$.

Elhorst (2003) considers estimation of spatial panel data models. The usual properties of ML estimates are dependent on the form of the contiguity matrix. The ML estimator of β is consistent and asymptotically normal for the common cases of a binary contiguity matrix and an inverse distance contiguity matrix. Furthermore, spatial panel models have the usual incidental parameters problem. That is, if the number of time periods is fixed, allowing the number of cross-section units to go to infinity is not sufficient to insure the consistency of the estimate of α. Consistency of the estimates of α and δ requires both the number of cross-sections and the number of time periods to go to infinity. Fortunately, as with the standard linear panel models, this inconsistency does not spill over to the estimates of the coefficients β.[13]

6. Effects of airport substitution on performance

We turn next to the effect of fare differentials on the cost performance of airlines operating at our 65 focal airports. The issue is whether the siphoning of passengers by alternative airports results in reduced efficiency at the focal airport.

6.1. **Cost Performance at the Smaller Airport Market.** Our hypothesis is that the load factors, LF_{rt}, are depressed in areas most affected by "drive-to-fly" behavior. Airlines may face adjustment costs in reconfiguring the deployment of aircraft and be saddled with larger planes than needed, for some period of time. In our model, we transform the load factor into logits, and estimate logistical regressions with panel features.

Alternatively, the performance effect may be reflected in reduced passenger volume from the airport, Pax_{rt}, or in reduced total passenger revenue, TR_{rt}. In

[13] *Matlab* programs for estimation of both the SAR and SEM models is available on Professor James P. LeSage's web site at www.spatial-econometrics.com.

summary, to get at the issue of how cheaper alternative airports affect the cost performance in the focal airport, we estimate these alternative models:

$$LF_{rt} = \alpha_r + \delta_t + \beta_0 FD_{rt} + \beta X_{rt} + \varepsilon_{rt} \tag{4}$$

$$Pax_{rt} = \alpha_r + \delta_t + \theta_0 FD_{rt} + \theta X_{rt} + \varepsilon_{rt} \tag{5}$$

$$TR_{rt} = \alpha_r + \delta_t + \theta_0 FD_{rt} + \theta X_{rt} + \varepsilon_{rt} \tag{6}$$

for $r = 1, ..., R$ and $t = 1, ..., T$. The time period for this study includes 16 quarters from 1996 to 1999. The α_r are the airport-specific effects and the δ_t are the time-specific effects. For any airport r and its best alternative airport k,

$$FD_{rt} = FI_{r,t-1} - FI_{k,t-1} \tag{7}$$

denotes the lagged fare differential at airport r, and X_{rt} denotes regressors with both airport and time variation. The typical estimation procedure is to difference each observation from its temporal sample mean in order to eliminate the airport-specific effects from the estimating equation, and to include a set of temporal dummy variables to capture the time-specific effects. This estimating equation produces the familiar "difference-in-difference" estimator for the restricted case of two time periods and no regressors.

7. Results

7.1. **Spatial econometric model of airport substitution.** The first general question is what determines the level of fares observed in the data? We approach this first question because it may be that market structure or other variables are driving the observed fare indexes. Table 4 reports panel regression model based on three models of what drives fare levels: ordinary least squares and two different models incorporating the spatial econometric features. We include the OLS estimates to have a baseline comparison for the spatial econometric specifications. Indeed, while the point estimates vary to some degree, the reported signs of the coefficients are remarkably constant across the three estimation procedures.

[**INSERT TABLE 4 HERE, Caption: Estimates of Spatial Panel Models of the Fare Index**]

Covariates in the model are mostly significant. The mean fare is found to be negatively and significantly related to the Herfindahl index. The coefficient of the weighted load factor is negative and significant in both models. Airport market density, as proxied by the local population, is negatively related to the fare index, and we find that the presence of a low cost carrier is associated with a significantly lower level of fares. Both these results reflect the local cost shifters in providing service out of the airport and are consistent with earlier studies.

The positive effect of gasoline prices suggests that fares are higher in the face of high fuel prices, although the coefficient of the jet fuel price index is unexpectedly negative and significant. The negative coefficient may be a statistical artifact owing to its high correlation with the gasoline price index.[14]

The proper interpretation of the coefficient of jet fuel is the marginal effect of an increase in jet fuel prices given constant gas prices: factors that have a differential impact on jet fuel relative to gas prices are being measured by the coefficients.[15] Gas prices capture variations in the implicit travel costs to an alternative airport and would affect passenger demand, reflecting changes in their disposable income

[14]As one might expect, there is a very strong correlation (0.87) between jet fuel and gas prices. Goldberger (1991) argues that "Researchers should not be concerned with whether or not 'there really is collinearity.' They may well be concerned with whether the variances of the coefficient estimates are too large – for whatever reason – to provide useful estimates of the regression coefficients." By this standard, the high correlation does not induce a "multicollinearity problem," since the coefficient estimates of these variables are extremely precise (p-values below 0.001). In any event, the estimated impacts associated with the focus variables in this study were robust to alternative specifications involving various combinations of the fuel variables.

[15]The fact that the average price paid for jet fuel is a function of long-term contracts, spot market prices, and point of sale could explain why the coefficient on jet fuel price index is negative. Unfortunately, the jet fuel price index may not capture the correct timing of when costs are incurred and their effect on fares; it is, however, the best publicly available data to proxy airline fuel expenses.

or confidence in the economy and consequently their willingness to pay. Fuel prices, on the other hand, represent a input cost driver for the carriers and capture changes in production.

