WILEY

Hubs and high fares: dominance and market power in the U.S. airline industry

Severin Borenstein*

This article estimates the importance of route and airport dominance in determining the degree of market power exercised by an airline. The results indicate that an airline's share of passengers on a route and at the endpoint airports significantly influences its ability to mark up price above cost. The high markups of a dominant airline, however, do not create much of an "umbrella" effect from which carriers with smaller operations in the same markets can benefit. The article suggests a number of possible explanations for this asymmetry.

"[T]here is still much to do before we can be confident that we have established a northeast stronghold that is as impervious as possible. Ideally we should control a major portion of the traffic at each of the cities in the northeast. The beauty of the niche strategy is not just the marketing identity and control that it gives us. In addition, it enables us to keep control of prices within our niche territory, thus insulating a significant portion of our traffic from the devastating effects of unbridled price competition."

—Randall Malin, Executive Vice-President of USAir, 1985.
Internal memo to the President and CEO of USAir.
(Exhibit in USAir-Piedmont Merger Case, July, 1987.)

1. Introduction

■ It has by now been well established that airline pricing does not closely reflect the perfect contestability ideal.[1] A number of earlier works have shown that prices on a route increase when concentration increases. This article attempts to establish more clearly the sources of market power in the airline industry.

Two empirical findings presented here indicate that the correlation between route concentration and high prices cannot be adequately explained by the traditional theories in which high concentration facilitates tacit or explicit collusion. First, the high average prices that some airlines are able to sustain in concentrated markets do not permit all participants in the market to charge similar prices. An airline with a large share of the traffic on a route appears to exercise market power without creating an "umbrella" effect that allows other airlines to raise their prices as much.

[1] See Graham, Kaplan, and Sibley (1983), Bailey, Graham, and Kaplan (1985), Call and Keeler (1985), and Morrison and Winston (1987).

344

Second, one source of market power on city-pair routes seems to be the size of a carrier's operations at the endpoints of the route. When a carrier serves a large share of the passengers who travel to or from the endpoints of a route, its attractiveness to passengers who travel on the route itself is enhanced. This tends to increase the airline's share on the route and its average price.

There is substantial anecdotal evidence that an airline with a dominant share of the traffic at an airport has a competitive advantage on routes that include that airport.[2] Among the many factors that may allow a dominant carrier at an airport to deter entry or lessen the competitiveness of those that do enter, a distinction can be drawn between competitive advantages that occur naturally and those that result from institutions created by the airlines. In the former category, one would probably include the dominant reputation acquired by a carrier as a natural consequence of offering most of the flights to and from a city. The latter group encompasses frequent-flyer programs and reward systems for travel agents that pay bonuses when the agent books more travel with one airline to the exclusion of others. In addition, control of the computer reservation systems used by travel agents has been argued to give an airline advantages over its competitors. Finally, at crowded airports, there is some evidence that an airline with large-scale operations may be able to inhibit potential competitors' abilities to obtain gates and other facilities necessary for entry or expansion of service at that airport.

The following section sets out the arguments for anticompetitive interpretations of the frequent-flyer plans and travel agent bonus programs. It also discusses other factors that may work to the advantage of an incumbent, both in deterring entry and in competing with other firms if entry does occur. Section 3 presents the equations that I estimated in order to evaluate the effect of airport and route dominance. It also presents the econometric technique for estimation and describes the data set used. The results, presented in Section 4, indicate that share of traffic at endpoint airports and share of traffic on the route both have significant positive effects on the price that an airline charges. Conclusions and policy implications are discussed in Section 5.

2. The advantages of airport and route dominance

■ As the quote at the beginning of this article indicates (and many other statements of airline managers have supported), airlines value airport dominance for the insulation such dominance may give them from competition.[3] As is common in many industries, the same factors that might give advantages to an incumbent firm if entry occurs are also likely to discourage entry in the first place. Thus, marketing devices or other factors that give an advantage to a dominant airline may result in it gaining larger shares of passengers on a route, as well as greater market power given its share of traffic.

One of the best-known marketing devices in the airline industry is frequent-flyer programs (FFPs). These programs give a gift, usually free travel, to a customer after he or she has conducted a certain amount of business with the airline. FFPs have been effective in

---

[2] The quote above is representative of the views of many airline executives. In the USAir-Piedmont merger case, Piedmont's Vice-President for Planning stated that they would never consider entering the Pittsburgh-Washington, D.C. (National Airport) market because of USAir's dominant position at Pittsburgh. He said, however, that Piedmont might compete with USAir from its own hub, Baltimore, to Pittsburgh because "that is strength against strength." (USDOT, Docket 44719, USAir-Piedmont Merger Case, transcript p. 615, testimony of Richard T. James, July 23, 1987.) See also *Wall Street Journal,* July 20, 1987 and Borenstein (1989).

[3] For a summary of these views, see Levine (1987). Levine's views are particularly important because he has managed airlines, regulated them, and studied them as an academic. He was a high-ranking policy maker at the Civil Aeronautics Board in the late 1970s, an Executive Vice-President of Continental Airlines, and then CEO of New York Air in the early 1980s. His evidence is first-hand if, at points, anecdotal. Furthermore, to the extent that barriers to entry are effective if they are perceived to exist, Levine's views that they exist are important in and of themselves.

attracting repeat business, especially from the most lucrative group of customers, business travelers. Since FFPs were first implemented in 1980, many car rental agencies, motel and hotel chains, and credit cards companies have begun to offer similar programs.

It is noteworthy that the users of such programs are firms that sell many heterogeneous products, differentiated at least by location, and that the payoff schedules are nonlinear.[4] The marginal bonus from additional business with one of these companies increases with the amount of business conducted.[5] Furthermore, these firms derive much of their revenue from business people who are making purchases for which they do not directly bear the full cost. Yet, the bonuses are given directly to the purchaser rather than to the purchaser's company.

One key to loyalty inducement from FFPs seems to be the extensiveness of the airline's route network. In the 1987 USAir-Piedmont merger case, for instance, the joint applicants argued that their comparatively small route structures meant that it took longer for customers to accumulate mileage towards bonuses, and the fact that they offered few attractive "payoff" destinations meant that the bonuses were less valued when they were received. These factors, they argued, put them at a disadvantage in the use of FFPs relative to the larger airlines.[6] Though some of these difficulties can be addressed by forming affiliated FFPs, in which many airlines participate in the same program, the transaction, bargaining, and coordination costs of such arrangements are recognized to be substantial.[7]

When an airline offers extensive service from a traveler's home airport, its FFP becomes more attractive for two reasons. First, since the bonus value is an increasing marginal function of the mileage or points accumulated, the traveler will have an incentive to concentrate his business with just one or a few airlines. The customer is likely to choose the airline that he expects to be travelling with most often in the future: the one with the most service on the routes he flies and the one that flies the most routes from his home. Second, since the most common bonus gift is a certificate good for free travel on the airline to the customer's choice of destination (with restrictions in some cases, such as remaining within the continental U.S.), the expected value of such a bonus will be greater to a customer if the airline serves more destinations, with more direct service, from his likely point of departure.

It has also been widely stated that a primary purpose of these programs is to offer kickbacks on business purchases in the form of a gift to the agent who does the buying for the business.[8] When the buyer places an unusually high value on the bonus *relative* to the value she places on marginal payments for the purchased travel—as results from this principal/agent problem—the FFP increases in effectiveness. Although such an incentive might raise a travel-purchasing firm's costs, FFPs also increase the compensation received by its employees. Furthermore, such compensation is not taxed. Thus, one can imagine an allocation of costs and benefits from such kickbacks in which the only net loser is the government.[9]

Though the frequent-flyer program is probably the most well-known airline marketing device, a similar, but less publicized program for travel agents may have as large or larger effects. Travel agent commission override programs (TACOs) pay bonuses to travel agents

---

[4] Borenstein (1988a) presents a model that highlights the uses of FFPs by a firm that sells multiple products.

[5] See Banerjee and Summers (1987) for a table of the increasing marginal bonus values from increased mileage on frequent-flyer programs.

[6] See U.S. Department of Transportation, Docket 44719, USAir-Piedmont Acquisition Case, Exhibit JA-T-1, p. 16–17, May 22, 1987. Also, see Levine (1987) for a thorough discussion of the need for an extensive network.

[7] See Levine (1987) and USDOT, Docket 44719, USAir-Piedmont Merger Case, JA-T-1, p. 17.

[8] See, for example, Levine (1987), Banerjee and Summers (1987), and Borenstein (1988a).

[9] This may explain why firms that are large purchasers of air travel, such as IBM and GM, have not objected vehemently to frequent-flyer programs. Few firms have implemented strict monitoring of frequent-flyer miles acquired by their employees during business trips.

who generate some specified level of revenues for the airline. While FFPs rely in part on the principal/agent relationship between employees and employers, TACOs rely solely on the principal/agent relationship between air travel buyers and travel agents.

