

What Happened to Airline Market Power?

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September 3, 2012

Abstract: From 1990 to 2010, average U.S. domestic airfares declined by about one-third in real terms, while operating costs have changed very little. Three critical changes to the industry since deregulation have had a large influence on airfares: (i) the formation of hubs and the associated efficiencies and marketing power from hub dominance, (ii) the increase in average load factors, and (iii) the expansion of low-cost carriers. In this paper, I examine how these and other factors have contributed to the decline in airfares. I estimate the impact of cost, demand and market power indicators on the average price a carrier charges on a route. Grouping the 20-year estimation period into 4 sub-periods of 5 years each, I estimate the same equation for each of the sub-periods. I find evidence suggesting that the impact of airport dominance has greatly declined over the 20 years, with the direct impact becoming negative in the most recent period, 2006-2010. Similarly, I find that price premia for business-oriented routes have declined substantially in the last decade. These changes are estimated to possibly be as large as the impact of the dramatic cost shocks and load factor changes that have occurred over the 20-year period. The changes greater on the higher end fares than on low fares, and greater on the higher-priced routes, consistent with a decline in the exploitation of market power. I then examine changes in “share gap,” which is the differential share of passengers a carrier captures on a route depending on the airline’s competitive position in the customer’s origin city. In contrast to the price results, I find no decline in share gap in the recent period and no decline in its association with airport dominance, suggesting that customer loyalty to the local dominant airline remained as strong in recent years as in the 1990s.

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I. Introduction

From 1990 to 2010, average U.S. domestic airfares fell about one-third in real terms. Operating costs have varied over time, but the variation has been much smaller than the price change and has not been particularly well correlated with price changes over time. Three other critical changes to the industry since deregulation greatly influenced fares: (i) the formation of hubs and the associated efficiencies and marketing power from hub dominance, (ii) the increase in average load factors (which are likely due in part to hub operations), and (iii) the expansion of low-cost carriers. In this paper, I focus on explaining the price declines over this twenty-year period.²

I begin with some motivating analysis in section II that documents trends in the industry that might affect costs, demand and market power. I show that load factors increased steadily over this time. Low-cost carriers (LCC) expanded their market shares both within routes they already served and by expansion into new routes. However, prices fell nearly as much on routes with no LCC presence as on routes that LCCs entered during this period. And prices fell more on routes with no LCC entry than on routes that already had LCC presence in 1990. I also show that average price premiums at dominated airports have fallen since the late 1990s and that there is some evidence that airport dominance has declined. Finally, summary data suggest that the decline in prices from 1990-2010 was due to a downward narrowing of the distribution of average fares across routes: average price on routes at the low end of the distribution hardly changed at all, while routes on the high end of the distribution saw very large price declines.

Section III examines these effects econometrically. Following a well-traveled path of markup equation estimation in the airline industry, I estimate the impact of cost, demand and market power indicators on the average price a carrier charges on a route. The approach isn't novel, though I attempt to refine some of the variables that have been used in prior analysis. The primary contribution that I attempt to make is in examining the change in the estimates over time. Grouping the 20-year estimation period into 4 sub-periods of 5 years each, I estimate the same equation for each of the sub-periods. Though many of the factors have a fairly stable impact over time, I find evidence suggesting that market power has declined in the most recent sub-period, 2006-2010, compared to earlier periods. In particular, while the price impact of high market share on a route has remained about

² Borenstein (2011) shows that the decline from just after deregulation in 1979 until 1990 was about 10%. Unfortunately, data availability and reliability are not as good for that period, so I focus on the larger decline since 1990.

the same, the price impact of airport dominance appears to have declined substantially. The changes are found to be greater on the higher end fares than on low fares, consistent with a decline in the exploitation of market power.

Section IV takes a different approach to examining the evolution of market power by studying changes in “share gap,” which is the differential share of passengers a carrier captures on a route depending on the carrier’s airport dominance at the airport from which the customer originated. In contrast to the price results of section III, I find little or no decline in share gap in the most recent sub-period compared to the three earlier sub-periods and no decline in the association of share gap with airport dominance. I extend this analysis back to 1984, however, and show that the share gap phenomenon and its association with airport dominance were much weaker in the 1980s.

Thus, at this point in this research, I don’t offer a clear answer to the title question. From the markup equation analysis, it appears that airline market power, particularly from airport dominance, has declined in recent years – and that explains a significant share of the decline in real fares – but the share gap analysis yields a result that is hard to square with that view. I conclude in section V with some thoughts on future directions that might reconcile these findings.

II. Some Motivating Analysis

I focus on the period 1990-2010. In particular, I study the second quarter of each year which spans different seasonal weather and travel periods. Figure 1 shows the decline in an index of real airfares during this period.³ Of course, the price decline invites the question of cost changes. Figure 1 also presents an index of the real average cost per available seat-mile (ASM) for domestic service. It demonstrates that airline costs per seat-mile flown declined somewhat in the 1990s, but increased in the last decade to end the period at about the same level as 1990. The figure shows the impact of the fuel price rise in the 2003-2008 period and spike in the second quarter of 2008. But in aggregate, including fuel costs, the cost of flying a seat has changed fairly little, despite the fact that the scale of

³ The average price series presented in figure 1 is a modified Paasche price index. For each year, I estimate the regression $Fare = \gamma_0 + \gamma_1 \cdot D + \gamma_2 \cdot D^2 + \epsilon$ where D is the non-stop distance between the ticket origin and destination. For every trip in year t , I then calculate the fitted-value fare that would result from the regression for year $t - 1$. The ratio of the total actual fares paid in year t to the fares implied by the regression for year $t - 1$ indicates the change in real fares. All dollar figures discussed here are inflated to 2009 dollars. The results are quite similar using a Laspeyers index – essentially evaluating the change in total cost for the period $t - 1$ trips using a regression for year t . They are also fairly similar doing the same analysis for pairs of non-adjacent years, including comparing 1990 to 2010.

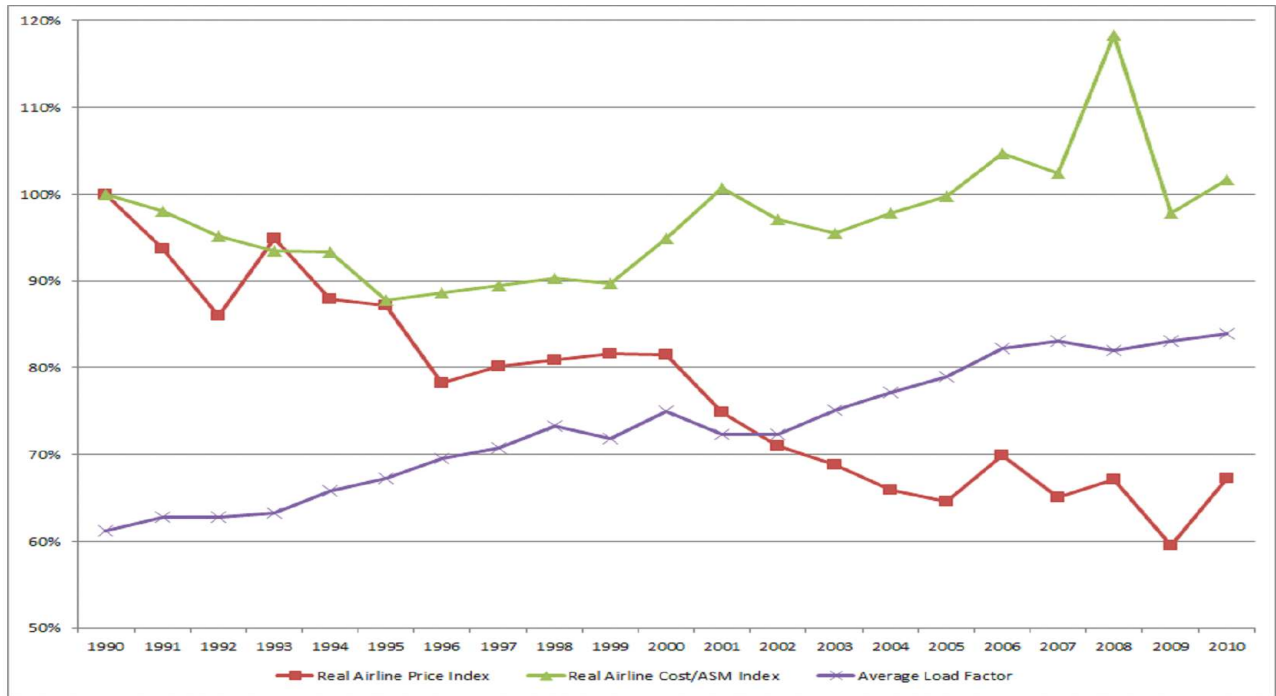


Figure 1: Changes in Average Price, Operating Cost/Available Seat-Mile, and Load Factor

the industry increased by about 20%.

That doesn't mean that costs per passenger or passenger-mile haven't changed. Figure 1 also shows that the average load factor – the share of seats filled – has increased steadily throughout this period, rising from 61% to about 84%. Since the majority of airline costs are fixed with respect to customers given the flight schedule – Borenstein and Rose (2008) suggest about 80% of costs are fixed once the flight schedule is set – this increase in load factor allows those costs to be spread over about one-third more customers.

The decline in average fares has been widely attributed to the expansion of low-cost carriers (LCCs), particularly Southwest, but also Jet Blue, Air Tran and others. Borenstein (2011) shows that the operating expenses per available seat-mile (ASM) of LCCs were 20% to 35% lower than the legacy airlines during this period. Figure 2 shows that low-cost carriers have expanded over this period, from 9% of passenger-miles in 1990 to 29% in 2010.⁴ Figure 2, also shows the percentage of passengers-miles flown on routes with LCC

⁴ While this trend has been nearly monotonic, there was a deviation in 2007 when America West, which had historically been considered a LCC, purchased and merged with the larger US Airways, which was among the highest-cost airlines. The combined airline, which took the US Airways name, has so far reported costs that put it solidly among the legacy airline costs.



Figure 2: Measures of Low-Cost Carrier Market Penetration

presence. This measure depends in part on whether one considers multiple airports in the same SMSA as part of the same market. Figure 2 presents the calculation both ways.