In order to include a complete set of carrier, temporal and airport fixed-effects dummies, there are 159 parameters, while the sample contains 2080 observations. Nevertheless, the fixed effects are also highly statistically significant and an important control for time invariant sources of unobserved variation in the airports.

The spatial econometric models are reported in Table 4 as well. These results are important because they confirm a tight economic linkage between the 65 local airports and best alternative near-by airports. The estimated spatial correlation coefficient is approximately 0.5 in both the SAR and SEM models. Recall that the SAR model is one allowing spatial autocorrelation in the dependent variable explicitly, via the contiguity matrix that identifies the spatially-lagged influence of fare levels at the larger airports on its neighboring small-to-medium airport. The SEM model works by allowing spatial error correlation.

No matter how one models the process that generates fare differentials between alternative airports, the direction of the relationship is positive. The results suggest that a \$1 decrease in fares at the alternative airport results in less than a \$1 decrease in fares at the local airport. As the fares at the alternative airport become relatively cheaper, travelers have a greater incentive to drive to the alternative airport. Perhaps because of relatively low load factors and inefficient scale of operations prevailing at many smaller airports, the decreases in passenger volume will result in a less than proportional decrease in fares at the local airport. At least for price-sensitive travelers, driving-to-fly helps to drive equilibrium fares close together, as the high correlation between these fare indexes shows, be it in the spatial autogressive (SAR) model or the spatial error (SEM) model. We interpret this result to show that passengers are cognizant of travel discounts in the distant market and being siphoned away from the local airport when favorable differentials are available.

[INSERT TABLE 5 HERE, Caption: Panel Regression Estimates of Performance Models]

Table 5 reports the panel regression models aimed at measuring the cost performance effects of the fare differentials.[16] In these models we look at the effect of the one-quarter lagged fare differential directly on performance, under the assumption that price sensitive passengers respond to this differential by substituting the alternate airport in response. We find that a relatively high FD_{rt} in the previous quarter is highly significant in reducing the passenger volume and total revenue out of the focal airport, and it reduces the average load factors achieved by carriers as well. This result is striking and may explain in part the fact that these airports often remain unattractive for entrants, despite the high fares prevailing. Low passenger volume and load factors may imply added profit risks of entry, and slow the adjustment.

We turn next to the effect of carrier airport entry on the fare index itself. Of the 65 airports in our data, 25 airports present the opportunity to observe performance before and after entry has occurred. We restrict our next sample to quarterly observations on airports where entry is observed, as well as observations on their alternative airports and estimate again the models presented above in Table 4. Now we can examine the procompetitive effect on the fare index by adding a indicator variable for quarters after entry has occurred, *postentry*. Because the sample smaller,(*800 observations*), we do not include airport fixed effects. Thus, there is some sacrifice of detail in the model, but the results are indicative of what would likely be found in a much larger sample. Key results are reports briefly in Table 6. Across all the three models we employed earlier to explain fare index, the effect of entry is highly significant. Entry leads to a reduction in fare indexes, effects that are especially large after controlling for spatial effects that link the local airport with its alternative.

[16]Reported results are based on models with the mean fare differential; other results, not reported here, were based on median fare differentials and are qualitatively similar.

[INSERT TABLE 6 HERE, Caption: Spatial Panel Models of the Fare Index in Airports where Entry Occurred]

8. Conclusions

The concepts of mean and median fare differentials between pairs of alternative airports were introduced into our analysis for several purposes. First, they provide a ready measure of the attractiveness of distant airports to travelers who are willing and able to accept the time costs to receive lower fares. Likewise, these fare differentials indicate opportunities for new entrants to enter profitably. Our empirical analysis suggests that, in medium-to-small airports, there are important competitive effects of alternative airports. The fact that consumers are willing to drive some distance to purchase cheaper flight options links airports in price competition. Operation decisions at each airport are not made in isolation of pricing decisions made at alternative airports. When fare differentials are high, entry is more likely to occur in one form or another. Moreover the cost performance in the focal market suffers in terms of the passenger volume achieved and the load factors on flights emanating from the airport. Higher production costs and consequently higher ticket prices lead to a siphoning of business from the local airport toward the alternative larger airports. Airline carriers find themselves in a bad equilibrium. These conditions probably retard the rate of competitive entry, because of the additional risks of entry that may be perceived. If the fare differential becomes sufficiently large, then entry is encouraged, suggesting earnings are expected to be sufficient to offset the risk of low passenger volume.

Our results also shed light on why today we observe the opposite phenomenon, travel from large to smaller local airports. Carriers have begun to enter and/or expand their presence in secondary airports. For example, between 1996 and 2002, passengers flying out of Manchester Airport nearly quadrupled from .5 million to 1.85 million, while passengers flying out of Boston Logan Airport dropped 10 percent, down to 11 million. (Estabrook, 2003) Congestion and higher landing fees at large airports have raised the full cost, ticket price plus driving costs, reducing the fare differential. Increased passenger volume has raised load factors and lower production costs, making these airports more attractive for carrier entry.

A final aspect of fare differentials worth considering is that they may be a symptom of entry barriers that are not specified in the model. For example, Dresner et al. (2001) find that carrier yields rise with airport congestion and allocation of airport gates through exclusive use. Unfortunately, information on these entry barriers is publicly available only for medium and large airports.