As with frequent-flyer programs, the TACO bonuses are usually a nonlinear function of revenues generated. Because the marginal returns are increasing, the programs can effectively "attach" travel agents to certain airlines. The bonuses are generally in the form of increased commissions on the agent's sales, or free travel for the agent to sell and keep all of the resulting revenue. Such programs, however, work only to the extent that the principal cannot fully monitor the travel agent and costlessly judge the quality of the information the agent delivers. Of course, this asymmetry in information costs is much of the reason that travel agents exist to begin with. As has been pointed out in the reputation literature, it is rarely profitable for a seller to maintain optimal quality—in this case the travel agent's quality of information—when the buyer cannot monitor perfectly.[10] In a recent survey of travel agents, more than half reported that their choice of airline for a customer is "usually" (24%) or "sometimes" (27%) influenced by TACOs. Thirteen percent said "rarely" and 35% said "never."[11] As with FFPs, an airline offering the most opportunities for building up "points" (revenues, in this case) and offering the most valued set of bonuses will be the most effective in inducing loyalty through a TACO program. These aids to inducing loyalty are likely to favor the airlines with more flights to and from a city.

As TACOs may induce travel agents to present biased information to travellers, computer reservation systems (CRSs) may allow the airlines that own them to present biased information to both travel agents and consumers. Nearly all travel agents use a CRS to obtain schedule and price information. Despite federal regulation of CRS displays, the airlines that own these systems are still thought by many to bias them in such a way that their own flights are featured more prominently than those of their competitors.[12] CRS-bias may reenforce the advantages of airport dominance because in cities dominated by a carrier that owns a CRS, more of the travel agents will choose to use the dominant airline's CRS.[13] This preference for the dominant airline's computer system is due in part to the more extensive and timely information that it offers about that carrier's flights. It may also reflect the travel agents' or travelers' preferences for the dominant airline due to FFPs and TACOs. In either case, the preferences of some buyers (travellers and travel agents) for the locally dominant airline can lead to choosing that airline's CRS. The display bias could then exist even when trips are being booked for a traveller who does not prefer the dominant airline.

Discussions of airport dominance and entry deterrence in the airline industry over the past few years have focused to a great extent on the availability of two critical inputs, slots and gates.[14] A slot is the right to have a plane take off or land at an airport during a certain time period. Gates are physical assets, i.e., the building and jetways. When a single airline controls most of the gates at an airport, not only may it be able to refuse to sell or lease facilities to entrants, it may also influence the decision of the airport operator, usually a local government, regarding expansion of the airport to accommodate new entrants.[15] Sim-

---

[10] See, for instance, Shapiro (1982).

[11] See *Travel Weekly,* June 29, 1988, p. 94.

[12] See Levine (1987), USDOT, Docket 44719, USAir-Piedmont Merger Case, JA-T-1 and JA-T-2, and USDOT (1988). For a view defending the efficiency of CRS display decisions, see *Regulation* (1985).

[13] For evidence of the strong correlation between CRS-share and local-traffic share of the owner-airline, see USDOT (1988).

[14] See Levine (1987), *Wall Street Journal,* July 20, 1987, Borenstein (1988b), as well as the records in USDOT, Docket 43825, Texas Air-Eastern Merger Case, 1986; Docket 43837, TWA-Ozark Merger Case, 1986; and Docket 44719, USAir-Piedmont Merger Case, 1987.

[15] For anecdotal evidence of such behavior, see *Wall Street Journal,* July 20, 1987 and USDOT, Docket 44719, USAir-Piedmont Merger Case, AWA-T-1.

ilarly, at airports where a market for takeoff and landing slots exists, control of a dominant share of the slots can allow an airline to inhibit profitable entry. Such market power must not be confused, however, with price premia that reflect competitive rents to these scarce inputs. A method of diagnosing such scarcity rents is presented in the following section.

Concern with entry barriers at airport facilities naturally leads to the question of whether flights to different airports in the same metropolitan area compete with one another, e.g., do flights from Kennedy airport to Detroit effectively discipline prices on the La Guardia to Detroit flights? Most antitrust analyses of this question have focused on the standard criterion for judging market boundaries—the cross-elasticity of demand—but in so doing they have ignored an important aspect of airline competition: demand segmentation. If the group of consumers with large cross-elasticities between two local airports (e.g., travellers with low time values) can be separated out, competition for those customers need not discipline the prices charged to travelers with strong preferences between the airports.[16] Restricted discount fares are probably quite effective in sorting customers by their time values. Thus, we would expect to see the presence of competing metropolitan airports affect the restricted discount fares more than the fares charged to business travellers. In the empirical work presented here, flights to different airports are assumed to be in separate markets. The degree of actual substitutability remains for future work.[17]

3. Estimation of the effect of route and airport dominance

■ I present two different approaches to analyzing the effects of route and airport dominance on the prices that an airline charges. The first is a cross-section estimation of a carrier's markup over cost, similar to those done in previous studies, except I include effects of the airport and route share of the observed carrier as well as airport and route concentration variables.[18] The second approach is a cross-section estimation of the ratio of two observed airlines' prices on a route as a function of the ratios of the airlines' costs, service qualities, and shares of traffic on the route and at the endpoints. The second approach may be more effective in revealing the market power that a carrier obtains, relative to the airlines with which it competes, when it has a dominant position in a market. The results of the two approaches are broadly consistent.

□ **Estimating a pricing equation.** In the first approach, I estimate a pricing equation as a function of costs, market demand characteristics, service quality, and factors that are hypothesized to influence a carrier's market power. Interpretation of the coefficients of many variables is complicated, however, by the fact that a single variable will have influence in more than one of these categories, e.g., a higher load factor may lower the airline's cost per passenger, but it will also lower the perceived quality of service. In order to examine the effects of the variables on different types of fares, I estimate the equation with three different dependent variables: the 20th percentile, 50th percentile (median), and 80th percentile fare paid to the observed carrier on the observed route.[19] The unit of observation is an airline-

---

[16] Borenstein (1985) presents such a model of price discrimination when buyers are heterogeneous in their costs of brand switching.

[17] For anecdotal and some rough empirical work on this subject see testimonies in USDOT, Docket 43825, Texas Air-Eastern Merger Case, 1986, and Docket 44719, USAir-Piedmont Merger Case, 1987.

[18] Bailey, Graham and Kaplan (1985) also include a variable for the observed airline's route share, which they find to have a significant positive effect even after controlling for route concentration. Using the framework of Bresnahan (1989), I estimate a supply relation in which the cost function is not explicitly stated or estimated, but rather inferred from cross-sectional variation in prices and product attributes.

[19] These percentiles are from the distribution of fares weighted by the number of passengers paying each fare, not from a distribution that gives equal weight to each fare listed by the airline. Though the median fare is highly correlated with the mean fare, which most previous studies have used, the median fare is less likely to be affected by reporting errors that cause inclusion of some abnormally high or low fares.

route pair in the third quarter of 1987. The data set includes observations on the nine largest domestic airlines at that time.[20] Each observation includes all origin-to-destination ("local O & D") passengers travelling one-way or round-trip on a route on the observed carrier.[21] Further explanation of the sample and construction of the variables is given later in this section and in the Appendix.

The variables describing market structure are the observed airline's share of the passengers transported in the market and the Herfindahl index, constructed from the shares of all carriers in the market. The structure of the "markets" at the endpoint airports might be measured by studying either the airlines' shares of passenger enplanements or their shares of originating passengers at the airports. The former measure includes passengers changing planes at the airport, while the latter does not. The results presented here use measures based on the number of originating passengers, but they change very little when the enplanement-based measures are used. The first equation estimated is then

$$
\begin{aligned}
\ln P_{ij} = {} & \alpha_i + \beta_1 \ln DISTANCE_j + \gamma_1 \ln LOADFAC_{ij} + \gamma_2 \ln EQUIP_{ij} \\
& + \gamma_3 \ln FREQ_{ij} + \gamma_4 \ln CIRC_{ij} + \gamma_5 STOP_{ij} + \gamma_6 PLANECHG_{ij} \\
& + \delta_1 ORGSHARE_{ij} + \delta_2 ORGHERF_j + \delta_3 RUTSHARE_{ij} + \delta_4 RUTHERF_j \\
& + \delta_5 \ln COMPCOST_{ij} + \delta_6 \ln TOURIST_j + \sum_{k=1}^{24} \rho_k APT_k,
\end{aligned}
\tag{1}
$$

where i indexes the airline, j indexes the route, and the Greek letters used to represent the coefficients give a rough indication of the way in which the variable is hypothesized to affect price. The α's are the firm-specific constant terms for estimation of fixed effects (discussed below), the β's are associated with variables that primarily affect production cost, the γ's are associated with variables that affect both cost and service quality, the δ's are associated with variables that primarily indicate market power, and the ρ's are associated with the scarcity rents from operations at one of the 24 possibly congested airports in the U.S., as explained below. The variables, which are described more completely in the Appendix, are defined here and their expected effects are discussed:

— P_{ij} is the xth percentile fare, $x = 20, 50, 80$, paid to the observed airline on this route. Round-trip tickets are broken down as two one-way trips, for which the fare on each trip is half the round-trip fare.