But LCCs are not the whole story, at least not as direct competitors. Figure 3 breaks out the change in average fares into 4 categories by LCC presence: routes with an LCC present in both 1990 and the observed year, routes with no LCC in 1990 or the observed year, routes with LCC “entry” (present in observed year, but not at beginning) and routes with LCC “exit” (present at beginning, but not in observed year). I use quotes here on entry and exit, because these categories do not consider LCC presence during the intervening years between 1990 and the observed year. So, each point reflects the change between 1990 and the observed year categorized by LCC presence in those two year. Figure 3 demonstrates that routes that experienced the entry of LCCs saw the largest fare decline (about 42%), but routes with no LCC presence also saw very substantial declines (32%), larger than on routes where LCCs were present throughout (24%), though the latter still had much lower fare *levels*.

LCC expansion is one piece of the larger argument that price declines have resulted in significant part from the decline in market power among the legacy airlines. Much of the market power concern has been at dominated airports. Market power associated with

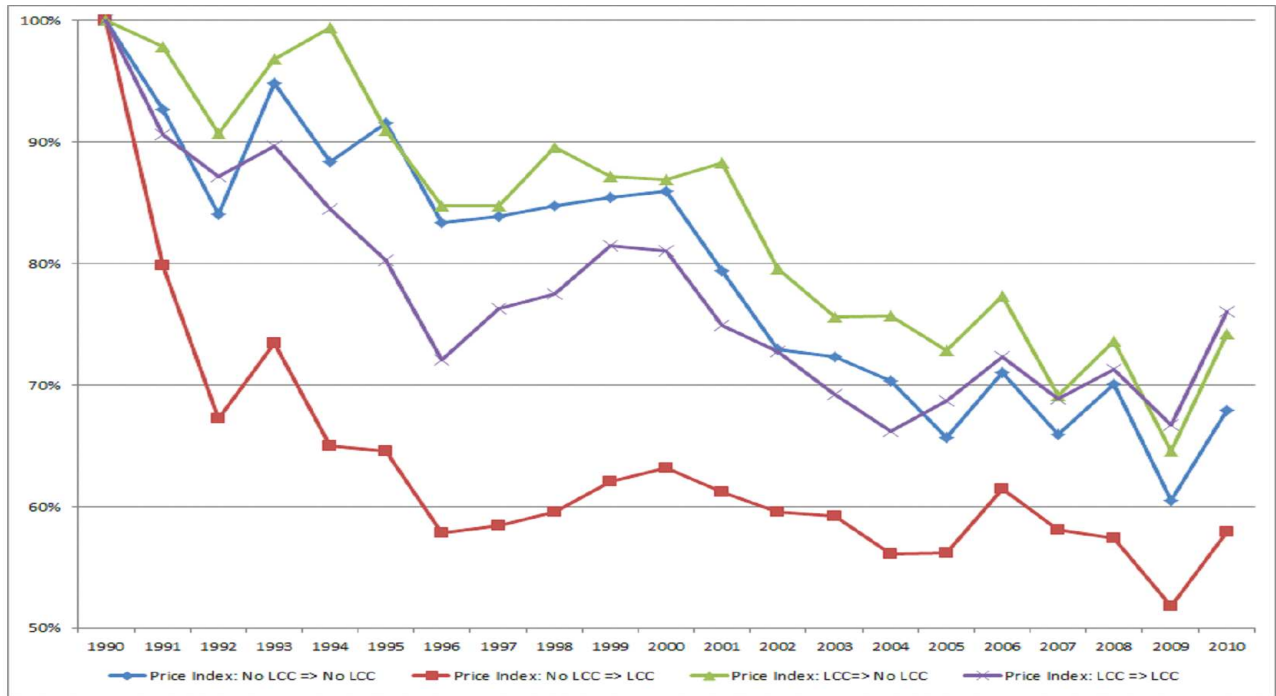


Figure 3: Price Change since 1990 by LCC Presence

airport dominance was first suggested by Levine (1987) and investigated empirically by Borenstein (1989). Later work by Evans and Kessides (1993), among others, also found that airport dominance was associated with high prices that were not cost-related. In general, these are hub airports where a large share of the passengers at the airport are just changing planes. Increased prices, and the inference of market power, have been found for customers flying to or from the airport, but not those changing planes at these airports.

The lower line of figure 4 presents the average fare premium for passengers flying to or from the 10 “hubbiest” large airports of the 1990s, that is, with the largest share of passengers who were changing planes.⁵ This figure runs from 1986 to 2010. All of these airports were dominated by one or two airlines in the 1990s. The trend towards smaller premia at these airports is clear.⁶ The change was especially pronounced with the economic downturn in late 2008. This alone is not evidence of either the rise or fall of airport-dominance market power, but it suggests that those airports dominated by legacy

⁵ These are Atlanta, Charlotte, Cincinnati, Denver, Dallas/Ft. Worth, Detroit, Memphis, Minneapolis, Chicago O’Hare and Pittsburgh.

⁶ The airport premia are calculated in much the same way as the price index shown in figure 1. The prices paid at each airport are compared to the industry-wide quadratic function of price on distance estimated for that year. The premium is the ratio of the total fares paid to those that would have been paid on average nationally according to the regression.

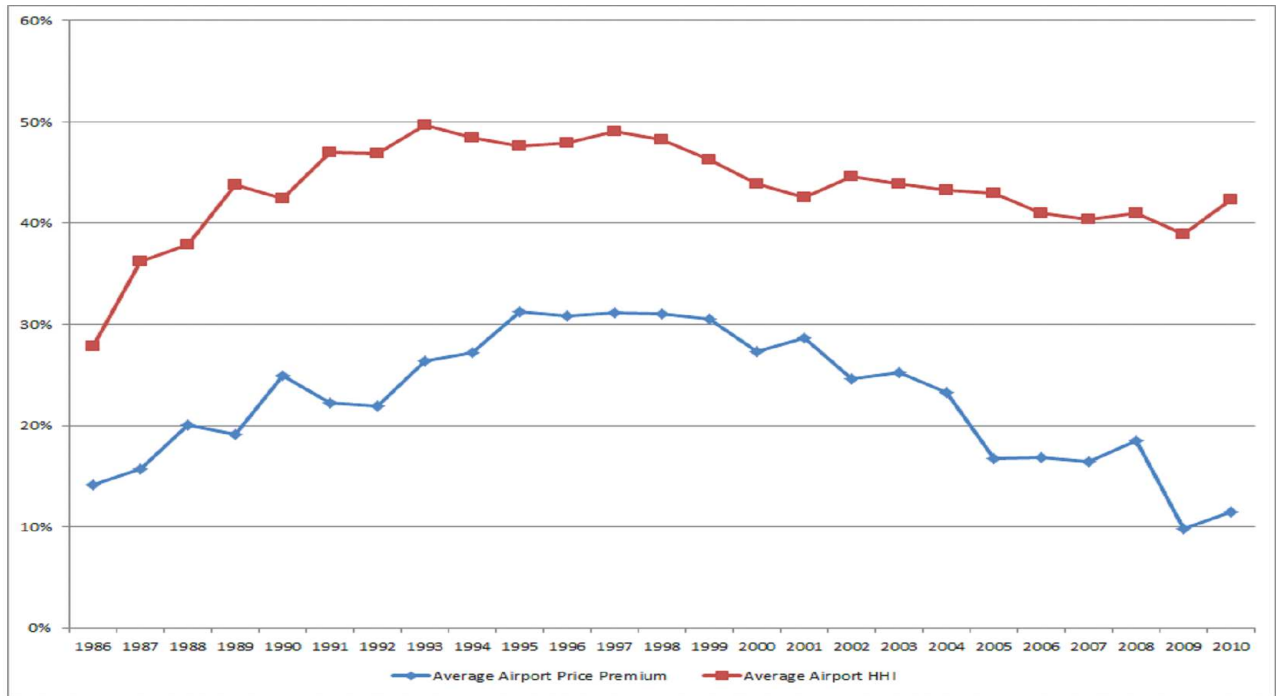


Figure 4: Price Premia and Concentration at 10 Largest Hub Airports

carriers are now much more in line with other airports. More generally, as shown by Borenstein and Rose (2008), the variance in airport premia across the 50 top airports declined substantially after the late 1990s.

While the price data suggest that the once-dominated hub airports are less so now, data on industry structure suggest a less dramatic change at the dominated hub airports. The top line of figure 4 presents the Herfindahl index of passenger shares at the same 10 airports, measured as the share of customers whose ticket originates at that airport.⁷ A gradual downward trend is evident, though 2010 suggests some reversal of that trend.

As the hub premium analysis in figure 4 suggests, the change in average fares has not been

⁷ The competitive advantage of airport dominance is argued to derive both from airport facility control and from network-based marketing devices, such as frequent flyer programs and corporate discounts that are based on the carrier selling a bundle of routes. Airport constraints include gate leases and related contracts with the airport that allow an airline to reduce gate and ticket counter capacity available to potential entrants. Snider and Williams (2011) describe these constraints in detail, as well as the policy change that took effect around 2000, which they argue greatly lessened market power at dominated airports. Network-based marketing devices, in contrast, are designed to market a bundle of products to customers who regularly take flights from a given airport. Market power due to airport constraints is probably better reflected by the share of flights or boarding passengers that a carrier has at the airport. Market power due to network marketing devices is probably better reflected by the share of customers whose ticket originates at the airport.