It would be useful to extend this analysis to the question of what determines the entry and the equilibrium fare differentials in a cross section of airports similar to those included in our sample. If it were possible to extend the panel to a longer time frame, the effects of entry on these measures of fare differentials may be assessed using spatial panel econometric methods. Our short panel would not suffice to test the hypothesis that entry erodes the differential, for it requires a richer sample of entry events and enough periods before and after the entry event to estimate the model. Nevertheless, consistent with competitive theory, we find, in a limited set of observations on carrier airport entry, some evidence that entry is having the pro-competitive effect of reducing fare indexes in periods following carrier entry.

[**INSERT TABLE 7 HERE, Caption: Appendix: Complete List of Airports in Sample**]

Table 1. *Fare Differences at Alternative Airports for a fixed set of destinations from the Origin Airports*

Origin Airport		Alternative Airport		mean fare difference ($)	travel miles
Providence, RI	PVD	Boston	BOS	-77.791	60
Atlantic City	ACY	New York-JFK	JFK	-64.799	132
Colorado Springs	COS	Denver	DEN	-51.392	91
Newburgh NY	SWF	New York-JFK	JFK	-22.841	85
Islip long island	ISP	New York-JFK	JFK	-20.057	44
Manchester NH	MHT	Boston	BOS	-14.487	55
Allentown PA	ABE	Newark	EWR	8.23	75
Westchester-White Plains	HPN	New York-JFK	JFK	83.272	37
Burmingham, Al	BHM	Atlanta	ATL	174.441	149
Chattanouga	CHA	Atlanta	ATL	204.303	125
Albany, NY	ALB	New York-JFK	JFK	206.591	174
Melbourne Fl	MLB	Orlando	MCO	270.355	62
Jacksonville	JAX	Orlando	MCO	277.934	169
Greenville-Spartanburg	GSP	Atlanta	ATL	361.518	167
Columbia SC	CAE	Charlotte	CLT	368.972	101

Note: The mean fare difference is calculated, for the second quarter of 1998, as the difference between the (passenger-weighted index) mean airfare to the top 50 destinations from each origin airport and, for the same destinations, the index of mean airfare from the alternative airport.

Table 2. *Variable Definitions*

FI-mean	Lespeyre index of mean fares at the local airport
FI-median	Lespeyre index of median fares at the local airport
FD-mean	difference between mean fare indexes at the local and alternative airport, previous quarter
FD-median	difference between median fare indexes at the local and alternative airport, previous quarter
jet fuel	index of jet fuel prices
gas prices	index of gasoline prices
load factor	weighted load factor for flights originating at airport
market revenue	total revenue for flights originating at airport
low cost	binary for the presence of a low cost carrier at airport
HHI	Herfindahl index divided by 1000
pop	SMSA population (in thousands) at the local airport
income	SMSA per capita personal income (in thousands) at the local airport
Delta	binary indicating Delta serves airport
American	binary indicating American serves airport
Continental	binary indicating Continental serves airport
America West	binary indicating America West serves airport
Northwest	binary indicating Northwest serves airport
Trans World	binary indicating Trans World serves airport
United	binary indicating United serves airport
US Airways	binary indicating US Airways serves airport
Southwest	binary indicating Southwest serves airport

Table 3. *Summary Statistics*

Variable	Mean	Standard Deviation	Minimum	Maximum
FI-mean	324.175	110.857	41.509	566.449
FI-median	266.255	88.771	39.810	485.030
FD-mean	122.952	118.755	-140.478	393.041
jet fuel	57.088	10.647	37.500	74.400
gas prices	100.850	7.950	84.500	110.800
load factor	0.632	0.072	0.422	0.875
market revenue	4153177	4626167	24221	32600000
low cost	0.390	0.488	0.000	1.000
HHI	3.201	1.730	1.130	10.000
pop	2550.180	4888.418	113.823	21200.000
income	25.428	4.624	11.190	42.376
passengers	811.610	1425.411	10.313	9397.473
Delta	0.824	0.381	0	1
American	0.725	0.447	0	1
Continental	0.484	0.500	0	1
America West	0.194	0.395	0	1
Northwest	0.646	0.478	0	1
Trans World	0.400	0.490	0	1
United	0.635	0.482	0	1
US Airways	0.632	0.482	0	1
Southwest	0.180	0.384	0	1

Table 4. *Estimates of Spatial Panel Models of the Fare Index*

	Ordinary Least Squares			Spatial Autoregressive			Spatial Error Correlation		
Coefficient	Estimate	t-statistic	p-value	Estimate	t-statistic	p-value	Estimate	t-statistic	p-value
jet fuel	-2.094	-4.96	0.001	-0.620	-7.84	0.001	-0.858	-9.821	0.001
gas prices	1.680	4.280	0.001	0.537	5.661	0.001	0.692	6.546	0.001
load factor	-49.828	-4.510	0.001	-71.938	-7.536	0.001	-88.443	-9.022	0.001
low cost	-6.699	-3.410	0.001	-6.163	-3.180	0.001	-5.357	-2.869	0.004
pop	-0.028	-3.780	0.001	-14.596	-2.007	0.045	-28.076	-3.788	0.001
income	3.137	2.870	0.004	3.533	9.098	0.001	4.761	11.440	0.001
HHI	5.428	6.220	0.001	5.050	5.939	0.001	5.951	6.689	0.001
Delta	7.006	2.690	0.007	8.796	3.411	0.001	12.448	4.739	0.001
American	9.835	4.580	0.001	7.420	3.605	0.001	7.172	3.511	0.001
Continental	-3.578	-1.560	0.119	-6.430	-2.829	0.005	-3.280	-1.490	0.136
America West	7.615	2.520	0.012	8.348	2.810	0.005	10.135	3.590	0.001
Northwest	-1.393	-0.550	0.583	-6.621	-2.639	0.008	-5.278	-2.132	0.033
Trans World	-2.857	-0.690	0.490	-4.028	-0.981	0.327	-2.791	-0.729	0.466
United	3.936	1.420	0.156	3.365	1.227	0.220	2.914	1.083	0.279
US Airways	-20.222	-6.720	0.001	-13.671	-4.548	0.001	-15.534	-5.295	0.001
Southwest	3.671	1.730	0.084	0.454	0.227	0.820	-2.134	-1.105	0.269
ρ	0	–	–	0.571	20.146	0.001	0.538	24.535	0.001