— $DISTANCE_j$ is the nonstop mileage from one endpoint of the route to the other. One would expect $DISTANCE$ to have a positive effect on price, but that the elasticity would be less than one, since the airline's cost of transporting a passenger increases less than linearly with distance of his trip. (expected sign: positive)

— $LOADFAC_{ij}$ is the average load factor of flight segments on which the airline carries passengers travelling on the observed airline route. Load factor may affect fares in three ways. As the load factor on flights increases, the per-passenger cost of the flight declines, thus possibly lowering fares. On the other hand, flights with high load factors fly full more often and are more likely to operate at peak demand times. The opportunity cost of

---

[20] The airlines included are American, USAir, Continental, Delta, Eastern, Northwest, Piedmont, TWA, and United. Though Continental and Eastern were owned by the same holding company (Texas Air Corporation) during the time of the sample, they were operated as separate companies. They had quite different cost structures, reputations, and geographical areas of operation. The results discussed below are changed slightly when the airlines are treated as one for the purpose of route and airport share calculations. The changes tend to reenforce the finding that large airport and route shares yield market power.

[21] "Through" and "connecting" passengers, those traveling on a given flight or route but for whom one of the endpoints is neither an origin nor a destination, are not counted as passengers on the route. All "local" passengers on the route who make zero or one plane changes in each direction of their trip are included. See the Appendix for further details.

aircraft in use on a specific route is higher during these times, possibly increasing fares. Finally, as the load factor increases, the quality of service decreases, thus lowering consumers' reservation prices for the flight. (sign: indeterminate)

— $EQUIP_{ij}$ is the average size of aircraft on flights that carry passengers travelling on the observed airline/route. On flights of more than 500 miles, larger equipment has a lower per-seat-mile cost and therefore would be expected to lower the cost of providing air travel where it is used.[22] On the other hand, the quality of the product is higher on larger planes, which are generally more comfortable and are thought to be safer.[23] This might increase demand for the product, and, thus, increase the price. (sign: ?)

— $FREQ_{ij}$ is the average frequency of flights that carry passengers travelling on the observed airline/route. Routes with very high flight frequency will have lower per-flight costs, controlling for the load factor, because aircraft utilization (hours per day) is generally greater for the aircraft used on such routes.[24] Of course, greater flight frequency also lowers frequency delay, as defined and investigated by Douglas and Miller (1974), thus increasing the value of the product. This effect will be greater for those who value their time more highly, who are, presumably the people who pay the higher fares. (sign: ?)

— $CIRC_{ij}$ is circuity of travel, defined as the average total routing mileage of passengers travelling on the observed airline/route ($TOTMILE$) divided by $DISTANCE$, the nonstop origin-to-destination mileage. Controlling for stops, plane changes, and load factors, greater circuity of travel raises production costs and lowers product quality. The former effect would tend to raise price, while the latter would tend to lower it. (sign: ?)

— $STOP_{ij}$ is the average number of on-plane stops made by passengers travelling on the observed airline route. Holding constant the load factor, mileage, and plane changes, increased stops increase the airline's costs of a trip by reducing the average length of haul (takeoff to landing distance). At the same time, they decrease the quality and willingness to pay for the product. Thus, the net effect is ambiguous. (sign: ?)

— $PLANECHG_{ij}$ is the average number of change-of-plane stops made by passengers travelling on the observed airline route. The effects of $PLANECHG$ are expected to be essentially the same as those of $STOP$. (sign: ?)

— $ORGSHARE_{ij}$ is the weighted average of the observed carrier's share of daily passenger originations at the two endpoints of the observed route (in the third quarter of 1987). The weighting is according to the proportion of passengers on the route who originate their trips at each endpoint. Increases in $ORGSHARE$ may lead to greater market power and prices. (sign: +)

— $ORGHERF_j$ is the weighted average of the Herfindahl indices (measured as zero to one) for passenger originations at the two endpoints of the observed route. The weighting is the same as for $ORGSHARE$. The effects discussed in Section 2 indicate that an airline might prefer that its competition were many very small firms rather than one larger airline. On the other hand, tacit or explicit coordination among competitors that allows a reduction of competition, such as an agreement not to enter one another's route, is less costly to attain and more likely to succeed when there are few competitors to include. (sign: ?)

— $RUTSHARE_{ij}$ is the observed carrier's share of all local origin-to-destination passengers on the observed route. If there is not a complete umbrella effect from the market power

---

[22] See Bailey, Graham and Kaplan (1985). An F-test of whether this parameter differed on routes with average flight lengths of greater and less than 500 miles did not reject the restriction to a single value. In fact, the estimates were very similar.

[23] Existence of a quality-enhancement effect is demonstrated by the frequent mention of "spacious" or "comfortable" wide-bodied aircraft in airline advertisements.

[24] See the transcript of the oral testimony by Randall Malin, Vice-President of USAir in USDOT, Docket 44719, USAir-Piedmont Merger Case.

of a dominant firm, then, controlling for concentration on the route, the firm with a larger share would be expected to have higher prices. (sign: $+$)

—$RUTHERF_j$ is the Herfindahl index (measured as zero to one) for all local O & D passengers on the observed route. To the extent that a dominant firm's high prices create an umbrella that allows a few firms in a concentrated market to collude more easily, then increases in concentration will increase price, holding constant the observed firm's share. If, however, a dominant firm on a route has a competitive advantage, through marketing devices, advertising, or other means, it could possibly lower the profit-maximizing price for other firms in the market. (sign: ?)

—$COMPCOST_{ij}$ is the weighted average of the cost-per-seat mile (for a standardized-distance trip, to adjust for differences across carriers in average flight length) of all carriers on the route other than the observed carrier. The weighting is according to each carrier's share of passengers on the route. Since the prices of competing firms are clearly endogenous and inclusion of complete data on their operations is not possible,[25] the $COMPCOST$ variable, along with $RUTSHARE,$ is intended to indicate the competitiveness of other airlines on the route. Increases in the production costs of competitors would be expected to raise the price of the observed firm. (sign: $+$)

—$TOURIST_j$ is a measure of the relative tourist orientation of passengers on a route as a function of a tourism measure of the passengers' destination city. (See the Appendix for further description of the tourism measure.) A greater proportion of tourist travelers on a route would be expected to lower prices. (sign: $-$)

—APT_k is a dummy variable (adjusted for route distance as explained in the discussion of functional form below) that indicates whether one endpoint of the route is airport k. The associated parameters are intended to capture the scarcity rents if there is excess demand for gate or runway use at the airport.[26] These rents can be distinguished from the market power available to a dominant airline because the effect of scarcity rents on the price of flights will be the same for all airlines operating at an airport.[27] In contrast, market power, as reflected in a carrier's share of passenger originations at an airport, will differ among the airlines at an airport. Scarcity rents are thus identified and separated from airline-specific market power at an airport by estimating airport-specific effects on prices that are restricted to be the same across airlines. I estimate airport-specific price effects for the 22 airports that the FAA monitors for congestion problems,[28] as well as the airports in Orange County and Long Beach, California, each of which is under strict local limits on takeoffs and landings. One would expect these estimates to be positive. (sign: $+$)

☐ **Econometric issues.** *Endogeneity of explanatory variables.* A number of econometric issues arise in the estimation of equation (1), the most obvious and difficult of which is the possible endogeneity of some of the right-hand side variables. For those variables that are clearly endogenous and for which it seems that the cure—identification with instruments that fulfill the standard criteria for two-stage least-squares estimation, at the possible cost

---

[25] Many of the service-quality variables are not available for firms other than the largest trunk airlines.

[26] Similarly, higher prices at an airport might reflect other high (opportunity) costs, such as higher local fuel prices, wage rates, etc.

[27] If all routes from an airport are competitive, scarcity rents for the *marginal* unit of output (flights) will necessarily be equalized across uses of the slots or gates. In fact, even for inframarginal flights, the effect of scarcity rents on *price* would be the same. Though scarcity rents would be greater for inframarginal uses of the fixed factor than for marginal uses, if all uses were in competitive markets, the differences in scarcity rents would result from lower production costs, not higher prices, in some uses of the fixed factor.

[28] At four of these airports, the FAA has established slot allocation mechanisms (O'Hare, Kennedy, La Guardia, and Washington National). The other congested airports operate under "flow control," which is essentially a system of allocation by queuing. See U.S. Federal Aviation Administration (1987) for a list of the monitored airports.

of increased noise in the estimation—is better than the ailment—biased estimates—I have carried out the standard econometric procedure. For those cases in which there seem to be no usable instruments and the ailment is not likely to be very serious, I have chosen to press ahead with estimation that is possibly biased, but to then interpret the results in light of that possible bias. Finally, the following section also presents ordinary least-squares (OLS) estimates of equation (1), though a Hausman specification test does reject exogeneity for the *RUTSHARE* and *RUTHERF* variables.

One would expect a carrier's share of the passengers on a route (*RUTSHARE*) to be a function of the price it charges and therefore to be correlated with the error term, causing OLS estimation of equation (1) to be biased. One possible instrument for identifying *RUT-SHARE* is a measure of the presence of competing airlines at the endpoint airports. This is difficult to define, however, because as the discussion in the previous section has suggested, airport concentration and airport share can directly affect a firm's market power.