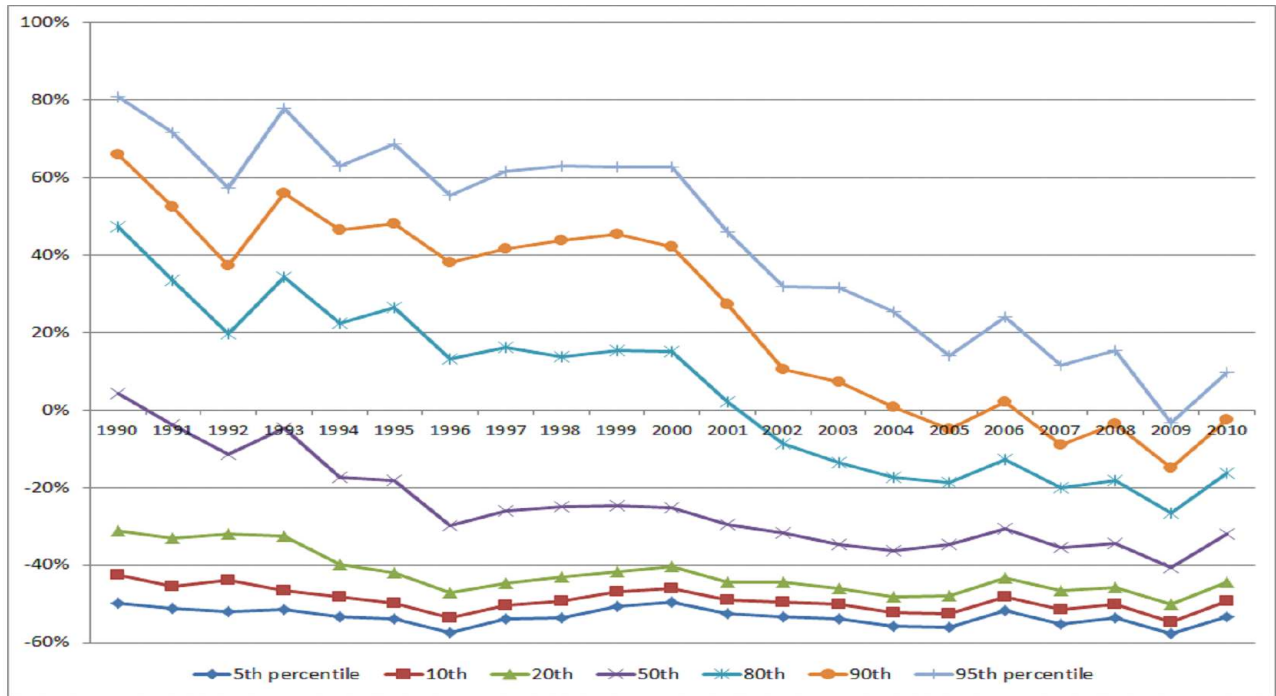


Figure 5: Distribution of Average Route Prices Relative to 1990 Benchmark

uniform across routes. In fact, the distribution has narrowed downward, with the primary change being declining average price on the most expensive routes. Figure 5 presents the distribution of deviation from a benchmark 1990 distance-adjusted fare formula.⁸ The routes with the lower average fares in the distribution have remained about constant in real terms since 1990, while the routes with the highest average fares have declined drastically, from about 80% above benchmark level in 1990 to about 12% above benchmark in 2010.⁹ Figure 5 is consistent with lower-priced routes being very competitive throughout the two decades while higher-priced routes having gotten more competitive over time, forcing prices on those routes down towards the most competitive routes. As with the hub analysis of figure 4, however, 2010 seems to have marked at least a partial reversal of the trend.

A second structural measure of dominant market share is “share gap,” studied by Borenstein (1991). This measure is seen in the industry as reflecting the marketing advantage an airline has in a local area. Share gap is the differential share an airline gets on a route as a

⁸ The 1990 benchmark formula is the regression described in footnote 3 for 1990.

⁹ Figure 5 presents the average fare relative to the 1990 benchmark at different points in the distribution over all routes (passenger weighted). The route at each percentile point changes over time; it does not follow the same routes over time. As a result, the change cannot be attributed to mean reversion for particular routes.

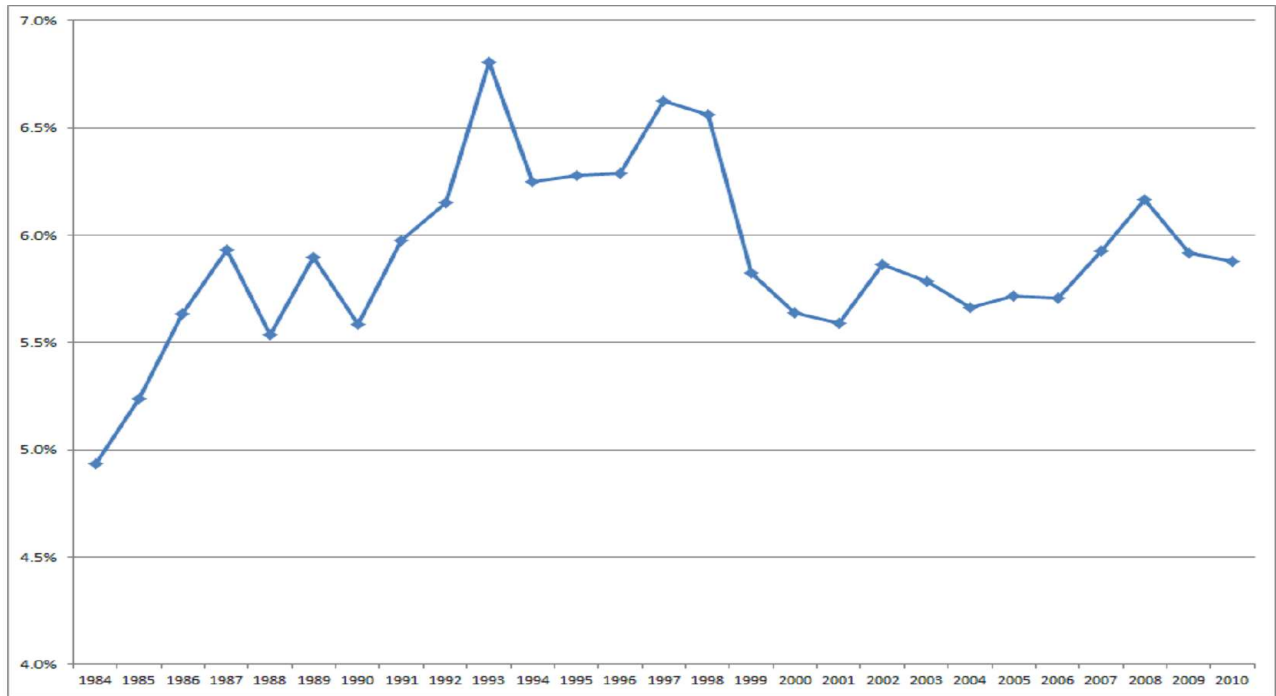


Figure 6: “Share Gap” Measure of Airport Dominance

function of the endpoint from which the passenger begins his or her trip. For instance, on Charlotte (CLT)-Dallas (DFW), US Airways is dominant at CLT and American Airlines is dominant at DFW. In the second quarter of 2010, US Airways had a 65% market share of passengers on this route who began their trip at CLT, but only a 38% share of those who began their trip at DFW. American had a 49% share of those who began their trip at DFW, but a 22% share of the CLT-originating travelers.¹⁰ The remainder in each direction went to Delta, United and other carriers, mostly on tickets with a change-of-plane at their own hub. Share gap has been present since at least the 1980s. Using 1986 data, Borenstein (1991) showed that share gap was significantly associated with airport dominance. A measure of share gap is presented in figure 6 for the period 1984-2010; its construction is detailed in the appendix. Roughly, it is the percentage of all passengers on a route that would have to be reallocated in order for each carrier to have balanced shares of each endpoint origination. Figure 6 shows that share gap was relatively low in the mid-1980s, peaked in the mid-1990s and declined before 2000, but has risen again somewhat since 2006, suggesting share gap has not followed the same pattern as the price-based indicators

¹⁰ Even these figures understate the share gap, because I treat one-way tickets as a half trip originating at the ticket origin. So, a round-trip travel that is purchased as two one-way tickets counts as a one-half trip origin at each endpoint, which biases share gap towards zero.

of market power in the previous figures.¹¹

In aggregate, these figures suggest that a significant component of the price changes over the last 20 years have been driven by lower costs, particularly from higher load factors among all carriers and higher nationwide market shares of lower-cost airlines. But they also suggest that there may have been appreciable declines in the market power of airlines that dominate airports. In the remainder of the paper, I explore these issues econometrically, examining both price changes and changes in share gap.

III. Changing price determinants

Pricing equations have been estimated for the airline industry many times, typically in the form of an equilibrium markup equation that accounts for both costs and demand faced by the airline.¹² In a simple uniform-price setting, a profit-maximizing firm sets

$$P = \frac{MC}{(1 + 1/\epsilon)}.$$

In theory, the equilibrium markup equation is the reduced form of a system of equations representing market demand, cost and the competitive interactions among carriers in the market (and potential entrants), which is part of what is captured in the equation by the elasticity, ϵ .

In all of these studies, costs, demand and competitive interactions are modeled imperfectly, because the true structures are much too complex and incompletely understood to be plausibly captured by a tractable and estimable econometric system of equations. Causal interpretation is always a source of concern. Still, I adopt this approach and attempt to include the major drivers with variables that capture these factors as accurately as possible. I also attempt to correct for the endogeneity issues that are of greatest concern. Nonetheless, the basic estimating equation is fundamentally a statistical relationship that requires economic interpretation in order potentially to infer causality.

The cross-sectional airline pricing regressions estimated here are similar to previous studies – multiple markets and multiple firms within most markets – but in this case

¹¹ Another suggestion that share gap doesn't track with price-based indicators is 2010, when all of the price-based indicators suggest some rebound in market power, but share gap declined slightly.

¹² A partial list includes Borenstein (1989), Evans and Kessides (1993), Brueckner, Dyer and Spiller (1992), Brueckner and Spiller (1994), Bamberger and Carlton (2003), Berry, Carnall and Spiller (2006), and Brueckner, Lee and Singer (2011b),.

repeated cross-sections for four 5-year sub-periods across the 20 years, 1991-2010. Most of the regressors are standard measures of cost, demand, and market power. I also incorporate a few factors that have generally not been included in previous studies or have been included in ways that may not measure the relevant factor as effectively. The goal is to understand how the impacts of some factors have changed over time (*i.e.*, changes in coefficients) and what the impact might be from changes in the levels of the factors (*i.e.*, changes in the means of regressors).

The data are taken primarily from U.S. Department of Transportation data sources. The Origin & Destination Database (known as DB1A/DB1B) is a 10% sample of all tickets used for travel in the United States that are collected at some point in the trip by a reporting airline. The data are aggregated to quarterly observations by airport itinerary of the ticket and fare paid. No information on date of travel (within the quarter) or restrictions or booking codes of the tickets is included. Any airline that carries at least 1% of U.S. passengers must report. The T-100 Segment Database is a census of virtually all airlines' flights including origin airport, destination airport, aircraft type, seats on board and passengers on board. This dataset provides information on number of flights, load factors, aircraft size and seating density. The third dataset is the Airline On-Time Performance data, which is used here to track the number of daily flights and flights within certain time windows that a carrier offers on a route.

In the dataset I construct, an observation is a unique set of year/airport-pair/airline/direct travel or change-of-plane. That is, one observation would include all passengers who traveled in a given (second quarter of a) year between two airports (aggregating both directions and points of ticket origin) on a given airline and took a direct flight, while a separate observation would include all passengers who traveled in the same time period on the same airport-pair and carrier, but changed planes at some intermediate airport. Observations on all change-of-plane airports for a given pair of endpoint airports are aggregated. Each directional trip is counted as one passenger-trip, so a round-trip ticket is counted as two-passenger trips, each with fare equal to one-half the reported fare.