Note: Dependent variable is FI-mean for all specifications. Estimates of temporal and cross-sectional fixed effects have been suppressed.

Table 5. *Panel Regression Estimates of Performance Models*

	Logit of Load Factor			Passengers			Market Revenue		
Coefficient	Estimate	t-statistic	p-value	Estimate	t-statistic	p-value	Estimate	t-statistic	p-value
FD-mean	-0.001	-2.690	0.007	-0.54	-9.660	0.000	-1.789	-6.130	0.000
jet fuel	-0.011	-4.560	0.000	-0.20	-0.440	0.657	-2.380	-1.040	0.297
gas prices	0.015	3.890	0.000	0.34	0.460	0.643	9.782	2.610	0.009
low cost	0.032	0.960	0.339	11.44	1.860	0.063	48.407	1.520	0.129
pop	0.000	-0.350	0.728	0.05	1.690	0.091	-0.001	-6.930	0.000
income	0.000	1.180	0.239	-6.16	-1.800	0.072	0.150	8.470	0.000
HHI	0.000	0.820	0.412	-1.89	-0.800	0.426	0.004	0.300	0.762
Delta	0.013	0.360	0.719	6.56	1.000	0.318	-78.571	-2.310	0.021
American	0.096	3.080	0.002	2.93	0.510	0.607	11.363	0.380	0.701
Continental	0.034	0.910	0.364	21.67	3.120	0.002	44.363	1.230	0.218
America West	-0.145	-2.430	0.015	-20.22	-1.840	0.066	34.841	0.610	0.540
Northwest	0.180	4.880	0.000	14.09	2.080	0.038	14.16	0.400	0.688
Trans World	-0.195	-2.670	0.008	-17.86	-1.340	0.182	322.570	4.660	0.000
United	0.050	1.270	0.204	16.36	2.270	0.023	0.870	0.020	0.981
US Airways	0.143	2.940	0.003	-13.91	-1.560	0.119	5.111	0.110	0.912
Southwest	-0.098	-2.370	0.018	31.46	4.160	0.000	467.231	11.920	0.000

Note: Dependent variable of each model listed in header. Estimates of temporal and cross-sectional fixed effects have been suppressed.

Table 6. *Spatial Panel Models of the Fare Index in Airports where Entry Occurred*

	Post-entry period		
	Estimated effect	t-statistic	p-value
Fare Index Models:			
OLS panel with carrier fixed effects	-4.075	-1.62	0.105
OLS panel with temporal and carrier fixed effects	-5.045	-1.94	0.053
SAR with carrier fixed effects	-8.245	-1.899	0.0575
SAR with temporal and carrier fixed effects	-8.477	-2.329	0.02
SEM with only carrier fixed effects	-18.671	-4.913	0
SEM with temporal and carrier fixed effects	-18.21	-4.828	0

Note: Dependent variable is FI-mean for all specifications. Models are specified with explanatory variables as reported in Table 4, except as noted for fixed effects. There are 25 entry events and 800 observations used.

Table 7: *Appendix: Complete List of Airports in Sample*

Focal Airport		Alternate Airport		Travel Time	Travel Miles
Albany, NY	ALB	Boston	BOS	164	182
Albany, NY	ALB	New York-La Guardia	LGA	155	163
Albany, NY	ALB	Newark	EWR	187	197
Albany, NY	ALB	New York-JFK	JFK	167	174
Allentown PA	ABE	New York-La Guardia	LGA	100	96
Allentown PA	ABE	Newark	EWR	73	75
Allentown PA	ABE	New York-JFK	JFK	108	104
Allentown PA	ABE	Philadelphia	PHL	72	73
Amarillo Tx	AMA	Lubbock, Tx	LBB	129	124
Asheville, NC	AVL	Charlotte	CLT	127	111
Asheville, NC	AVL	Greenville-Spartanburg	GSP	66	53
Asheville, NC	AVL	Knoxville TN	TYS	146	136
Atlantic City	ACY	Newark	EWR	101	107
Atlantic City	ACY	New York-JFK	JFK	133	132
Atlantic City	ACY	New York-La Guardia	LGA	128	129
Atlantic City	ACY	Philadelphia	PHL	56	56
Bangor, Me	BGR	Portland	PWM	142	135
Baton Rouge	BTR	New Orleans	MSY	82	80
Bufffalo, NY	BUF	Cleveland	CLE	195	308
Bufffalo, NY	BUF	syracuse	SYR	121	140
Burlington Vt	BTV	Albany NY	ALB	175	158
Burmingham, Al	BHM	Atlanta	ATL	148	149
Cedar Rapids, IO	CID	Des Moines	DSM	124	132
Charleston, SC	CHS	Columbia	CAE	104	101
Chattanouga	CHA	Atlanta	ATL	129	125
Chattanouga	CHA	Knoxville TN	TYS	106	105
Colorado Springs	COS	Denver	DEN	89	91
Columbia SC	CAE	Charlotte	CLT	107	101
Columbia SC	CAE	Greenville-Spartanburg	GSP	111	107
Corpus Christie	CRP	San Antonio	SAT	134	148
Dayton, OH	DAY	Cincinnati	CVG	77	78