Still, the airport dominance effects discussed earlier do not rely on the synergy of large-scale operations at both airports, while the likelihood of entry by a carrier does benefit from this synergy. This fact is used to identify route share.[29] The identifying omitted variable is the observed carrier's geometric mean of enplanements at the endpoints of a route divided by the sum across all carriers of the geometric mean of each carrier's enplanements at the endpoint airports.

$$GENPSH = \frac{\sqrt{ENP_{i1} \cdot ENP_{i2}}}{\sum_{j} \sqrt{ENP_{j1} \cdot ENP_{j2}}}, \qquad (2)$$

where j indexes all airlines, i is the observed airline, and ENP_{j1} and ENP_{j2} are airline j's average daily enplanements at the two endpoint airports during the third quarter of 1987.[30] In the first-stage estimation of *RUTSHARE,* both *ORGSHARE* and *GENPSH* are highly significant.

It is more difficult to argue that *GENPSH,* or some variable closely related to it, does not itself belong in equation (1), i.e., to argue that the identifying exclusion restriction is valid. The restriction is valid if an airline's current prices do not respond to threats of entry, but only to actual competition. This may in fact be the case, since an incumbent airline can adjust its prices in much less time than normally elapses between a competitor's announcement that it will enter a market and its actual entry.[31]

If *GENPSH* should, in fact, be included in the estimated equation, then use of it only as an instrument could lead to inconsistent estimates. I deal with this problem in two ways: first, by ignoring it and maintaining the assumption that *GENPSH* has no direct effect on price, and second, by creating another variable that is a direct measure of potential competition. *POTCOMP* is constructed in much the same way as *GENPSH,* but the numerator includes all airlines that carry less than 1% of the traffic on the observed route, i.e., potential competitors who are not yet significant in the market. The problem with the use of *POT-*

---

[29] Berry (1989) gives support to the importance of a carrier serving both endpoints of a route. His data on 1225 city-pair markets during 1980 indicate that the rate of entry was about 18 times greater for carriers serving both endpoints of a route (6.46%) than for those serving just one endpoint of a route (0.36%).

[30] I use enplanements rather than passenger originations in this case because the former is a better indicator of the size of an airline's investment in physical capital (and long-term labor contracts) at an airport. It is this aspect of the presence of other carriers at both endpoint airports that is likely to affect route share without being as highly correlated with the airport dominance advantages in marketing.

[31] For anecdotal evidence, see the transcript of the oral testimony by Randall Malin, Vice-President of USAir in USDOT, Docket 44719, USAir-Piedmont Merger Case, in which he states that USAir fears entry, but its pricing is based on the actual competition it faces. Of course, all markets benefit from some actual competition in that consumers can choose indirect routings if the prices of direct routings rise too much.

COMP is that it may itself be endogenous; the number and selection of airlines that serve both endpoints of the route, without serving the route itself, may depend on the prices that the observed firm charges on the route. In the alternative regressions discussed in the next section, GENPSH is still used to identify RUTSHARE, while POTCOMP is included directly in equation (1).

To the extent that RUTSHARE is endogenous, the route Herfindahl, RUTHERF, is also endogenous, since the square of RUTSHARE is one component of RUTHERF. I create an instrument for RUTHERF that is valid under the assumptions (a) that GENPSH is a valid instrument for identifying RUTSHARE, and (b) that the concentration of traffic on a route that is not carried by the observed airline is exogenous with respect to the price of the observed carrier, e.g., TWA's price on the Boston-Los Angeles route does not affect how the passengers it doesn't get are divided between American and United. Under these two assumptions, the instrument for RUTHERF is the square of the fitted value $\widehat{RUTSHARE}$ (from its first-stage regression) plus the "rescaled" sum of the squares of all other carrier's shares. The rescaling assures that a Herfindahl index calculated only for passengers who do not travel on the observed airline is unchanged.

$$IRUTHERF = \widehat{RUTSHARE}^2 + \frac{RUTHERF - RUTSHARE^2}{(1 - RUTSHARE)^2} \cdot (1 - \widehat{RUTSHARE})^2.$$

$$(3)$$

The variable IRUTHERF is then an excluded exogenous variable in the first-stage regression of RUTHERF that creates $\widehat{RUTHERF}$.

The assumption that the observed carrier's price does not affect the allocation of the traffic that it does not get is also critical to the exogeneity of the COMPCOST variable. If this allocation is not exogenous, then the weighting function used in constructing COMP-COST will depend on the observed carrier's price, and the constructed variable could be correlated with the residual.

The last variable for which endogeneity is explicitly recognized and addressed is LOAD-FAC, the average load factor of flights on which passengers in the observation travel. Within a single observation, there will be many different itineraries aggregated—some with on-plane stops, some with change-of-plane stops, and some with no stops. The excluded variable used to identify LOADFAC is LOADPOP, the weighted average across itineraries included in an observation of the sum of the populations of the cities through which a passenger would travel on the itinerary.[32]

One might argue that the choice by an airline to offer nonstop service on a route, versus direct service with on-plane stops or just connecting service, is itself endogenous. Therefore, though the populations used to construct LOADPOP are exogenous, the summing of them by itinerary may not be. A similar argument applies to the airline's choice of aircraft size (EQUIP), the frequency of flights on each airport-pair segment (FREQ), the average number of stops (STOP) and plane changes (PLANECHG) that a passenger makes, and the average circuity of her routing (CIRC). Due to the obvious shortage of identifying instruments, one can only recognize the possibility of these biases and attempt to interpret the estimation results with them in mind.

Pooling across airlines. By definition, the airport scarcity rent parameters must be equal for all airlines. The structure of the model, however, does not imply such restrictions on any of the other parameter estimates. A test for fixed airline effects rejected the null hypothesis of a common constant term, so the results presented here are estimated with separate constant

---

[32] The weighting is by the number of passengers using each itinerary included in the observation.

terms for each airline. A further test for the restriction of common parameter estimates across airlines for all variables fails to reject pooling at conventional significance levels.

When the unit of observation is a carrier-route pair, it is clear that the residuals from observations of different carriers on the same route will not be independent. In light of the large sample available and the fact that many routes have only one valid carrier observation, I have chosen to include only one carrier observation from each route. For each route on which there are multiple carrier observations in the sample, one observation was chosen randomly from among the airlines that carried at least 10 passengers per day on the route and at least 10% of the total traffic on the route.

Functional form. Profit maximization by a firm with market power implies that price will be proportional to the product of marginal cost and the inverse of the elasticity of demand faced by the firm. Previous studies of airline pricing have thus estimated markup equations using a multiplicative functional form.[33] This form imposes constant elasticities on the effect of the independent variables on fares. I also adopt this approach for most of the variables.

It seems particularly unlikely, however, that the effect on fares when an airline's route share changes from 1% to 2% is the same as when its share increases from 30% to 60%. For this reason, the route-share variable is entered in linear form, rather than its natural logarithm. A similar argument can be made for the effects of airport share (*ORGSHARE*). The arguments for route and airport share do not apply as strongly to the route and airport Herfindahl measures, but I have also chosen to estimate the effects of *RUTHERF* and *ORG-HERF* in linear form, primarily for ease of comparison and computation. The signs and approximate significance of the parameter values are quite robust to changes in the functional form from linear to log for each of these variables.

The inclusion of *STOP* and *PLANECHG* in linear form requires less justification. It seems more reasonable to assume that each additional stop or plane change would have the same proportional effect on price, rather than a declining marginal effect, as a log form would imply.

The log form would not be reasonable or possible for the zero-one airport scarcity variables. Entering them simply in linear form, however, still causes the scarcity rent to be a function of the fare that the passenger would otherwise pay. Scarcity rents due to shortages of airport capacity should impose the same cost regardless of the route the plane is flying, so these rents should be estimated as additive factors. That nonlinearity, however, would require iterative methods that would be quite difficult to use given the number of observations and variables. As a partial solution to this problem, I use the zero-one variable described above divided by the itinerary's nonstop route distance (in thousands of miles) as the scarcity variables. This adjusts, to some extent, for the bias that would otherwise assign greater scarcity rents to longer routes, which generally have greater fares.[34]

□ **Estimating a relative–price equation.** The discussion of airport dominance in the previous section indicates that the resulting market power might allow one carrier to charge higher prices than other airlines competing against it in a market. This effect can be estimated directly, using a model derived from equation (1), by comparing prices among carriers on the same route. This approach also allows the elimination of some of the variables in equation (1) because they will be the same for all carriers on a route. Essentially this approach allows one to control for the fixed-route effects.

In this case, the dependent variable is the ratio of one carrier's price—again, measured as the 20th, 50th, and 80th percentile fare paid to the airline—to the equivalent price of

---

[33] See, for instance, Graham, Kaplan, and Sibley (1983), Bailey, Graham and Kaplan (1985), and Peteraf (1986).