I include only coach class tickets that have no more than two flights in each direction.¹³ The analysis is also limited to routes on which there were at least 182 passenger trips in the DB1A/DB1B during a quarter, which corresponds to an average of 10 passengers per

¹³ Non-standard tickets that are not one-way or round-trip are excluded. Extreme fares – below \$20 and above 5 times the D.O.T.'s Standard Industry Fare Level index – are also excluded.

day in each direction. In addition, any carrier with less than a 1% market share on a route is excluded, as is any carrier reporting less than 91 passenger trips in the database for that route/quarter, the equivalent of an average of 5 passengers per day each way.

Dependent Variables: I consider three dependent variables – following Borenstein (1989), Snider and Williams (2011) and a number of other studies – the mean fare ($\ln Fare$) paid and the 20th ($\ln Fare_{20}$) and 80th ($\ln Fare_{80}$) percentile fare among passenger-trips included in the observation.¹⁴ The percentile fare regressions are intended to capture the unequal impact of some variables on fares at the high and low end of the distribution. All regressions are estimated with the natural log of the price as the dependent variable. As a result, for those right-hand side variables also in logs the coefficients can be interpreted as elasticities, or for dummy variables and those in levels as approximate percentage changes for a one-unit change in the right-hand side variable.

As is usually the case, many of the regressors would show up in more than one of the structural equations of market demand, cost and market power. A high load factor, for instance, lowers cost per customer, but also lowers quality and, as a result, demand. Thus, I don't formally partition the variables as demand, cost and market power drivers. This, of course, means that the economic and welfare interpretation of the estimation results is not as clear cut. The goal of the present exercise is more modest, to understand how these reduced-form relationships have changed over time, and how that has contributed to the change in average prices.

Causal Variables:

Nonstop Distance ($\ln NsDist$): I include a quadratic in log of distance. Equilibrium prices increase with distance, but neither a log-log or log-linear specification is likely to capture the relationship very accurately.¹⁵ None of the results I present change qualitatively with inclusion of the distance variables in log or linear form, or with inclusion of a higher-order polynomial.

Normalized Carrier Cost Index ($\ln NormCost$): A standard measure of costs in the industry is operating cost per available seat-mile (ASM). As documented by Borenstein and Rose (2008) and Borenstein (2011), the airlines known as low-cost carriers have much lower

¹⁴ Results for the median fare are extremely similar to those for the mean fare.

¹⁵ The DOT calculates a Standard Industry Fare Level (SIFL) twice yearly that is piece-wise linear and concave in distance.

operating cost per ASM than the so-called legacy carriers. Cost per ASM, however, declines substantially with an increase in the average length of the airline’s flights, as the airline is able to spread the fixed costs of ground operations over more seat-miles. Borenstein (2011) estimates an elasticity of -0.58 of cost/ASM with respect to average flight length. Using this elasticity, I normalize all carrier costs to a 750 mile average flight length – about the median in the sample.¹⁶ This normalized carrier cost reflects long-run marginal cost, suggesting a constant elasticity relationship with price, so the natural log of *NormCost* is included in the model.¹⁷

Average Load Factor (lnLoadFac): This variable captures the cost-reducing impact (per passenger) of operating flights with more seats filled.¹⁸ Full flights also lower quality, which would also be expected to lower price. As shown in the previous section, flights have become more full over time, probably due to improved information technology that allows more sophisticated yield management protocols. It may also be due to a change in the composition of passengers over time such that the marginal passenger now has a lower willingness to pay for elbow room.¹⁹ Load factor, however, is surely endogeneously determined: driven in part by idiosyncratic demand shocks and thus reflecting scarcity, which would raise load factor and prices.²⁰ Such shocks, however, should mostly be short-run phenomena to which an airline can adjust over time by re-deploying aircraft. Thus, I treat *LoadFac* as endogenous and instrument using the same airline’s load factor on the route a year earlier. The identifying assumption is that a carrier can fully adjust to such idiosyncratic shocks in less than a year, so the instrument is orthogonal to the component of *LoadFac* that is correlated with the error term.

If all costs were fixed by flight regardless of seats and passengers on board, then *LoadFac*

¹⁶ An alternative approach is to use carrier-year fixed effects, but results vary little from this more parsimonious approach.

¹⁷ Earlier versions of this paper also controlled for aircraft size and seating density. Although both are statistically significant and of the expected negative sign, their average impact in any year is captured in the *lnNormCost* variable. Including them captures only the cross-section within-airline variation, which is significant, but doesn’t change other variables to a meaningful extent. For parsimony, I exclude them from this analysis.

¹⁸ All change-of-plane travel on a route/carrier/quarter is aggregated regardless of change-of-plane point with the variable averaged over the different routings and flights using a passenger-mile weighted average.

¹⁹ As Spence (1975) points out, the preferences of the marginal customer will drive such decisions.

²⁰ Supply shocks, such as the exit of a competing carrier, could also have this impact.

would be expected to have a constant negative-one elasticity relationship to cost per passenger. That isn't the case, but constant elasticity still seems most appropriate under the constraint of a linear specification. A Hausman test for endogeneity of $\ln LoadFac$ strongly rejects exogeneity (t-statistic of 11) and indicates OLS estimation would yield a coefficient that is biased in the positive direction, such as would results from idiosyncratic demand shocks.

Airport Capacity Constraint ($\ln AirportConstraint$): Higher prices at some airports may reflect facility capacity constraints at certain times of the day rather than market power. In previous research, when this factor has been recognized it has generally been addressed with a dummy variable for certain airports.²¹ I borrow from Morrison and Winston (2007) to take an approach more grounded in estimation of the scarcity rent associated with such a constraint. Morrison and Winston estimate the net benefits from imposing optimal congestion pricing at each of the 74 airports in the FAA's Aviation System Performance Metrics (ASPM) database in 2005 which they report, including the 46 busiest airports. I calculate the net benefit per takeoff or landing. I then adjust the measure for other years using the difference in the number of aircraft operations at the airport, as explained in the appendix.²²

SMSA Population ($\ln SMSAPop$): This variable is the arithmetic average of the endpoint population SMSAs. It has been included in many prior studies, generally on the argument that higher endpoint population is associated with greater scale economies, though it is not clear what economies it would capture very effectively. I include it for comparability, though the results of interest are unchanged by dropping it. Due to the large variation in populations, SMSAPop most plausibly enters in natural log form.

Change-of-Plane Dummy Variables: I refine the past analyses somewhat by controlling for change-of-plane tickets differently depending on the observed carrier's and other's direct service in the market. Three mutually-exclusive dummy variables are used for change-of-plane observations. *COP-NoDir* is equal to one if this is a change-of-plane observation and less than 20% of all the passengers on the route travel on direct flights. *COP-OthDir* is

²¹ One approach that doesn't capture the effect very well has been to have a dummy variable for the few airports at which takeoff and landing slots are allocated through a market mechanism. These 4 to 6 airports, however, were designated in the 1980s and politics probably played as much of a role as actual constrained operation relative to some other busy airports.

²² This measure still fails to capture the time-varying nature of the constraint. While this is imperfect, there is no information on the time of the flight for which each ticket was used.

equal to one if this is a change-of-plane observation, more than 20% of all the passengers on the route travel of direct flights, but less than 20% of the observed carrier's passengers on the route travel direct. *COP-OwnDir* is equal to one if this is a change-of-plane observation, more than 20% of all the passengers on the route travel on direct flights, and more than 20% of the observed carrier's passengers on the route travel direct. The omitted category is observations on direct travel tickets.

SMSA Median Income Level (lnSMSAInc): This variable is the weighted-average income level of the endpoint SMSA's of the route. The weights are the shares of customers who originate their trip at each endpoint of the route. For instance, if 70% of the MSP-SFO customers originate in MSP, then SMSA Median Income Level for this route will put a 70% weight on the Minneapolis value and a 30% weight on the San Francisco value. This variable has been included in many studies to capture higher willingness-to-pay or customers flying to/from richer areas, but it may also capture higher labor and other operating costs in these areas. *SMSAInc* enters in log form so the coefficient is an estimated constant elasticity of equilibrium price with respect to the variable.

Business Share (BizShare): This is an estimate of the share of passengers on the route who are traveling for business purposes. The variable is constructed from the Business Travel Index (BTI) described in Borenstein (2010), which uses the 1995 American Travel Survey to estimate the business share of airline passengers flying to and from most major SMSAs and all states. For SMSAs with more than 100 trip observations in the survey, I use the SMSA BTI measures and otherwise I use the state BTI measures. I first create a value for travel in each direction that is the unweighted average of the BTI for originating passengers from one endpoint and destination passengers at the other endpoint. The *BizShare* variable is then the weighted-average of the indexes created for each directional travel where the weights are based on the share of customers who originate their trip at each endpoint, as with *SMSAInc*. Like all previous measures used for business share of travel, this approach has the weakness that it does not vary over time. This measure, however, is based on actual survey data, rather than inferred from weather, hotel revenues or other variables. *BizShare* is a limited variable that is bounded by zero and one in theory and a much smaller range in practice. Its impact is estimated in linear form so every one percentage point change in the business share of customers on the route is assumed to have an equal proportional impact on price.

Carrier Route Share (RouteShare): This is the share of passengers on the route transported by the observed carrier, including both direct and change-of-plane travel. This variable

is expected to capture the carrier-specific market power associated with being a major carrier on a route. *RouteShare* is potentially endogenous as idiosyncratic carrier-specific cost and demand shocks on the route, not captured by the other regressors, could lead the observed airline to adjust price relative to others carriers on the route, which would affect *RouteShare*. I instrument for *RouteShare* with a measure of enplanement shares at the endpoint airports used by Borenstein (1989): the observed carrier’s share of the sum of the geometric means of all carriers with non-zero enplanements at both endpoints of the route. The instrument appears to be very strong and a Hausman test strongly rejects exogeneity (t-statistic of 18) with the sign indicating that OLS would understate the positive causal effect of *RouteShare* on fares, as one would expect. The impact of *RouteShare* is estimated in linear form so every one percentage point change is assumed to have an equal proportional impact on price.