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Table 7 – continued from previous page

Focal Airport		Alternate Airport		Travel Time	Travel Miles
Dayton, OH	DAY	Columbia	CMH	75	79
Daytona Beach FL	DAB	Jacksonville	JAX	99	107
Daytona Beach FL	DAB	Melbourne	MLB	81	87
Daytona Beach FL	DAB	Orlando	MCO	69	65
Des Moines	DSM	Kansas City	MCI	179	189
Des Moines	DSM	Omaha	OMA	132	143
Eugene Or	EUG	Portland	PDX	120	128
Fresno, Ca.	FAT	Oakland	OAK	173	174
Fresno, Ca.	FAT	San Francisco	SFO	193	189
Fresno, Ca.	FAT	San Jose	SJC	165	157
Ft. Meyers	RSW	Ft Lauderdale	FLL	134	133
Ft. Meyers	RSW	Miami	MIA	148	147
Ft. Meyers	RSW	Tampa FL	TPA	135	143
Ft. Meyers	RSW	West Palm Beach FL	PBI	161	129
Ft. Wayne In	FWA	Indianapolis	IND	147	138
Grand Rapids	GRR	Chicago-Midway	MDW	191	189
Grand Rapids	GRR	Detroit	DTW	135	151
Greensboro, NC	GSO	Charlotte	CLT	104	101
Greensboro, NC	GSO	Raleigh-Durham	RDU	76	79
Greenville-Spartanburg	GSP	Atlanta	ATL	167	167
Greenville-Spartanburg	GSP	Charlotte	CLT	94	91
Greenville-Spartanburg	GSP	Columbia	CAE	112	107
Harlingen, Tx	HRL	Corpus Christie	CRP	163	129
Harrisburg-Middletown	MDT	Baltimore Washington International	BWI	98	96
Harrisburg-Middletown	MDT	Philadelphia	PHL	112	111
Huntsville, Al	HSV	Burmingham, Al	BHM	94	96
Huntsville, Al	HSV	Nashville	BNA	124	126
Islip long island	ISP	Newark	EWR	81	72
Islip long island	ISP	New York-JFK	JFK	52	44
Islip long island	ISP	New York-La Guardia	LGA	54	45

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Table 7 – continued from previous page

Focal Airport		Alternate Airport		Travel Time	Travel Miles
Jackson Miss	JSA	Baton Rouge	BTR	173	183
Jackson Miss	JAN	Memphis	MEM	187	211
Jackson Miss	JAN	New Orleans	MSY	173	186
Jacksonville	JAX	Orlando	MCO	163	169
Knoxville	TYS	Chattanooga	CHA	110	106
Lansing Michigan	LAN	Detroit	DTW	94	94
Lansing Michigan	LAN	Grand Rapids	GRR	54	56
Lexington Ky	LEX	Cincinnati	CVG	95	89
Lexington Ky	LEX	Louisville, Ky	SDF	78	75
Little Rock	LIT	Memphis	MEM	132	145
Louisville, Ky	SDF	Cincinnati	CVG	98	104
Louisville, Ky	SDF	indianapolis,IN	IND	136	130
Lubbock, Tx	LBB	Amarrillo	AMA	133	126
Lubbock, Tx	LBB	Midland Tx	MAF	193	163
Madison, Wisc	MSN	Chicago-Midway	MDW	144	153
Madison, Wisc	MSN	Chicago-Ohare	ORD	122	135
Madison, Wisc	MSN	Milwaukee	MKE	79	83
Manchester NH	MHT	Boston	BOS	60	55
Manchester NH	MHT	Portland	PWM	106	96
McAllen Tx	MFE	Corpus Christie	CRP	193	161
McAllen Tx	MFE	Harlingen,Tx	HRL	48	40
Melbourne Fl	MLB	Ft Lauderdale	FLL	153	161
Melbourne Fl	MLB	Orlando	MCO	65	62
Melbourne Fl	MLB	West Palm Beach FL	PBI	111	114
Midland Tx	MAF	Lubbock, Tx	LBB	198	167
Mobile AL	MOB	New Orleans	MSY	174	150
Mobile AL	MOB	Pensacola	PNS	88	70
Myrtle Beach	MYR	Charleston, SC	CHS	126	103
Myrtle Beach	MYR	Columbia	CAE	188	159
Newburgh NY	SWF	New York-La Guardia	LGA	83	75

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Table 7 – continued from previous page