[34] Estimation of the scarcity variables without this distance adjustment yields similar conclusions for the route-share and airport-share effects, but the results for some airports do change noticeably.

another airline on the route. The observations are limited to routes on which at least two carriers have at least a 10% market share and carry at least 10 passengers per day on the route. When equation (1) is differenced between airlines a and b on the same route, it becomes [35]

$$\ln P_a - \ln P_b = \alpha_a - \alpha_b + \gamma_1(\ln LOADFAC_a - \ln LOADFAC_b)$$

$$+ \gamma_2(\ln EQUIP_a - \ln EQUIP_b) + \gamma_3(\ln FREQ_a - \ln FREQ_b)$$

$$+ \gamma_4(\ln CIRC_a - \ln CIRC_b) + \gamma_5 (STOP_a - STOP_b)$$

$$+ \gamma_6(PLANECHG_a - PLANECHG_b) + \delta_1 (ORGSHARE_a - ORGSHARE_b)$$

$$+ \delta_3(RUTSHARE_a - RUTSHARE_b), \tag{4}$$

where the parameters are the same as in (1). The two observed airlines on a route are chosen randomly from among all those that meet the criteria discussed above.

The endogeneity issues involved in estimation of (4) are the same as for (1). With carrier-fixed effects, pooling of other parameter estimates across carriers again could not be rejected. The results are robust in sign and approximate significance of the estimates to changes from log to linear specification of $RUTSHARE$ and $ORGSHARE$. [36]

□ **The sample and the data.** Details of the data sets and the construction of each variable are given in the Appendix. This section gives a general description of the sample and data sources.

The sample includes observations on the nine largest domestic airlines in the U.S. (as of the third quarter of 1987) for service on 5,428 routes. Of these routes, there were 3,591 on which at least one of the nine carriers had a 10% share and carried at least 10 passengers per day. The 1,508 routes on which at least two of the carriers met these criteria were included in the relative-price regression. The source of most market and price data is the Department of Transportation's (DOT's) *Origin and Destination Survey Databank 1A* (DB1A)), a 10% random sample of all tickets sold in the U.S. The criterion for inclusion of a route was based on observation of a minimum total number of valid passenger trips, as explained in the Appendix. The source of most of the data on airline flight operations, e.g., *EQUIP, FREQ,* and *LOADFAC,* is the DOT's *Service Segment Data.* This is not a survey, but a complete census of all flights. The DOT continues to require airlines that operated before deregulation to submit these data, but it does not require these data from newer and small airlines.

4. Results and interpretations

■ Table 1 presents average yields (price per mile) at some of the most dominated airports in the U.S. and gives initial support for the observation that an airline charges higher prices when it has a dominant position at an airport. At these airports, the dominant airline

---

[35] The *COMPCOST* variable is omitted from the differenced equation, even though it differs across airlines on the same route. Its purpose in equation (1) was to proxy for the effects of other airlines on the route that are estimated directly in equation (4) for one other airline on the route and are otherwise the same for the two observed airlines.

[36] One additional problem might arise in this differenced form. If the proportional difference in fares is not stable across distances, e.g., if the difference grows more or less than proportionally on longer routes, then a heteroskedasticity problem might arise, biasing the estimates of the standard errors. A test for this, however, yielded no strong indication of a correlation between the estimated residuals and the route distance. The t-statistics when the squares of the residuals were regressed on *DISTANCE* were below one for the *LFR*20, *LFR*50, and *LFR*80 regressions.

TABLE 1   Comparisons of Average Fare per Mile (Yield) for Flights to/from Dominated Airports

Nonstop Route Distance (Miles)	<200	200–500	500–1000	1000–1500	1500–2000	>2000	All
All Domestic Flights	37.96	25.82	17.46	11.42	9.12	7.16	12.91
TWA—ST. LOUIS:	82% Enplanement Share, 60% Origination Share						
TW not to/from STL	34.37	28.63	18.50	12.63	9.32	8.37	10.86
TW to/from STL	62.08	33.71	19.27	14.70	11.68	7.79	18.50
Others to/from STL	—	25.37	17.98	11.00	8.61	7.61	14.41
NORTHWEST—MINNEAPOLIS:	77% Enplanement Share, 65% Origination Share						
NW not to/from MSP	58.57	32.76	20.47	12.59	9.36	7.85	14.41
NW to/from MSP	60.67	38.89	22.13	13.91	10.82	8.90	17.55
Others to/from MSP	45.59	33.15	18.70	11.10	8.38	7.88	14.89
USAIR—PITTSBURGH:	84% Enplanement Share, 63% Origination Share						
AL not to/from PIT	45.54	28.39	17.31	11.59	9.48	7.98	17.42
AL to/from PIT	53.49	31.69	15.22	13.26	9.60	8.72	20.32
Others to/from PIT	55.84	29.04	18.19	12.70	7.84	6.87	12.61
AMERICAN—DALLAS:	60% Enplanement Share, 47% Origination Share						
AA not to/from DFW	48.62	25.26	20.56	12.00	9.89	8.51	12.15
AA to/from DFW	30.28	20.08	20.77	15.49	15.55	9.11	17.24
Others to/from DFW	29.50	21.73	18.43	11.86	11.32	6.41	14.51
UNITED—CHICAGO O'HARE:	50% Enplanement Share, 43% Origination Share						
UA not to/from ORD	45.88	24.36	16.87	12.15	9.88	7.50	10.08
UA to/from ORD	64.94	33.10	20.06	9.32	8.78	6.05	14.19
Others to/from ORD	68.88	33.30	21.37	10.35	8.15	7.14	14.99
DELTA—ATLANTA:	55% Enplanement Share, 61% Origination Share						
DL not to/from ATL	36.73	28.84	18.62	11.97	10.10	6.17	12.68
DL to/from ATL	60.06	36.75	21.92	13.88	10.46	8.23	19.79
Others to/from ATL	50.34	31.20	19.17	12.92	8.99	8.38	17.44

Source: Department of Transportation, *Origin and Destination Survey,* Databank 1A, third quarter, 1987, domestic flights only.
Note: Yield calculations based on nonstop origin to destination mileage. Yields are in cents per mile.

generally charges higher prices than it does throughout the remainder of its system. A first-cut examination of possible cost factors doesn't seem to explain the price difference. First, airlines have somewhat higher load factors, thus lower per-passenger costs, on flights to and from their hubs than on their other flights. Second, passengers travelling to or from a carrier's hub take flights that are usually about as long or longer than the flights of the airline's other customers, so the fact that shorter flights have higher per-mile costs also does not appear to explain the hub/nonhub price difference. Table 1 also indicates that an airline's share of traffic at an airport, not just the concentration among all airlines at the airport, contributes to its market power; the dominant airline at these airports tends to charge higher prices than other major airlines with smaller operations there. Still, Table 1 does not allow one to separate the effects of airport dominance from the effects of route dominance, with which it is highly correlated. In the regression analysis, I attempt to make this distinction.

The results of estimating equation (1) are shown in Table 2. For ease of presentation, estimates of the carrier-fixed effects and the airport scarcity variables are omitted, but they are summarized below.[37] A Hausman specification test indicated that exogeneity of *LOAD-*

---

[37] Complete regression results are available from the author.