Normalized Costs of Competitors (lnCompCost): This is the log of a weighted average of the *NormCost* of all other carriers on the route where the weights are the market shares of the carriers (combining direct and change of plane traffic for each airline).²³ The effect of competitor costs has been approximated in some studies with a dummy variable indicating whether a carrier designated as an LCC has a market share on the route above a certain threshold. Substituting such an *LCC presence* dummy variable yields similar results for the other variables, but has less explanatory power. Like *NormCost*, specifying the natural log of competitor costs makes the most economic sense.²⁴

HHI Among Other Carriers on the Route (HHIother): This is the concentration among the share of the passengers on the route not served by the observed carrier. To be precise on a given route, for all carriers other than the observed carrier i :

$$HHIother = \frac{\sum_{\forall k \neq i} RouteShare_k^2}{(1 - RouteShare_i)^2}$$

Given a carrier’s route share it could benefit from having the remaining passengers concentrated on one carrier, easing coordination and potentially softening competition. Or it could benefit from having competition dispersed among many other airlines, giving the

²³ Observations that are dropped from the dataset due to too few passengers or small market share are still used in calculating this variable and the change-of-plane variables.

²⁴ The effect of competitor costs might be expected to depend on the route share of all carriers other than the observed carrier, because a carrier’s pricing may respond more to the costs of competitors if they have a large share of the market. Estimating separate effects for large and small other-carrier route shares, however, while statistically significant has very small economic significance.

observed carrier a stronger market position from which it might leverage brand advertising, use of loyalty programs or other marketing devices. The impact of *HHI_{other}* is estimated in linear form so every one percentage point change in the HHI among competitors, holding constant their aggregate market share, is assumed to have an equal proportional impact on price.²⁵

Airport Originations Share (AirportShare): This is the share of tickets originating at the airport that fly on the observed carrier (on the first segment of the ticket). *AirportShare* is the weighted average of origination shares at the two endpoint airports where the weights are the shares of all passengers on the route who originate their trip at each endpoint. This variable is intended to capture the network marketing power associated with airport dominance, as described by Levine (1987) and Borenstein (1996). The impact of *AirportShare* is also estimated in linear form.

There are a few data construction issues that are sufficiently important to mention here rather than just in the appendix: code sharing, interline ticketing and airport aggregation. I adjust for code-share commuter carriers by assigning to the associated major airline any trip on the commuter that appears to be flown as a code-share partner of the major. Such relationships are approximated by measures of change-of-plane tickets between carriers at an airport. If a commuter exchanged more than 910 passengers in the sample with a given airline at a given airport during a quarter (equivalent of about 100 passengers per day), I assume that they were code-share partners during that quarter. Code-share partners are aggregated in calculating market shares, airport share, prices, equipment, and load factor variables. The commuter carrier cost variables, however, are not aggregated into the code-share majors. There is no straight-forward way to do this, because cost data are reported at the firm level and most code-share partners fly for different majors at different airports.²⁶

An interline ticket is one that includes multiple carriers. For interline tickets that have only a single carrier in each direction (after the commuter code-share matching), I simply split the ticket and ticket price by direction and ignore the different carriers by direction. Once code-share partners are matched as described in the previous paragraph, there are

²⁵ As with *lnCompCost*, the variable could be interacted with route share. The difference for large versus small aggregate route share of other carriers is not statistically significant in most of the regressions and in no case substantially changes other results.

²⁶ See Forbes and Lederman (2007).

Means and Standard Deviations of Variables (weighted by passenger)						
		All Years	1991-1995	1996-2000	2001-2005	2006-2010
Average Fare (\$2009)	Mean	198.580	233.134	211.927	186.157	178.220
	Std Dev	89.301	109.041	105.603	74.079	61.939
20th Percentile Fare (\$2009)	Mean	126.155	145.344	128.071	119.643	119.128
	Std Dev	48.691	63.839	50.293	39.847	40.423
80th Percentile Fare (\$2009)	Mean	264.704	318.397	293.959	242.585	228.451
	Std Dev	151.642	180.064	194.370	123.511	88.467
Nonstop Distance (000) [NsDist]	Mean	1.015	0.934	0.963	1.053	1.072
	Std Dev	0.682	0.671	0.664	0.692	0.688
Normalized Carrier Cost (\$2009) [NormCost]	Mean	0.136	0.124	0.124	0.135	0.154
	Std Dev	0.041	0.027	0.030	0.040	0.050
Average Load Factor [LoadFac]	Mean	0.741	0.647	0.719	0.748	0.811
	Std Dev	0.108	0.103	0.095	0.093	0.083
Airport Capacity Constraint (\$2009) [AirportConstraint]	Mean	222.863	207.187	204.234	226.454	244.563
	Std Dev	188.272	159.355	155.580	190.086	222.086
SMSA Population (000,000) [SMSAPop]	Mean	6.120	6.436	6.030	6.120	6.011
	Std Dev	4.597	4.763	4.539	4.615	4.522
Change of Plane - NoDir	Mean	0.128	0.131	0.135	0.132	0.118
Change of Plane - OthDir	Mean	0.089	0.090	0.091	0.094	0.081
Change of Plane - OwnDir	Mean	0.018	0.017	0.017	0.018	0.019
SMSA Median Income (000 \$2009) [SMSAInc]	Mean	47.834	47.718	47.874	47.887	47.820
	Std Dev	4.611	4.811	4.697	4.526	4.490
Business Share [BizShare]	Mean	0.406	0.413	0.408	0.404	0.402
	Std Dev	0.076	0.078	0.077	0.075	0.075
Normalized Cost of Competitors (\$2009) [CompCost]	Mean	0.142	0.127	0.127	0.142	0.165
	Std Dev	0.032	0.019	0.022	0.028	0.035
Carrier Route Share [RouteShare]	Mean	0.550	0.560	0.550	0.540	0.555
	Std Dev	0.283	0.281	0.279	0.282	0.286
HHI Among Competitors [HHIOther]	Mean	0.545	0.532	0.555	0.547	0.542
	Std Dev	0.264	0.261	0.270	0.264	0.261
Airport Originations Share [AirportShare]	Mean	0.313	0.321	0.316	0.306	0.312
	Std Dev	0.174	0.163	0.169	0.173	0.184
Observations		280172	64992	70812	72500	71868

Table 1: Summary Statistics

very few directional interline tickets remaining in the data. I drop those that remain.

I present regressions in which all airports are considered to be in separate markets. I have carried out most of the analysis aggregating airports in the same SMSA that are considered to be close substitutes, following the groupings suggested in table 16 of Brueckner, Lee

and Singer (2011a). The qualitative results are not changed. Clearly, the airports are imperfect substitutes and neither approach is entirely correct.

Table 1 presents summary statistics for the entire sample used in the regressions over 20 years. Treating load factor as endogenous and instrumenting with year-before load factor requires dropping year 1990 from the regression analysis. The summary statistics of the transformed variables actually used in the regressions are in the appendix, table A1.

Results

The data summarized in table 1 are weighted by passengers in each observation. This approach, applied throughout the price analysis, essentially treats every passenger ticket as a separate observation. Standard errors are then clustered at the route level to adjust for the correlation of observations on the route. Clustering, of course, only changes the standard errors. The relationship estimated in this way should be seen as a weighted-average relationship where greater weight is put on routes with more traffic.

Table 2 presents 5 regressions with the dependent variable that is the log of average fare, one that covers the entire sample period 1991-2010, and the next four that break it into four periods of nearly equal length: 1991-1995, 1996-2000, 2001-2005, and 2006-2010. All regressions include fixed year effects. These regressions pool across years, but there are no fixed route effects. The identification is from the cross-sectional variation.

The pooled regression across all years, shown in the first column of coefficients, yields results mostly as predicted. Routes served with higher load factors have lower prices. The elasticity of price with respect to load factor suggests that increasing passengers on board by 10% lowers average fare, but by a smaller proportion, 7.9%, as would be expected if some costs are not fixed with respect to the number of passengers on the flight. If the coefficient on load factor reflected only cost impact – ignoring the impact on service quality and assuming 100% long-run passthrough of the cost impact – the coefficient would suggest that about 79% of costs are fixed at the flight level.

Carrier operating costs per ASM ($\ln Norm Cost$) have a very significant impact on price with an elasticity of about 0.53. The costs of competing carriers ($\ln Comp Cost$) also has a very significant, though smaller impact, about 0.29 elasticity. The elasticity of price with respect to endpoint populations is negative, as expected, -0.06. $\ln SMSA Pop$ has a standard deviation of 0.82 in the sample, suggesting that a one-standard-deviation increase

Dep Variable	All Years <i>lnFare</i>	1991-1995 <i>lnFare</i>	1996-2000 <i>lnFare</i>	2001-2005 <i>lnFare</i>	2006-2010 <i>lnFare</i>
<i>lnNsDist</i>	0.433*** (0.00414)	0.506*** (0.0108)	0.498*** (0.00821)	0.373*** (0.00660)	0.386*** (0.00592)
<i>lnNsDist^2</i>	0.0214*** (0.00351)	0.00537 (0.00761)	0.0541*** (0.00680)	0.0212*** (0.00578)	0.0646*** (0.00521)
<i>lnNormCost</i>	0.529*** (0.00573)	0.783*** (0.0219)	0.669*** (0.0123)	0.465*** (0.00824)	0.423*** (0.00730)
<i>lnLoadFac</i>	-0.789*** (0.0246)	-0.631*** (0.0517)	-0.779*** (0.0439)	-0.660*** (0.0379)	-0.593*** (0.0521)
<i>lnAirportConstraint</i>	0.0493*** (0.00222)	0.0519*** (0.00440)	0.0685*** (0.00380)	0.0415*** (0.00337)	0.0208*** (0.00297)
<i>lnSMSAPop</i>	-0.0564*** (0.00249)	-0.0418*** (0.00519)	-0.0489*** (0.00486)	-0.0572*** (0.00412)	-0.0598*** (0.00345)
<i>COP-NoDir</i>	0.121*** (0.00402)	0.146*** (0.00750)	0.130*** (0.00747)	0.0896*** (0.00700)	0.0996*** (0.00639)
<i>COP-OthDir</i>	0.128*** (0.00428)	0.106*** (0.00885)	0.145*** (0.00872)	0.109*** (0.00765)	0.131*** (0.00664)
<i>COP-OwnDir</i>	0.106*** (0.00253)	0.112*** (0.00502)	0.106*** (0.00545)	0.0980*** (0.00472)	0.111*** (0.00390)
<i>lnSMSAInc</i>	0.268*** (0.0209)	0.206*** (0.0469)	0.188*** (0.0387)	0.272*** (0.0320)	0.220*** (0.0262)
<i>BizShare</i>	0.791*** (0.0251)	1.027*** (0.0601)	1.101*** (0.0484)	0.587*** (0.0410)	0.707*** (0.0316)
<i>lnCompCost</i>	0.288*** (0.00872)	0.382*** (0.0236)	0.407*** (0.0181)	0.250*** (0.0132)	0.128*** (0.0105)
<i>RouteShare</i>	0.365*** (0.0135)	0.292*** (0.0290)	0.435*** (0.0285)	0.355*** (0.0234)	0.386*** (0.0189)
<i>HHlother</i>	-0.0474*** (0.00778)	0.00117 (0.0197)	-0.0404** (0.0166)	-0.0581*** (0.0119)	-0.0134 (0.00930)
<i>AirportShare</i>	0.140*** (0.0152)	0.330*** (0.0345)	0.251*** (0.0338)	0.119*** (0.0252)	-0.0853*** (0.0198)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
R-squared	0.677	0.775	0.735	0.634	0.642
<i>Observations</i>	280,172	64,992	70,812	72,500	71,868

Observations weighted by passengers . Robust standard errors, clus
*** p<0.01, ** p<0.05, * p<0.1

Table 2: Regression of $\ln(\text{Average Fare})$ for entire period and sub-periods

of the variable would reduce price by about 5%. Prices appear to be substantially higher in wealthy SMSAs than poorer ones with an elasticity of 0.27. A one standard deviation increase in *lnSMSAInc* increases average price by about 2.7%. And, as expected, business oriented routes have significantly higher prices than others. The *BizShare* variable has a standard deviation of 0.08, so the coefficient estimate of 0.79 implies that a one-standard

deviation increase in the share of business travelers on the route increases the average fare by about 6%.