Focal Airport		Alternate Airport		Travel Time	Travel Miles
Newburgh NY	SWF	Newark	EWR	86	77
Newburgh NY	SWF	New York-JFK	JFK	95	85
Norfolk, Va	ORF	Washington National	DCA	186	190
Oklahoma City	OKC	Dallas-Ft Worth	DFW	184	200
Oklahoma City	OKC	Dallas-Love	DAL	182	204
Oklahoma City	OKC	Tulsa OK	TUL	119	127
Omaha	OMA	Des Moines	DSM	128	142
Omaha	OMA	Kansas City	MCI	159	172
Palm Springs	PSP	Burbank	BUR	111	121
Palm Springs	PSP	Los Angeles	LAX	116	125
Palm Springs	PSP	San Diego	SAN	133	144
Palm Springs	PSP	Santa Anna	SNA	94	100
Pensacola	PNS	Mobile AL	MOB	85	70
Portland, Me	PWM	Bangor, Me	BGR	142	136
Portland, Me	PWM	Boston	BOS	108	103
Providence, RI	PVD	Boston	BOS	64	60
Providence, RI	PVD	New York-La Guardia	LGA	161	167
Richmond	RIC	Dulles International	IAD	126	129
Richmond	RIC	Norfolk	ORF	88	86
Richmond	RIC	Washington National	DCA	111	113
Roanoake, Va	ROA	Greensboro	GSO	124	102
Roanoake, Va	ROA	Richmond	RIC	197	193
Rochester	ROC	Buffalo	BUF	59	61
Rochester	ROC	Syracuse	SYR	83	93
Sarasota	SRQ	Ft. Meyers	RSW	99	94
Sarasota	SRQ	St. Petersburg-Clearwater	PIE	57	44
Sarasota	SRQ	Tampa FL	TPA	68	53
Savanna, Ga	SAV	Charleston, SC	CHS	125	110
Savanna, Ga	SAV	Jacksonville	JAX	133	128
South Bend In	SBN	Chicago-Midway	MDW	93	93

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Focal Airport		Alternate Airport		Travel Time	Travel Miles
South Bend In	SBN	Chicago-Ohare	ORD	105	109
Springfield, Mo	SGF	St Louis	STL	198	224
St. Petersburg, FL	PIE	Orlando	MCO	104	102
St. Petersburg, FL	PIE	Tampa FL	TPA	24	17
Syracuse	SYR	Albany NY	ALB	128	145
Syracuse	SYR	Buffalo	BUF	123	141
Syracuse	SYR	Rochester	ROC	84	93
Tallahassee FL	TLH	Jacksonville	JAX	182	184
Tucson	TUS	Phoenix	PHX	112	120
Tulsa	TUL	Oklahoma City	OKC	119	127
Westchester-White Plains	HPN	New York-La Guardia	LGA	36	30
Westchester-White Plains	HPN	Newark	EWR	55	49
Westchester-White Plains	HPN	New York-JFK	JFK	45	37
Witchita Ks	ICT	Kansas City	MCI	193	215
Witchita Ks	ICT	Oklahoma City	OKC	150	173
Witchita Ks	ICT	Tulsa OK	TUL	173	189