TABLE 2   **Regression Results**

Dependent Variable:	Equation 1—2SLS			POTCOMP Variable Included			Ordinary Least Squares		
	ln FR20	ln FR50	ln FR80	ln FR20	ln FR50	ln FR80	ln FR20	ln FR50	ln FR80
ln DISTANCE	0.4138*	0.3348*	0.3559*	0.4061*	0.3274*	0.3489*	0.4067*	0.3318*	0.3662*
	(0.0103)	(0.0124)	(0.0133)	(0.0098)	(0.0118)	(0.0127)	(0.0093)	(0.0112)	(0.0120)
ln LOADFAC	−0.0754*	−0.0425	−0.0240	−0.0779*	−0.0445	−0.0258	−0.0762*	−0.0427	−0.0232
	(0.0264)	(0.0318)	(0.0341)	(0.0264)	(0.0318)	(0.0342)	(0.0263)	(0.0318)	(0.0341)
ln EQUIP	−0.0160	−0.0050	−0.0691*	−0.0140	−0.0031	−0.0673*	−0.0136	−0.0043	−0.0718*
	(0.0187)	(0.0225)	(0.0242)	(0.0186)	(0.0225)	(0.0242)	(0.0186)	(0.0225)	(0.0241)
ln FREQ	0.0140#	0.0236*	0.0428*	0.0144#	0.0237*	0.0427*	0.0128#	0.0233*	0.0440*
	(0.0078)	(0.0094)	(0.0101)	(0.0078)	(0.0094)	(0.0101)	(0.0077)	(0.0093)	(0.0100)
ln CIRC	0.1458*	0.1272*	0.2062*	0.1352*	0.1190*	0.1980*	0.1296*	0.1258*	0.2124*
	(0.0412)	(0.0497)	(0.0533)	(0.0407)	(0.0491)	(0.0529)	(0.0399)	(0.0482)	(0.0516)
STOP	−0.0470	−0.0340	−0.1327*	−0.0482#	−0.0354	−0.1336*	−0.0432	−0.0343	−0.1320*
	(0.0292)	(0.0352)	(0.0377)	(0.0291)	(0.0352)	(0.0378)	(0.0290)	(0.0350)	(0.0375)
PLANECHG	−0.0293*	−0.0776*	−0.0616*	−0.0342*	−0.0818*	−0.0652*	−0.0298*	−0.0782*	−0.0596*
	(0.0111)	(0.0134)	(0.0144)	(0.0113)	(0.0136)	(0.0146)	(0.0111)	(0.0133)	(0.0143)
ORGSHARE	0.0345	0.1254#	0.1191#	0.0365	0.1227#	0.1205#	0.0819#	0.1229*	0.1228†
	(0.0549)	(0.0661)	(0.0710)	(0.0536)	(0.0647)	(0.0696)	(0.0426)	(0.0514)	(0.0551)
ORGHERF	−0.0699	−0.0893	0.0766	−0.0684	−0.0750	0.0934	−0.0264	−0.0660	−0.0033
	(0.0623)	(0.0751)	(0.0806)	(0.0633)	(0.0764)	(0.0822)	(0.0543)	(0.0656)	(0.0702)
RUTSHARE	0.1120#	0.0288	0.2238*	0.1196†	0.0564	0.2470*	0.0899*	0.0596#	0.1259*
	(0.0606)	(0.0731)	(0.0784)	(0.0577)	(0.0697)	(0.0749)	(0.0270)	(0.0326)	(0.0349)
RUTHERF	0.1559†	0.1822†	−0.1787†	0.1262#	0.1286	−0.2302*	0.1128*	0.1323*	−0.0120
	(0.0696)	(0.0839)	(0.0901)	(0.0659)	(0.0795)	(0.0855)	(0.0329)	(0.0397)	(0.0425)
ln COMPCOST	0.5042*	0.7010*	0.8374*	0.5000*	0.6929*	0.8309*	0.5134*	0.6944*	0.8580*
	(0.0453)	(0.0546)	(0.0586)	(0.0450)	(0.0543)	(0.0584)	(0.0430)	(0.0519)	(0.0556)
ln TOURIST	−0.0187*	−0.0558*	−0.0991*	−0.0183*	−0.0552*	−0.0986*	−0.0180*	−0.0553*	−0.1007*
	(0.0058)	(0.0070)	(0.0076)	(0.0058)	(0.0070)	(0.0076)	(0.0058)	(0.0070)	(0.0075)
POTCOMP				−0.0589†	−0.0449	−0.0380			
				(0.0289)	(0.0348)	(0.0375)			
R-SQUARED	0.683	0.494	0.508	0.683	0.493	0.507	0.683	0.494	0.511
OBS	3591	3591	3591	3591	3591	3591	3591	3591	3591

Note: Standard errors in parentheses (asymptotic except for OLS).
\# = Significant at 10% level.
† = Significant at 5% level.
* = Significant at 1% level.

FAC could not be rejected at any reasonable significance level, so I present the results with *LOADFAC* assumed exogenous.[38]

    The first set of regressions, labeled "Equation 1," indicates quite clearly that analyses that focus only on concentration of routes will ignore some of the most important factors in airline competition. The individual airline's share of traffic on the route and at the endpoint airports seems to be a principal determinant of a carrier's ability to raise the price of its product. Controlling for overall concentration of a route, a 1% increase in a carrier's share on the route is estimated to increase its prices by between 0.03% and 0.22%. *Ceteris parabus,* a dominant airline on a route with a 70% share of the traffic might be able to charge from 2% to 12% higher prices than its rivals which only have 10% shares. It is

―――――――――

[38] When *LOADFAC* is treated as endogenous, the parameter estimates are somewhat larger for *ORGSHARE*, but all standard errors are larger. The other parameter estimates change very little.

somewhat surprising that the estimated effect is greater on the 20th and 80th percentile fares than on the median fares, but a Chow test fails to reject equality of the three estimates.

The effect of an airline's share of traffic at the endpoints of a route ($ORGSHARE$) is also significant and may not be uniform across types of fares. The proportional effect on the high-end prices is estimated to be about three times the size of the effect on the low-end prices. The difference between these estimates is statistically significant at the 10% level. A stronger effect on high-end fares would be consistent with market power resulting from FFPs, since the people who pay full coach fares are much more likely to be active FFP members than those who fly on deep-discount fares. Ignoring the effect of airport dominance on a carrier's route share, an increase of one standard deviation in $ORGSHARE$ is estimated to directly raise the carrier's 20th percentile price by about 0.5%, its 50th percentile price by about 1.6%, and its 80th percentile price by about 1.6%. A carrier that dominates both ends of a route, with 50% of the originations, is estimated to charge median and high-end prices 6% greater than the prices of an airline with a very small presence at the two airports.[39]

Controlling for the observed carrier's share on the route, increases in concentration on the route appear to raise the carrier's low-end prices, but lower its high-end prices. If, for instance, firm 1 carried half of the passengers on a route and two other carriers split the other half evenly, then a merger between the two other carriers—which would raise the route Herfindahl by 0.125, or slightly more than half of one standard deviation—is estimated to increase firm 1's low-end price by 1.9% and decrease its high-end price by 2.2%. Increased concentration at the endpoint airports may lower the low-end price and raise the high-end prices, but these estimates are not significantly different from zero.

Clearly, the effects of $ORGSHARE$ and $RUTSHARE$ are related. Borenstein (1989) estimates that a dominant presence at an airport significantly increases an airline's share of the passengers on any route that includes that airport. A 1% increase in the share of originations at an airport is estimated to cause an increase in share on a route of up to 0.33%, depending on the share of the route that the carrier already possessed. Thus, the increase in airport dominance would also increase fares indirectly by increasing its share of traffic on each route that the carrier serves from the airport.

The other estimated parameters are, for the most part, consistent with expectations when they are significant. The effects of route distance ($DISTANCE$) and competitor's cost ($COMPCOST$) are positive with elasticities less than one, as expected. The load factor variable ($LOADFAC$) is negative, though significant only for the low-end prices.[40] The frequency variable ($FREQ$) is positive, and significantly more positive for the high-end fares than for the low-end fares.[41] This is consistent with the higher value that business travellers place on frequent service.[42]

Both the number of on-plane stops ($STOP$) and plane changes ($PLANECHG$) have negative coefficients, indicating that these lower-quality products sell for lower prices. The

---

[39] Though no data are available to determine the value of the frequent-flyer bonuses awarded by airlines, it seems quite unlikely that this could substantially explain the airport dominance effects observed here. Borenstein (1988a) argues that realistic calculations indicate that this additional value from FFP bonuses could account for at most one or two percentage points in fare differences. Furthermore, it seems unlikely that the value of FFP bonuses would have much effect on the willingness-to-pay of travellers flying on deep-discounts, who are less likely to be FFP members or to cash in mileage. Nonetheless, even if the real value of FFP bonuses is comparatively small, their loyalty-inducing effect could be much larger if the kickback aspect of these programs played a significant role.

[40] When $LOADFAC$ is estimated as endogenous, the negative effects are much larger—a change in the opposite direction than one would expect if simultaneity biases were present—but they are estimated much less precisely.

[41] A Chow test rejects the restriction to a common parameter for $FREQ$ in the three regressions.

[42] Though increases in frequency increase the value of the product for some travellers, in a competitive market this would not result in higher prices unless frequent flights were more costly. After controlling for load factor, frequent flights may actually be less costly because they allow more intensive use of ground labor. Thus, though the price increase may be seen as "justified"' as a payment for higher quality, it might more accurately be seen as reflecting market power.

point estimates imply a discount of 3% to 13% for each on-plane stop and 3% to 8% for each plane change that a passenger must make. Controlling for stops and plane changes, however, the circuity of routing ($CIRC$) causes a statistically significant increase in fares. The size of this effect is still fairly small in magnitude; the circuity of an average trip is estimated to raise traveler's costs by about 1.4% over the price of a flight with no circuity. On net, a trip that requires one plane change is estimated to have a lower 80th percentile price compared to a nonstop flight, as long as the total flight mileage does not exceed the nonstop distance by more than 30%.

The measure of tourism ($TOURIST$) on a route is significant and negative, as expected. The effect is significantly stronger for the high-end prices than for the low-end prices. If a route is primarily discretionary travel, it appears that the carriers do not lower their deep-discount fares much, but they do make more tickets available at the moderate discount and "supercoach" (unrestricted discount) fares.

The by-carrier constant terms (not shown) are all significantly different from zero. The differences between the highest and lowest carriers is 30% for the 20th percentile prices and 20% for the 80th percentile prices. The results are consistent in indicating the lowest prices, (controlling for all of the right-hand side variables) for Continental, Eastern, and Piedmont, and the highest prices for United and Delta.

The airport scarcity estimates (not shown) indicate significant positive effects at the two largest airports, O'Hare in Chicago (+3–5%) and Hartsfield in Atlanta (+1–3%), as well as at Denver (+2–4%) and Cleveland (+0–3%). A number of airports also showed consistently negative and significant effects, ranging from 1% to 7% in most cases.[43]

Inclusion of the potential competition variable does not change the results substantially, though it may have a significant effect itself, at least on lower fares.[44] The estimated impact is rather small, however, with an increase in $POTCOMP$ of one standard deviation causing a price decrease of less than 1%.