The change-of-plane variables are positive, which runs counter to some analyses that assume that change-of-plane routings are priced lower. The coefficient on *COP-NoDir* suggests that a change-of-plane ticket on a route with little or no direct service is about 13% more expensive on average than tickets for direct service on routes of comparable distance and other characteristics. This may seem surprising, but it is important to note that this holds constant the competition and normalized cost variables; such routes on average are substantially less concentrated. The *COP-OthDir* effect is about 14% and the *COP-OwnDir* effect is about 11%. The coefficient on *COP-OwnDir* is perhaps not that surprising, as a carrier with direct service on a route might not want to encourage customers to take an indirect routing in which they occupy seats on two flights and require more resources for baggage handling, boarding, etc. The coefficient on *COP-OthDir* is more puzzling, though it seems to be quite robust over time. It suggests that carriers offering change-of-plane service charge higher prices if a competitor is offering direct service on the route than if no airline is offering direct service on the route.

The airport share of the observed airline has a significant positive impact on the average fare charged. The airport share variable implies that a route on which the observed carrier dominates both endpoint airports, with origination shares of 50% at both endpoints would lead that carrier to charge an average price that is about 7% higher than if the carrier had minimal airport shares at the endpoints. Within the sample, the standard deviation of *AirportShare* is 0.17, so a one-standard deviation change moves average fare by about 2.4%. This effect is apart from the impact of having a greater share of the traffic on an individual route. It's also important to note that this cross-sectional static approach does not capture the potential entry deterrence of airport dominance, which may lead to higher market shares on routes.

The impact of the carrier's route share, apart from airport dominance, is quite substantial. The estimate implies that a carrier with a 50% market share has a 20% higher average price than one with a negligible share. Within the sample, the standard deviation of *RouteShare* is 0.28, so a one-standard deviation change moves average fare by about 11%.

The columns for the 4 sub-periods indicate that some of these estimates have been fairly stable over time but others have not. The direct impact of *AirportShare* has fallen

drastically from the early 1990s to be slightly negative in the most recent period. This is consistent with the decline of airport dominance premia while airport concentration has fallen only slightly, as was shown in figure 4 and in table 1. The remaining airport premia reflects in part the fact that airport dominance is associated high route shares, and the impact of route share has been stable. The impact of the concentration among competing carriers, HHI_{other} , does not have a substantial effect in any of the sub-periods. Even the largest effect, in the third sub-period, implies a one-standard deviation increase in HHI_{other} lowers prices by less than 2%.

The decline in the impact of competitor costs, $\ln CompCost$, is consistent with the earlier finding that prices have declined by more on routes with no LCC presence than on routes with LCC presence throughout the period. The LCC effect, while more widespread now, does not have as large an impact on relative price as it had in earlier periods. The decline in the coefficient on $\ln NormCost$ is also consistent with a smaller gap between the prices of LCCs and non-LCCs, as documented in Borenstein (2011).

The impact of the airport constraint variable peaked in the second sub-period. Recalling that this variable is taken from a single cross-section of estimated scarcity for 1995, adjusted for relative growth in airport usage for other years, this suggests that fare premia at the more-constrained airports peak in the second sub-period and were much lower in the most recent period.

The business share variable is substantially lower in the 2000s than in the 1990s, consistent with figure 5 indicating that fares fell much more on the most expensive routes of the 1990s, which were almost certainly dominated by business travelers. It's also consistent with widespread industry reports that corporate travel offices more aggressively sought out low fares starting around 2000.

Interpretation

Taking the regression as a causal model, a change in average fares over time could result from either a change in the means of some regressors or a change in the estimated coefficients. Both seem to have occurred over the period studied here. I first consider changes in the means of regressors.

Table 1 indicates that the means of most of the regressors have not changed dramatically over time. In some cases, this is because the underlying variables do not capture time variation – such as with population, income, or business share – but even many of the

others that are measured annually show little variation. The major exceptions are carrier cost, competitor cost, and load factor.

The mean of $\ln LoadFac$ increased by 23 log points from the first to the last sub-period. To analyze the impact, I take the regression coefficients of the full-period regression. The elasticity of -0.789 implies that the change in average load factor would explain a price decline of about 18 log points or about 16%.²⁷

At the same time, the mean of $\ln NormCost$ increased by 18 log points so the estimated elasticity of 0.53 implies an increase in price of 9 log points.²⁸ Likewise, the 24 log point increase in $\ln CompCost$ with an estimated elasticity of 0.288 implies an increase in price of about 7 log points. So, the increases in operating costs are estimated to have increased prices by a total of about 16 log points or about 17%.

These calculations are not independent, however, because an increase in load factor mechanically increases the standard industry cost measure used in carrier cost and competitor cost variables – operating cost per available seat-mile. This occurs because an increase in load factor is, by definition, an increase in the number of passengers per available seat-miles. In this case, increasing load factor from 64% to 81% means that the passenger-related costs increase by about 26% if such costs are linear in the number of passengers. If such costs comprise 20% of total costs (at a 64% load factor) – a ballpark number suggested by Borenstein and Rose (2008) and roughly consistent with the estimated coefficient on $\ln LoadFactor$ – then the rise in load factor increases both $NormCost$ and $CompCost$ by about 5%. By the estimates in table 2, this would result in a total price increase 4 log points.²⁹ So the *net* impact of the load factor increase would be a price decrease of about 14 log points, but that is approximately offset by other cost increases of about 16 log points. Most of those other cost increases are probably in fuel costs, the price of which averaged more than twice as high in the last subperiod than in the first.

²⁷ It is worth noting the curious result that the coefficient on $\ln LoadFac$ is larger in the pooled sample than in any of the four sub-periods, despite the fact that the regressions all have year fixed effects that remove any mean price shifts over time. Using the coefficient estimates in the sub-periods lowers the implied impact by one to four percentage points.

²⁸ The mean of $\ln NormCost$ is passenger weighted for each subperiod, so the fact that it rises indicates that the growth in the share of passengers served by LCCs is outweighed by the increase in the costs of all carriers.

²⁹ I get this number by adding the coefficient on $\ln NormCost$, 0.53, to the coefficient on $\ln CompCost$, 0.29 and multiplying the sum by 5%.

Interpretation of the changes in coefficients is less straightforward. For instance, the decline in the coefficient on *BizShare* from 1.027 to 0.707 – while the mean of the variable remained at about 0.4 – by itself implies a change in the mean of the dependent variable of about -0.13, a decline of about 12%. Such a calculation, however, implicitly assumes that there is no associated change in the constant term (or year fixed effects) or in any other coefficients. Put differently, it implicitly assumes that the change in the price on very business-oriented routes relative to leisure routes has taken place entirely through reduction in average prices on business routes, not increases in average prices on leisure routes. In reality, some of each has probably occurred, though the narrowing downward of prices shown in figure 5 suggests that more of the change has been on business routes. The much greater change in the (proportional) impact of the *BizShare* variable on high-end than on low-end fares, as we will see in the next subsection, also suggest more of this change reflects a price declines in business markets. If so, then more than half of the decline in average fares may be attributable to the reduction of relative prices for business travelers.

Similarly, the decline in the coefficient on *AirportShare* from 0.330 to -0.085 in isolation implies a decrease in the dependent variable of about 0.12 – an average price decrease of 11% – but this attributes the entire decline in the co-variation of *AirportShare* and *lnAverageFare* to reductions in price at the most concentrated airports, none to increases at the less concentrated airports. Either would cause the coefficient to decline, but they would have different implications for the constant term and therefore for average price levels.³⁰ Still, it seems likely that the 11% interpretation is an upper bound on the impact of the decline in the effect of airport dominance.

The same issue arises with many of the other variables for which coefficient estimates change substantially over the four sub-periods, most importantly the own and competitor cost variables. The decline of these coefficients certainly reflects the narrowing of fares between LCCs and legacy carriers, but it is hard to know how much is a rise in prices of LCCs and how much is a fall in legacy carrier prices.

Differential Impact on High-End and Low-End Fares

Table 3 presents the same regressions as in table 2, but with the 20th and 80th percentile

³⁰ One could attempt to interpret changes in the constant term as well, but it is unclear how one could associate changes in the constant term with specific changes on other coefficients.