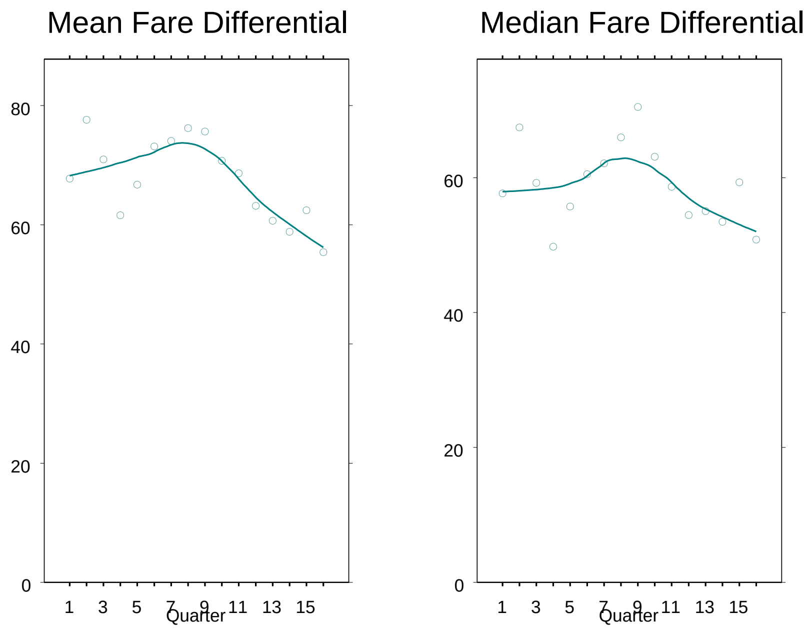

FIGURE 1. Airline fare differentials, per driving hour, Birmingham to Atlanta

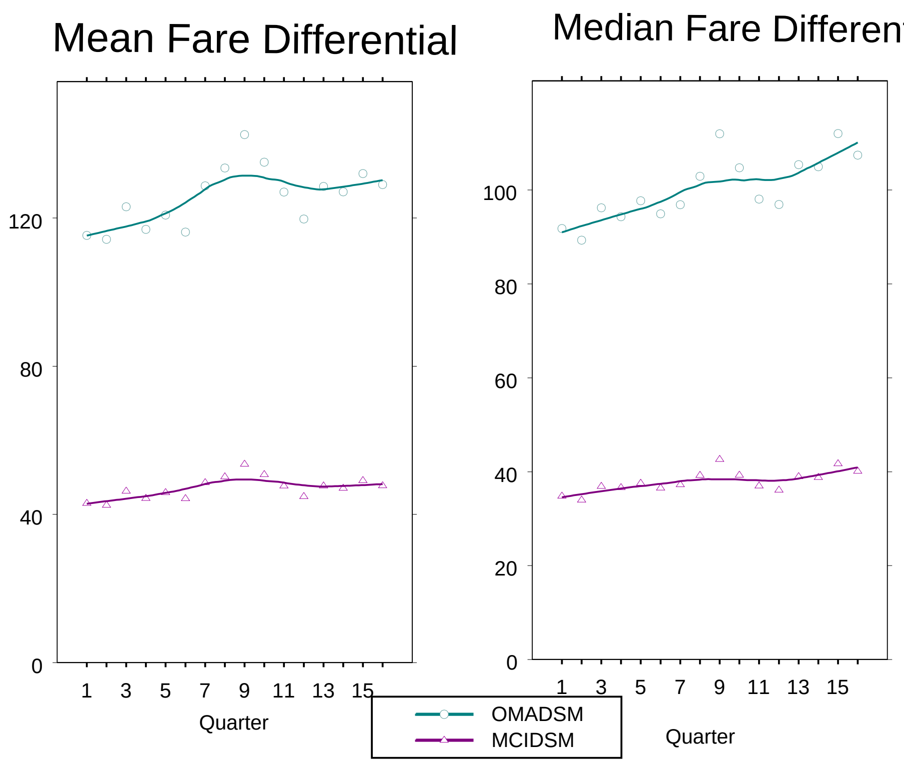

FIGURE 2. Mean and median fare differentials between Des Moines Airport (DSM) and its two alternatives, Omaha (OMA) and Kansas City (MCI)

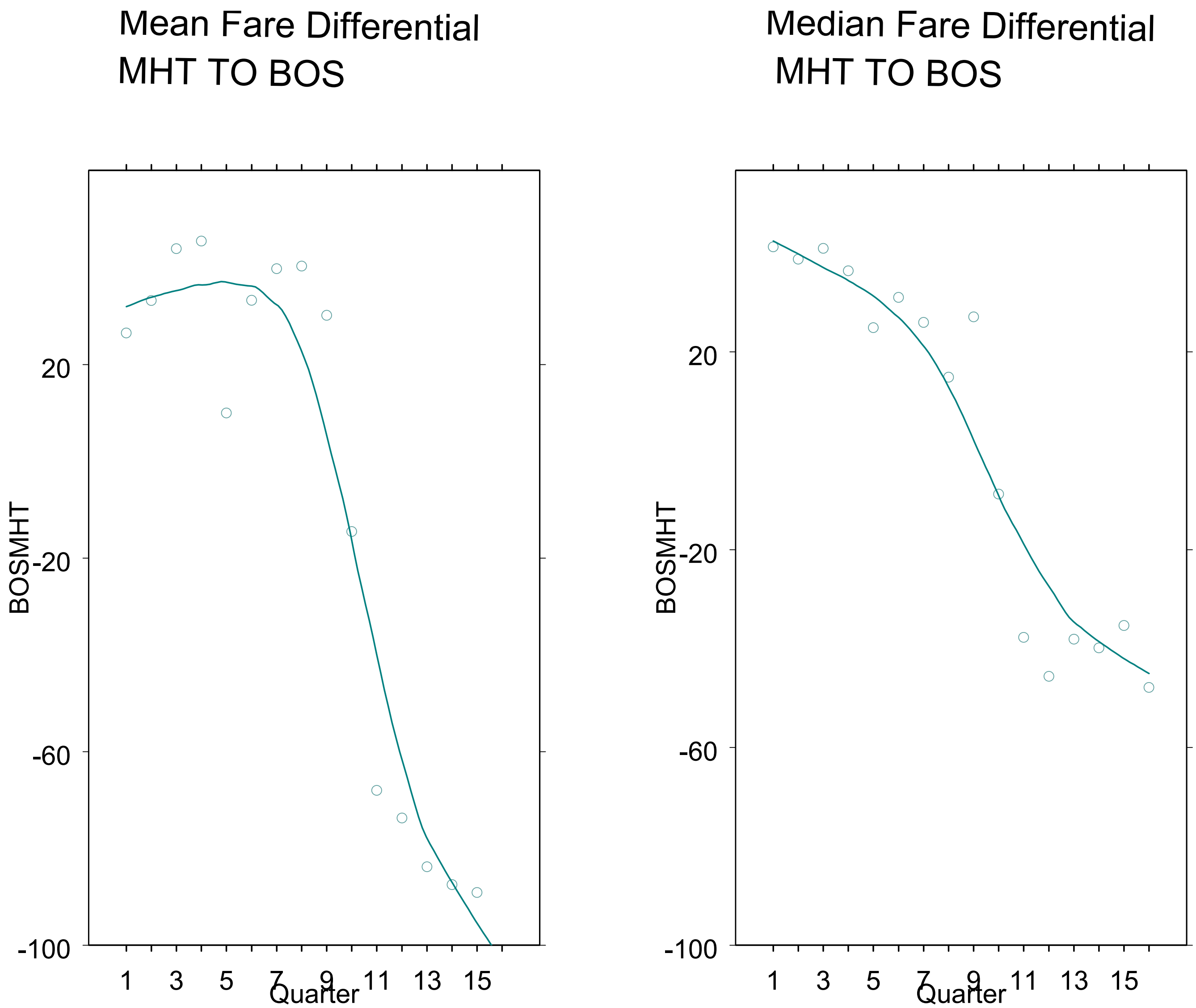

Figure 3. Effect of Entry on Fare Differentials at Manchester (MHT) relative to Boston (BOS)

References

[1] Bamberger, G. and D. Carlton. "Predation and the Entry and Exit of Low-Fare Carriers," in Darin Lee (Ed.) Advances in Airline Economics, Volume 1: Competition Policy and Antritrust, April 2006, Elsevier Science, Amsterdam.