Results from the relative-price regressions. The results from the estimation of equation (1) indicate that a dominant carrier on a route and at the endpoint airports benefits from its size without creating much of an umbrella effect from which other airlines in a market might also benefit. One would thus expect to observe a carrier that is dominant on a route (or at the endpoints of a route) charging higher prices than its competitors on the route. The results from the estimation of equation (4), shown in Table 3, lend support to this conclusion.

Though the estimated signs of the effects of route and airport share are consistent with those found in (1), the standard errors are much larger than in (1). This seems to result primarily from two conditions. First, the instrument used to identify the difference in route shares is less effective, though still statistically significant, in this estimation than it is in identifying $RUTSHARE$ in equation (1). This means that the fitted value for the difference in route shares is closer to being a linear combination of the other right-hand side variables in the second-stage regression. Second, the difference in $RUTSHARE$ between two carriers on the same route is highly correlated with the difference in $ORGSHARE$, much more so than in (1).

Still, a test for the joint significance of $RUTSHARE$ and $ORGSHARE$ is significant at the 1% level for all three measures of fare differences between the two carriers. The problems of collinearity are also evident when $RUTSHARE$ differences are excluded from the regression. The estimated effect of $ORGSHARE$ differences increases, and the standard errors of

---

[43] The airports with consistently negative estimates are Dallas/Ft. Worth, Los Angeles, Newark, La Guardia, Kennedy, Miami, Houston Intercontinental, Las Vegas, Kansas City, and Ft. Lauderdale.

[44] This result, however, may in part be due to the endogeneity of $POTCOMP$. If there is simultaneity bias, then one would expect it to be in this direction; higher prices would induce potential competitors to enter the market and thus decrease $POTCOMP$.

TABLE 3   Regression Results for Equation (4)

Dependent Variable:	Equation (4)			RUTSHARE Excluded		
	ln FR20	ln FR50	ln FR80	ln FR20	ln FR50	ln FR80
ln LOADFAC	0.0277	0.0713†	0.0727†	0.0307	0.0790*	0.0793*
	(0.0254)	(0.0348)	(0.0350)	(0.0246)	(0.0325)	(0.0329)
ln EQUIP	−0.0239	−0.0293	−0.0161	−0.0148	−0.0065	0.0036
	(0.0224)	(0.0307)	(0.0309)	(0.0168)	(0.0222)	(0.0225)
ln FREQ	0.0116	0.0038	0.0115	0.0183*	0.0209†	0.0263*
	(0.0131)	(0.0179)	(0.0180)	(0.0071)	(0.0094)	(0.0095)
ln CIRC	0.0955	0.2309†	−0.0793	0.0509	0.1181†	−0.1768*
	(0.0845)	(0.1156)	(0.1163)	(0.0434)	(0.0574)	(0.0581)
STOP	−0.0688*	−0.0983*	−0.0589	−0.0599*	−0.0759†	−0.0396
	(0.0290)	(0.0396)	(0.0399)	(0.0248)	(0.0328)	(0.0332)
PLANECHG	−0.0690	−0.0722	−0.0765	−0.0946*	−0.1370*	−0.1325*
	(0.0437)	(0.0598)	(0.0601)	(0.0137)	(0.0181)	(0.0183)
ORGSHARE	0.0013	0.0275	0.1393	0.0742†	0.2117*	0.2986*
	(0.1234)	(0.1688)	(0.1698)	(0.0360)	(0.0476)	(0.0482)
RUTSHARE	0.0929	0.2346	0.2029			
	(0.1501)	(0.2053)	(0.2065)			
R-SQUARED	0.269	0.193	0.196	0.310	0.268	0.262
OBS	1508	1508	1508	1508	1508	1508

Note: Standard errors in parentheses (asymptotic for equation (4)).
\# Significant at 10% level.
† Significant at 5% level.
* Significant at 1% level.

these estimates uniformly decrease.[45] If the estimated effect of *ORGSHARE* is taken to represent both its direct impact on prices and its indirect impact through changes in route share, then an airline with 50% of the traffic at each endpoint of a route is estimated to charge high-end prices about 12% above those of a competitor with 10% of the traffic at each endpoint.[46]

With the exception of the coefficients on *LOADFAC*, the other parameter estimates are consistent with those for equation (1) when they are significant, but are much noisier than in the previous estimation. *LOADFAC* is positive, however, and is significant for the 50th and 80th percentile prices. In the estimates of equation (1), these parameters are negative, though only the 20th percentile price is significant. While it may be the case that routes with greater traffic density, and thus higher load factors, generally have lower prices, the carrier with a higher load factor on a given route may have more connecting traffic and, thus, a higher opportunity cost for its seats.

Table 4 presents descriptive statistics about the data.

6. Conclusion

■ It would be futile and probably unwise for the government to try to deter airlines from forming hubs. There is substantial evidence that hub-and-spoke air transport systems allow

---

[45] The exclusion of *ORGSHARE* also causes increases in the estimated effect of *RUTSHARE* and decreases in the standard errors of these estimates.

[46] When *RUTSHARE* and *RUTHERF* are excluded from estimation in equation (1), a 1% increase in *ORGSHARE* is estimated to increase 20th percentile prices by 0.24%, 50th percentile prices by 0.26%, and 80th percentile prices by 0.24%, with each estimate significant at the 1% level.

TABLE 4   Descriptive Statistics

Variable	Mean	Standard Deviation	Minimum Value	Maximum Value
FR20	100.39181	35.03261	22.000000	329.0000
FR50	129.44138	42.80130	27.000000	359.0000
FR80	187.20496	64.50795	38.000000	537.0000
DISTANCE	1084.31245	735.55589	104.000000	5083.0000
LOADFAC	0.60549	0.09730	0.122500	0.9098
EQUIP	112.75177	27.89284	60.000000	271.9000
FREQ	625.90671	296.73157	10.000000	2892.0000
CIRC	1.07538	0.11688	1.000000	1.9004
STOP	0.07648	0.14027	0.000000	1.3700
PLANECHG	0.67084	0.41736	0.000000	1.0000
ORGSHARE	0.24215	0.13054	0.021172	0.8647
ORGHERF	0.25409	0.09610	0.115841	0.8622
RUTSHARE	0.54185	0.26561	0.100300	1.0000
RUTHERF	0.49539	0.22374	0.126600	1.0000
COMPCOST	0.08126	0.00613	0.047570	0.1037
TOURIST	0.01413	0.01443	0.002760	0.0700
POTCOMP	0.15904	0.15919	0.000000	0.8259
GEOENPSH	0.37518	0.23438	0.023785	1.0000
TOTMILE	1145.45001	750.93607	105.000000	5176.0000

Carrier Constant Terms

American	0.14035	——	0.000000	1.0000
USAir	0.10109	——	0.000000	1.0000
Continental	0.14119	——	0.000000	1.0000
Delta	0.17989	——	0.000000	1.0000
Eastern	0.07185	——	0.000000	1.0000
Northwest	0.09385	——	0.000000	1.0000
Piedmont	0.11000	——	0.000000	1.0000
TWA	0.05068	——	0.000000	1.0000
United	0.1111	——	0.000000	1.0000

Airport Scarcity Variables

Chicago—O'Hare	0.06684	0.38755	0.000000	7.3529
Atlanta	0.06774	0.47633	0.000000	9.5238
Dallas/Ft. Worth	0.05458	0.33186	0.000000	5.6818
Los Angeles	0.03601	0.26880	0.000000	9.0909
Denver	0.04351	0.25607	0.000000	5.0251
Newark	0.05391	0.37602	0.000000	8.6957
San Francisco	0.03279	0.26906	0.000000	6.4103
NYC—La Guardia	0.05019	0.32954	0.000000	5.4348
St. Louis	0.05246	0.34632	0.000000	5.3476
Boston	0.04294	0.29508	0.000000	5.4054
NYC—Kennedy	0.01838	0.22041	0.000000	5.4645
Miami	0.03279	0.29524	0.000000	9.6154
Detroit	0.06064	0.41425	0.000000	8.2645
Minneapolis	0.04714	0.32313	0.000000	6.9444
Pittsburgh	0.06885	0.50103	0.000000	9.4340
D.C.—National	0.06332	0.39799	0.000000	7.0423
Houston Inter.	0.04329	0.31689	0.000000	6.9930
Philadelphia	0.05101	0.34121	0.000000	5.1020
Las Vegas	0.01711	0.14516	0.000000	4.2373
Kansas City	0.03315	0.26959	0.000000	6.5789
Ft. Lauderdale	0.02314	0.19532	0.000000	5.5866
Cleveland	0.04694	0.36762	0.000000	9.4340
Orange County	0.01394	0.13913	0.000000	2.9240
Long Beach	0.00214	0.05381	0.000000	2.7322

Note: Based on the 3591 observations used in the regressions for equation (1).

more efficient use of aircraft and other inputs than the point-to-point systems developed under government regulation. Still, dominance of major airports by one or two carriers, in many cases the result of hub formation, appears to result in higher fares for consumers who want to fly to or from these airports. As the quote at the beginning of this article suggests, such strongholds seem to insulate the dominant carrier from competition. Furthermore, the market power of a dominant airline does not spill over substantially to other airlines serving the same airport or routes.