Dep Variable	All Years <i>lnFare20</i>	1991-1995 <i>lnFare20</i>	1996-2000 <i>lnFare20</i>	2001-2005 <i>lnFare20</i>	2006-2010 <i>lnFare20</i>	All Years <i>lnFare80</i>	1991-1995 <i>lnFare80</i>	1996-2000 <i>lnFare80</i>	2001-2005 <i>lnFare80</i>	2006-2010 <i>lnFare80</i>
<i>lnNsDist</i>	0.420*** (0.00384)	0.521*** (0.0108)	0.459*** (0.00734)	0.354*** (0.00642)	0.389*** (0.00617)	0.421*** (0.00532)	0.498*** (0.0135)	0.487*** (0.0122)	0.355*** (0.00829)	0.371*** (0.00673)
<i>lnNsDist^2</i>	0.0134*** (0.00347)	0.0266*** (0.00823)	0.0162** (0.00694)	0.00288 (0.00630)	0.0615*** (0.00567)	-0.00163 (0.00454)	-0.0306*** (0.00974)	0.0266*** (0.0100)	0.00240 (0.00731)	0.0510*** (0.00586)
<i>lnNormCost</i>	0.324*** (0.00538)	0.484*** (0.0183)	0.345*** (0.0104)	0.278*** (0.00828)	0.293*** (0.00778)	0.564*** (0.00683)	0.824*** (0.0251)	0.741*** (0.0163)	0.475*** (0.0105)	0.460*** (0.00887)
<i>lnLoadFac</i>	-0.450*** (0.0223)	-0.392*** (0.0487)	-0.472*** (0.0368)	-0.251*** (0.0331)	-0.416*** (0.0502)	-1.055*** (0.0304)	-0.809*** (0.0619)	-1.111*** (0.0590)	-0.952*** (0.0497)	-0.821*** (0.0582)
<i>lnAirportConstraint</i>	0.0201*** (0.00207)	0.0249*** (0.00425)	0.0291*** (0.00349)	0.0104*** (0.00320)	0.00907*** (0.00317)	0.0665*** (0.00272)	0.0655*** (0.00515)	0.0915*** (0.00497)	0.0635*** (0.00409)	0.0290*** (0.00337)
<i>lnSMSAPop</i>	-0.0518*** (0.00232)	-0.0430*** (0.00487)	-0.0351*** (0.00443)	-0.0543*** (0.00408)	-0.0652*** (0.00371)	-0.0655*** (0.00307)	-0.0450*** (0.00665)	-0.0586*** (0.00678)	-0.0708*** (0.00511)	-0.0659*** (0.00406)
<i>COP-NoDir</i>	0.127*** (0.00380)	0.114*** (0.00715)	0.143*** (0.00672)	0.103*** (0.00664)	0.125*** (0.00698)	0.119*** (0.00507)	0.165*** (0.00947)	0.118*** (0.0102)	0.0922*** (0.00872)	0.0873*** (0.00746)
<i>COP-OthDir</i>	0.128*** (0.00404)	0.0942*** (0.00846)	0.137*** (0.00810)	0.0992*** (0.00711)	0.154*** (0.00693)	0.125*** (0.00540)	0.109*** (0.0112)	0.133*** (0.0118)	0.116*** (0.00963)	0.123*** (0.00769)
<i>COP-OwnDir</i>	0.0768*** (0.00230)	0.0845*** (0.00553)	0.0827*** (0.00486)	0.0605*** (0.00410)	0.0841*** (0.00388)	0.105*** (0.00333)	0.112*** (0.00706)	0.101*** (0.00775)	0.102*** (0.00621)	0.109*** (0.00471)
<i>lnSMSAInc</i>	0.164*** (0.0191)	-0.00178 (0.0439)	-0.00457 (0.0337)	0.248*** (0.0314)	0.214*** (0.0290)	0.401*** (0.0250)	0.416*** (0.0585)	0.410*** (0.0509)	0.364*** (0.0384)	0.261*** (0.0293)
<i>BizShare</i>	0.337*** (0.0239)	0.455*** (0.0574)	0.421*** (0.0410)	0.210*** (0.0400)	0.405*** (0.0358)	1.043*** (0.0306)	1.464*** (0.0744)	1.490*** (0.0659)	0.748*** (0.0514)	0.818*** (0.0364)
<i>lnCompCost</i>	0.221*** (0.00854)	0.362*** (0.0276)	0.305*** (0.0155)	0.190*** (0.0131)	0.100*** (0.0118)	0.320*** (0.0104)	0.403*** (0.0280)	0.462*** (0.0239)	0.265*** (0.0168)	0.159*** (0.0126)
<i>RouteShare</i>	0.337*** (0.0124)	0.220*** (0.0271)	0.402*** (0.0258)	0.297*** (0.0206)	0.394*** (0.0194)	0.452*** (0.0168)	0.402*** (0.0357)	0.541*** (0.0379)	0.470*** (0.0295)	0.426*** (0.0222)
<i>HHIother</i>	-0.00596 (0.00753)	0.0133 (0.0192)	-0.0175 (0.0136)	-0.00912 (0.0121)	0.0263** (0.0108)	-0.0407*** (0.00952)	0.0261 (0.0241)	-0.0231 (0.0227)	-0.0552*** (0.0150)	-0.0161 (0.0108)
<i>AirportShare</i>	0.00214 (0.0138)	0.182*** (0.0337)	0.0813*** (0.0267)	0.00491 (0.0210)	-0.169*** (0.0212)	0.169*** (0.0195)	0.388*** (0.0437)	0.260*** (0.0483)	0.109*** (0.0337)	-0.0308 (0.0244)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.647	0.738	0.699	0.608	0.600	0.571	0.697	0.613	0.498	0.544
Observations	280,172	64,992	70,812	72,500	71,868	280,172	64,992	70,812	72,500	71,868

Observations weighted by passengers . Robust standard errors
*** p<0.01, ** p<0.05, * p<0.1

Table 3: Regressions using 20th and 80th percentile prices

fares in each observations as the dependent variable, rather than the mean fare. A number of differences between the high-end and low-end fares are evident. The cost factors – normalized operating costs (own and competitors’) and load factor – have a larger effect on the high-end fares than the low-end. Own cost and load factor capture quality differences as well as cost, quality differences that likely are more valued by customers buying higher-

priced tickets, which probably explains why higher costs raise high-end fares more and higher load factors lower high-end fares more. The “demand inelasticity” variables – business share and SMSA income – also have a much larger impact on high-end fares. Among the competition variables, the route share variable has somewhat more impact on high-end fares, while the HHI among competitors has little effect on either low or high end fares. The most striking difference is in airport share, where the impact on the high-end fares is at least double in each of the first three sub-periods and far less negative in the fourth sub-period. Analysis of both the low-end and high-end fares suggest that market power from airport dominance has declined markedly in the last few years, but at any point in time the impact of airport dominance has clearly been larger on the high-end fares.

IV. The Evolution of Share Gap

“Share Gap” has long been recognized in the airline industry as a significant phenomenon in the competitive landscape that reflects the marketing advantages of a dominant airline. Borenstein (1991) explored the relationship between share gap and airport origination share using 1986 data. That study found that share gap was very significantly associated with airport share and that the effect was stronger on more business-travel oriented routes, though the latter effect was not significant in all specifications.

I apply the same basic approach here, but I apply it to the years 1984-2010, studying five five-year sub-periods from 1986 to 2010 and an additional period of 1984-85, again using only data from the second quarter of each year. The idea is to look at the difference in a carrier’s shares on a route depending on which end of the route the passenger originates from and the carrier’s passenger-trip origination share on all *other* routes from each airport. Differencing by point of trip origin eliminates nearly all factors that would typically be thought to affect airline choice, including price, service quality, and frequency.³¹ The only factors that survives the differencing are ones that are differentially associated with the passenger’s point of trip origin. Airport dominance captures many of those factors, including advertising density, probability of membership and activity in frequent flyer program, corporate marketing and discount programs. Airport dominance and pricing premia have been attributed in part to preferential treatment of the largest local airline by the local airport authority, most recently by Snider and Williams (2011). While that effect

³¹ On domestic U.S. travel, airlines do not differentiate fare availability for a given flight based on the passenger’s point of ticket origin. This is not the case for international travel.

is probably important, analysis of share gap eliminates the influence of such preferential treatment, except to the extent that it allows an airline to position itself more favorably for passengers whose trip originates *from* the area than for passengers traveling *to* the area.

Borenstein (1991) suggested two other factors that could differ by point of origin: ownership of the computer reservation system used by local travel agents and convenient flight schedules for locally originating passengers, particularly flights departing from the airport in the morning and returning in the evening. The CRS issue largely disappeared in the early 1990s first with DOT regulation of CRS displays and then with increased use of internet ticketing from vendors that are unaffiliated with a specific airline.

Borenstein (1991), found that while the schedule convenience variable was highly statistically significant and had a substantial impact, it had almost no effect on the estimates of the impact of airport dominance, being nearly orthogonal. Using similar criteria as Borenstein (1991), I created a schedule convenience variable from the U.S. Department of Transportation's database of delayed flights for 1988-2010. The data are not available for earlier years. Schedule convenience remains quite significant in all years for which it could be created, but including it in regressions for those years still had almost no impact on other parameter estimates. Results including the schedule convenience variable are presented in the appendix. I focus here on regressions without it in order to include earlier years in the data.

Following Borenstein (1991), I estimate the impact of airport dominance on a logistically transformed directional route share difference variable. Define $DirRtShr_{ijk}$ as carrier k 's share of the passengers on the route ij who begin their trip at airport i . This variable has support from zero to one and some observations are near the boundary, so to maintain the assumption of a normally distributed error term, I logistically transform the route share variables and then take the difference by point of origin:

$$d\lg DirRtShr_{ijk} = \ln\left[\frac{DirRtShr_{ijk}}{(1 - DirRtShr_{ijk})}\right] - \ln\left[\frac{DirRtShr_{jik}}{(1 - DirRtShr_{jik})}\right]$$

This dependent variable is then regressed on two right-hand side variables representing the difference in airport dominance of the observed carrier and of competing carriers on the route:

$$dAptShr_{ijk} = AptShr_{ik} - AptShr_{jk}$$

and

$$dOthAptShr_{ijk} = \frac{\sum_{\forall m \neq k} RouteShare_{ijm} \cdot (AptShr_{im} - AptShr_{jm})}{\sum_{\forall m \neq k} RouteShare_{ijm}}.$$

In all cases, the *AptShr* variable is measured omitting the traffic on the observed route.

Borenstein (1991) randomly chose one carrier per route to avoid the issue of correlation among observations on the route. I have estimated the regressions this way and also using all observations, in both cases with standard errors clustered at the route level. The coefficients are similar from these two approaches, but the standard errors are about 50% larger with the former approach. With that caveat, I report the results from using all observations.

Borenstein (1991) also found some evidence that share gap was more evident on business-oriented routes, using the differenced airport share variables interacted with the business share on the route. I use the newer measure of business share on the route introduced above. For ease of interpretation, I construct a business route dummy variable that is equal to one if the *Business Share* variable is above its median value for the entire sample:

$$dBizAptShr_{ijk} = BizDummy_{ij} \cdot dAptShr_{ijk}$$

and

$$dBizOthAptShr_{ijk} = BizDummy_{ij} \cdot dOthAptShr_{ijk}$$

Table 4 reports results from regressions with and without the *BizDummy* interaction effect. In contrast to the results from the price regressions, the airport dominance effect on share gap seems as large in the most recent period as in earlier years. The coefficients are quite stable across the four sub-periods from 1991 to 2010. Moreover, the R^2 is about the same in 2006-2010 as in the earlier periods back to 1991. The relationship seems hardly to have changed at all over the 20 year period.