[2] Beck, N. and J. N. Katz, 1995. "What to do (and not to do) with time-series cross-section data." *American Political Science Review* 89: 634-647.

[3] Berry, Steven T. "Estimation of a Model of Entry in the Airline industry." *Econometrica.* Vol. 60, No. 4 (July 1992), 889-917.

[4] Borenstein, Severin. "Hubs and High Fares: Dominance and Market Power in the U.S. Airline Industry," *The RAND Journal of Economics*, Vol 20, No. 3 (Autumn, 1989), 344-368.

[5] Borenstein, Severin and Nancy L. Rose,"Competition and Price Dispersion in the U.S. Airline Industry," *Journal of Political Economy* (1994), 653-683.

[6] Boguslaski, Charles, Harumi Ito and Darin Lee, "Entry Patterns in the Southwest Airlines Route System," *Review of Industrial Organization* 25: 317-350, 2004.

[7] Brueckner, Jan and Nichola Dyer, and Pablo Spiller. "Fare Determination in Airline Hub and Spoke Networks." *The Rand Journal of Economics*, Vol. 23, No. 3 (Autum1992), 309-333.

[8] Dresner, Martin, Jiun-Sheng Chris Lin, and Robert Windle. "The Impact of Low-Cost Carriers on Airport and Route Competition," *Journal of Transport Economics and Policy September*, 1996, pp. 309-328.

[9] Dresner, Martin, Robert Windle and Yuliang Yao."Airport Barriers to Entry in the U.S.," *Journal of Transport Economics and Policy,* 36(2), 2002, pp. 389-405.

[10] Elhorst, J. Paul. "Specification and Estimation of Spatial Panel Data Models," *International Regional Science Review*, 2003, pp. 244-268.

[11] Estabrook, Barry. "Smaller Airports Are Growing in Stature," *The New York Times*, December 21, 2003.

[12] Evans, William N. and Ioannis N. Kessides, "Localized Market Power in the U.S. Airline Industry, " *Review of Economics and Statistics* (1993),66-75.

[13] Goldberger, Arthur S. *A Course in Econometrics*. (Cambridge, MA: Harvard University Press) 1991.

[14] Goolsbee, Austan and Chad Syverson, "How Do Incumbants Respond to the Threat of Entry? Evidence from Major Airlines," *National Bureau of Economic Research Working Paper* 11072, January 2005.

[15] Green, William E. *Econometric Analysis*. 4th Edition.(Upper Saddle River, NJ: Prentice Hall) 2000.

[16] Hardle, W. *Applied Nonparametric Regression.*. Econometric Society Monographs. (Cambridge University Press: Cambridge UK) 1990.

[17] Hartmann, Monica E. "A Structural Model of Airline Safety." *Ph.D. Dissertation*, Department of Economics, University of Virginia, 2000.

[18] Hausman, Hall, and Griliches, "Economic Models for Count Data with an Application to the Patents-R*Econometrica* 52 (1984).909-938.

[19] Hsu, Chaug-ing and Yai-hui Wu, "The market size of a city-pair route at an airport," *Annals of Regional Science* Vol. 31 pp. 391-409 (1997).

[20] Ishii, Jun, Sunyoung Jun, and Kurt Van Dender (2005)."Air travel choices in multi-airport markets." *Unpublished Department of Economics and Institute of Transportation Studies Working Paper UCI-ITS-WP-05-3* University of California, Irvine.

[21] Ito, Harumi, and Darin Lee (2003a). "Low Cost Carrier Growth in the U.S. Airline Industry: Past, Present, and Future," *Unpublished,Department of Economics Working paper* Brown University, April 9, 2003.

[22] Ito, Harumi, and Darin Lee (2003b). "Incumbent Responses to Lower Cost Entry: Evidence from the U.S. Airline Industry," *Unpublished Department of Economics Working Paper* , Brown University, December 11, 2003.

[23] Morrison, Steven A. "Actual, Adjacent, and Potential Competition: Estimating the Full Effect of Southwest Airlines," *Journal of Transport Economics and Policy* Vol. 35, Part 2, May 2001 pp. 239-256.

[24] Morrison, Steven A. and Clifford Winston, 1990. "The Dynamics of Airline Pricing and Competition," *American Economic Review Papers and Proceedings* Vol. 80, Part 2, pp. 389-393.

[25] Reiss, Peter and Pablo Spiller. "Competition and Entry in Small Airline Markets." *Journal of Law and Economics* Vol. 32, No.2 (October 1992), 179-202.

[26] Russon, M.G. and N.F. Riley, "Airport Substitution in a Short Haul Model of Air Transportation," *International Journal of Transport Economics* Vol. XX - No. 2 June 1993.

[27] Transportation Research Board, National Research Council. *Entry and Competition in U.S. Airlines: Issues and Opportunities*. Special Report (Washington: National Academy Press) July 1999.

[28] Whinston, Michael D. and Scott C. Collins, 1992."Entry and Competitive Structure in Deregulated Airline Markets: An Event Study Analysis of People Express," *Rand Journal of Economics* Vol. 23, pp. 445-462.

[29] Windle, Robert and Martin Dresner, "Competitive Responses to Low Cost Carrier Entry," *Transportation Research Part E* (1999), 59-75.