The interesting temporal variation of interest seems to be in the 1980s. The coefficients are slightly smaller and the R^2 of the regression is less than half for 1986-1990, suggesting that less of the variation in share gap was explained by airport dominance at that time. This was a time when airlines were distinctly less sophisticated in their use of frequent-flyer plans and other marketing programs, which might explain the weaker association of airport dominance with share gap. The regressions for 1984-1985 suggest a much weaker relationship, both smaller coefficients and less statistical significance, indicated by the R^2 dropping to below 0.04. The association of share gap with airport dominance strengthened greatly in the 1980s and showed no signs of abating in the last decade.

Dep Variable:	1984-2010 dlgDirRtShr	1984-1985 dlgDirRtShr	1986-1990 dlgDirRtShr	1991-1995 dlgDirRtShr	1996-2000 dlgDirRtShr	2001-2005 dlgDirRtShr	2006-2010 dlgDirRtShr
<i>dAptShr</i>	0.874*** (0.0177)	0.317*** (0.0613)	0.739*** (0.0298)	0.914*** (0.0305)	0.891*** (0.0270)	0.906*** (0.0178)	0.911*** (0.0184)
<i>dOthAptShr</i>	-0.807*** (0.0261)	-0.0987 (0.0673)	-0.560*** (0.0472)	-0.836*** (0.0390)	-0.848*** (0.0367)	-0.866*** (0.0272)	-0.875*** (0.0290)
Observations	254,027	12,822	41,336	41,552	48,388	54,073	55,856
R-squared	0.461	0.031	0.217	0.443	0.497	0.573	0.595

Dep Variable:	1984-2010 dlgDirRtShr	1984-1985 dlgDirRtShr	1986-1990 dlgDirRtShr	1991-1995 dlgDirRtShr	1996-2000 dlgDirRtShr	2001-2005 dlgDirRtShr	2006-2010 dlgDirRtShr
<i>dAptShr</i>	0.819*** (0.0319)	0.154 (0.113)	0.695*** (0.0631)	0.865*** (0.0715)	0.834*** (0.0579)	0.827*** (0.0300)	0.857*** (0.0283)
<i>dBizAptShr</i>	0.0822** (0.0365)	0.235* (0.134)	0.0541 (0.0709)	0.0650 (0.0754)	0.0855 (0.0614)	0.124*** (0.0356)	0.0916*** (0.0352)
<i>dOthAptShr</i>	-0.626*** (0.0429)	0.117 (0.112)	-0.381*** (0.0936)	-0.650*** (0.0740)	-0.658*** (0.0718)	-0.674*** (0.0451)	-0.684*** (0.0401)
<i>dBizOthAptShr</i>	-0.293*** (0.0508)	-0.319** (0.132)	-0.262** (0.107)	-0.285*** (0.0845)	-0.305*** (0.0788)	-0.309*** (0.0532)	-0.339*** (0.0516)
Observations	254,027	12,822	41,336	41,552	48,388	54,073	55,856
R-squared	0.465	0.038	0.219	0.446	0.501	0.580	0.601

Observations weighted by passengers . Robust standard errors, clustered by route, in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Share Gap Regressions

V. Conclusion

The first decade of this century was financially disastrous for U.S. airlines, in large part because of weak demand and rising fuel costs. While the airlines continued to improve efficiency by putting more passengers on each flight (as well as by reducing labor costs through bankruptcy proceedings), these changes were not enough to keep up with declining prices.

This analysis suggests that airline pricing power at dominated airports also declined over the decade, particularly in the very weak economy of the last few years. Both summary data and regression analysis indicate that airport dominance lead to much smaller price premia in the last half-decade than at any time in the previous 15 years. Large market share on individual routes, however, was as strongly associated with higher margins in the 2000s as in the 1990s.

Despite this apparent decline in the market power associated with airport dominance,

the share gap analysis suggests that customers still demonstrated as much preference for the local dominant airline over the last decade as they did in the 1990s, and much more than in the 1980s. It is not obvious how to reconcile these findings with the declining price premia at dominated airports.

It's possible that airlines match prices with such speed and precision that most travelers make decisions among carriers offering very similar fares for their trip. The network marketing devices associated with airport dominance and indicated by share gap drive decisions among otherwise nearly equally attractive choices. Borenstein (1991) presents analysis that suggests this view is unlikely to hold. That analysis shows that the share gap association with airport dominance is about as strong when average prices differ substantially across carriers on a route as when they are nearly the same.

One possible explanation is that hub dominance market power weakens when the cost of entry declines, that is, when excess capacity leads existing airlines and new startups to venture into markets where incumbents are trying to maintain price premia. Consumer preferences for the local dominant airline may remain strong, but the cost to competitors of trying to overcome that preference may decline when the industry has slack capacity as it has had since 2000. This hypothesis has a number of implications – for new entry, market share instability, and pricing – that I am now pursuing.

APPENDIX (incomplete)

Means and Standard Deviations of Variables (weighted by passenger)		All Years	1991-1995	1996-2000	2001-2005	2006-2010
<i>InFare</i>	Mean	5.195	5.321	5.234	5.152	0.387
	Std Dev	0.442	0.544	0.502	0.387	0.337
<i>InNsDist</i>	Mean	-0.207	-0.311	-0.265	-0.165	0.677
	Std Dev	0.682	0.704	0.683	0.677	0.659
<i>InNsDist^2</i>	Mean	0.508	0.593	0.537	0.485	0.573
	Std Dev	0.591	0.652	0.612	0.573	0.544
<i>InNormCost</i>	Mean	-2.045	-2.115	-2.124	-2.050	0.325
	Std Dev	0.318	0.247	0.270	0.325	0.352
<i>InLoadFac</i>	Mean	-0.311	-0.450	-0.340	-0.300	0.138
	Std Dev	0.163	0.178	0.149	0.138	0.113
<i>InAirportConstraint</i>	Mean	4.988	4.929	4.929	5.000	1.072
	Std Dev	1.071	1.085	1.059	1.072	1.068
<i>InSMSAPop</i>	Mean	1.509	1.550	1.494	1.512	0.813
	Std Dev	0.822	0.851	0.824	0.813	0.811
<i>Change of Plane - NoDir</i>	Mean	0.128	0.131	0.135	0.132	0.118
<i>Change of Plane - OthDir</i>	Mean	0.089	0.090	0.091	0.094	0.081
<i>Change of Plane - OwnDir</i>	Mean	0.018	0.017	0.017	0.018	0.019
<i>InSMSAInc</i>	Mean	3.863	3.860	3.864	3.864	0.095
	Std Dev	0.098	0.104	0.100	0.095	0.095
<i>BizShare</i>	Mean	0.406	0.413	0.408	0.404	0.402
	Std Dev	0.076	0.078	0.077	0.075	0.075
<i>InCompCost</i>	Mean	-1.976	-2.075	-2.084	-1.971	0.213
	Std Dev	0.233	0.175	0.192	0.213	0.234
<i>RouteShare</i>	Mean	0.550	0.560	0.550	0.540	0.555
	Std Dev	0.283	0.281	0.279	0.282	0.286
<i>HHIOther</i>	Mean	0.545	0.532	0.555	0.547	0.542
	Std Dev	0.264	0.261	0.270	0.264	0.261
<i>AirportShare</i>	Mean	0.313	0.321	0.316	0.306	0.312
	Std Dev	0.174	0.163	0.169	0.173	0.184
Observations		280172	64992	70812	72500	71868

Table A1: Summary Statistics of Regressors

Dep Variable:	1988-2010 dlgDirRtShr	1988-1990 dlgDirRtShr	1991-1995 dlgDirRtShr	1996-2000 dlgDirRtShr	2001-2005 dlgDirRtShr	2006-2010 dlgDirRtShr
<i>dAptShr</i>	0.903*** (0.0178)	0.761*** (0.0295)	0.922*** (0.0302)	0.899*** (0.0271)	0.921*** (0.0177)	0.915*** (0.0186)
<i>dOthAptShr</i>	-0.853*** (0.0263)	-0.642*** (0.0585)	-0.855*** (0.0387)	-0.855*** (0.0369)	-0.882*** (0.0271)	-0.881*** (0.0290)
<i>dSchdConv</i>	0.320*** (0.0398)	0.440*** (0.100)	0.488*** (0.102)	0.417*** (0.0896)	0.398*** (0.0517)	0.153*** (0.0366)
Observations	225,066	25,197	41,552	48,388	54,073	55,856
R-squared	0.512	0.284	0.450	0.501	0.581	0.596

Dep Variable:	1988-2010 dlgDirRtShr	1988-1990 dlgDirRtShr	1991-1995 dlgDirRtShr	1996-2000 dlgDirRtShr	2001-2005 dlgDirRtShr	2006-2010 dlgDirRtShr
<i>dAptShr</i>	0.848*** (0.0325)	0.704*** (0.0660)	0.877*** (0.0705)	0.845*** (0.0583)	0.848*** (0.0297)	0.861*** (0.0285)
<i>dBizAptShr</i>	0.0822** (0.0367)	0.0718 (0.0734)	0.0585 (0.0743)	0.0804 (0.0615)	0.111*** (0.0351)	0.0918*** (0.0354)
<i>dOthAptShr</i>	-0.669*** (0.0441)	-0.451*** (0.124)	-0.674*** (0.0741)	-0.665*** (0.0727)	-0.702*** (0.0458)	-0.690*** (0.0404)
<i>dBizOthAptShr</i>	-0.298*** (0.0513)	-0.280** (0.137)	-0.276*** (0.0849)	-0.306*** (0.0793)	-0.288*** (0.0538)	-0.339*** (0.0519)
<i>dSchdConv</i>	0.310*** (0.0392)	0.446*** (0.101)	0.479*** (0.102)	0.412*** (0.0909)	0.372*** (0.0495)	0.152*** (0.0339)
Observations	225,066	25,197	41,552	48,388	54,073	55,856
R-squared	0.516	0.287	0.453	0.506	0.587	0.603

Observations weighted by passengers . Robust standard errors, clustered by route, in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A4: Share Gap Regressions with Schedule Convenience Variable

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