It is possible that the marketing devices that have come into existence since deregulation—frequent flyer programs, travel agent commission override bonuses, and the biases due to computer reservation systems—provide some of the explanation for the advantages of airport dominance. Other sunk costs of entry, such as advertising and the setup of new airport facilities, may also play important roles. The empirical work presented does not allow one to determine the extent to which each of these factors permits an airline with a dominant endpoint share to raise its price.

Though the link between airport dominance and high fares seems clear, a welfare analysis of increased airport concentration must also include the benefits that may accrue from hub operations.[47] There may be cost savings that are not fully passed along to consumers, but still increase total surplus in the form of profits. Greater flight frequency, easier connections, and more nonstop flights may also be associated with these route systems. In this regard, the estimated impact of these quality factors on price, presented in the previous section, should not be interpreted as hedonic prices.[48] These possible benefits of mergers or other increases in airport shares should be weighed against the higher prices that seem likely to result.

Appendix

■ Each observation in the sample is a unique airline/route combination. A route is a pair of airports, one being the origin of a person's directional trip and the other being the destination. A round-trip ticket is considered to be two directional trips on the route, and the fare paid on each directional trip is taken to be half of the round-trip fare. A one-way ticket is simply one directional trip.

The source of the ticket and price data is Databank 1A (DB1A) of the Department of Transportation's *Origin and Destination Survey,* as processed by Boeing Computer Services, for the third quarter of 1987. The DB1A is a random 10% sample of all tickets that originate in the U.S. on domestic carriers.[49] The Boeing processing eliminates all tickets that are not either one-way or round-trip travel, such as open-jaw (e.g., LAX-BOS-SEA) and circle trips (e.g., LAX-MIA-MSP-LAX). It also removes tickets that involve more than one change of plane on any directional trip.

For preparation of the data set used in this study, the following tickets were also eliminated from the sample:
(a) Tickets that included at least one segment designated as first-class travel.
(b) Tickets that included travel on more than one airline on a directional trip (known as interline tickets).
(c) Tickets that include an origin, destination, or change of plane at an airport outside of the U.S. or an airport within the U.S. that is not one of the 200 largest U.S. airports.[50]
(d) Tickets indicating flights of which there is no record in the Service Segment Data, as described below. (These amounted to fewer than 1% of passengers. See footnote 52.)
(e) Tickets indicating fares of less than $10. (These are presumed to be keypunch errors or reporting of frequent-flyer bonus trips, which unfortunately is not done in any consistent way.)

---

[47] Carlton, Landes, and Posner (1980) propose one approach to analyzing some of these benefits.

[48] Obviously, the simultaneous effect of these factors on costs confuses the analysis. Even if that were not the case, however, Spence (1975) demonstrated that a firm with market power will make the quality/price trade-off only so as to reach a Pareto optimum with the marginal consumer. If, as is probably the case in airline travel, inframarginal buyers value quality improvements more than marginal buyers, then the parameter estimates, though a reflection of the marginal buyer's valuation, would underestimate the average buyer's valuation of quality.

[49] Databank 1A (O & D DB1A), the Service Segment Data, and Nonstop Market Data described below are available from the Transportation Systems Center in Cambridge, MA.

[50] This excludes very few domestic flights, as the 200th largest airport is in Deadhorse, Alaska, where an average of 96 passengers were enplaned each day.

The Service Segment Data is a census of every flight operated by the largest pre-deregulation airlines. Because these are simply counts of the number of people on board each flight, these data are considered a more accurate reflection of total numbers of passengers than the DB1A sample. These data are available only for the larger airlines.

Each airline's number of enplanements at each airport is drawn from the Nonstop Market Data, a census similar to the Service Segment Data that includes all airlines.

The construction and sources for each variable follow.

FR20, FR50, FR80—The 20th, 50th, and 80th percentile fares paid by passengers travelling a given airline/itinerary. *Source:* DB1A.

DISTANCE—Nonstop mileage from origin to destination of a directional trip (ignores change-of-plane or on-flight stops). *Source:* DB1A.

COST—The standardized cost per available seat-mile (ASM) of an airline. For the seventeen airlines for which data were available (which includes the nine airlines on which price observations were included in the regressions), the cost per ASM was regressed on a constant and average length of haul (average takeoff to landing distance for all domestic flights of the airline). The residual for each carrier was then added to 0.08, approximately the average cost per ASM for a carrier with the industry mean length of haul, to arrive at a standard cost per ASM for the carrier. *Source:* Air Carrier Traffic Statistics and Air Carrier Financial Statistics, USDOT.

LOADFAC—Average load factor on flight segments used by passengers travelling on the observed route on the observed airline. An airline's average load factor on a flight segment is calculated as the carrier's total revenue passenger-miles on planes flying from the first airport to the second, divided by the carrier's total available seat-miles between those two airports during the quarter. The load factor for one possible itinerary (which specifies all change-of-plane points and on-plane stops) for the route is then a weighted average of the average load factors on each segment of the directional trip where the weights are the nonstop distance between the cities of each segment. *LOADFAC* is the weighted average of load factors for the possible itineraries that could be used to travel the observed airline/route, where the weights are the number of passengers on the airline who used each possible itinerary.[51] *Source:* Service Segment Data.

LOADPOP—The value of the total population variable for an itinerary is the sum of the populations of all cities in which the traveler is on the ground (origination, destination, and all on-plane or change-of-plane stops). *LOADPOP* is the weighted average of the total population variable across possible itineraries that could be used to travel the observed airline/route, where the weights are the number of passengers on the airline who used each possible itinerary. *Source:* Itinerary data from Service Segment Data, population data from 1987 Statistical Abstract of the U.S.

EQUIP—Average number of seats on planes carrying passengers on the observed airline/route. For a given itinerary, the equipment size variable is a weighted average of the average number of seats on each segment, where the weights are the distances of each segment. *EQUIP* is the weighted average of the equipment size variable across possible itineraries that could be used to travel the observed airline/route, where the weights are the number of passengers on the airline who used each possible itinerary. *Source:* Service Segment Data.

FREQ—For a given itinerary, the frequency-of-flights measure is the minimum number of flights operated (during the third quarter of 1987) by the carrier on any flight segment of the itinerary. *FREQ* is the weighted average of these flight-frequency measures across possible itineraries that could be used to travel the observed airline/route, where the weights are the number of passengers on the airline who used each possible itinerary. *Source:* Service Segment Data.

TOTMILE—Average total routing mileage flown between origin and destination by passengers on the observed airline. *Source:* DB1A and Service Segment Data.

CIRC—*TOTMILE/DISTANCE*. *Source:* DB1A and Service Segment Data.

STOP—For a given itinerary, the number of stops is the sum of the average number of stops made by passengers of the airline in flying on each of the segments of the itinerary.[52] *STOP* is the weighted average of the number of stops across possible itineraries that could be used to travel the observed airline/route, where the weights are the number of passengers on the airline who used each possible itinerary. *Source:* Service Segment Data.

PLANECHG—The average number of plane changes made by passengers flying on the observed airline/route. Each passenger ticket included in the sample includes at most one change of plane on each directional trip. *Source:* DB1A.

ORGSHARE—The weighted average, across the two endpoints of the observed route, of the observed airline's share of passenger originations at the airports, where the weight for one endpoint is the proportion of travelers on the route who originated their travel (origination point of the ticket, not of the observed directional trip) at that endpoint of the route. *Source:* DB1A.

ORGHERF—The weighted average, across the two endpoints of the observed route, of the Herfindahl indices of passenger originations at the airports, where the weight for one endpoint is the proportion of travelers on the

---

[51] See footnote 52 for exclusion of certain routes due to lack of flight data.

[52] Some segments of the DB1A do not actually correspond to single-plane service because carriers occasionally change aircraft, but retain the same flight number on a routing. Thus, there could be segments in the DB1A for which there is no record of single-plane service in the Service Segment Data. These itineraries were eliminated from the data set as explained in exclusion (d).

route who originated their travel (origination point of the ticket, not of the observed directional trip) at that endpoint of the route. *Source:* DB1A.

RUTSHARE—The total number of directional trips on a route is the sum of qualifying trips (where a round-trip is two directional trips) after the exclusions discussed above. All scheduled jet airlines are included in the measure of the total. *RUTSHARE* is the proportion of this total that travelled on the observed airline. *Source:* DB1A.

GENPSH—Defined in text. *Source:* Nonstop Market Data.

POTCOMP—

$$POTCOMP = \frac{\sum_i \sqrt{ENP_{i1} \cdot ENP_{i2}}}{\sum_j \sqrt{ENP_{j1} \cdot ENP_{j2}}},$$

where j indexes all airlines, i indexes all airlines that carry less than 1% of the traffic on the observed route, and ENP_{j1} and ENP_{j2} are airline j's average daily enplanements at the two endpoint airports during the third quarter of 1987. *Source:* Nonstop Market Data.

ENP—The observed carrier's average daily number of domestic passenger enplanements at an airport (measured in thousands). *Source:* Nonstop Market Data.

RUTHERF—The Herfindahl index of concentration on the observed route, where the market shares are as described in *RUTSHARE*. *Source:* DB1A.

COMPCOST—The weighted average of the *COST* variable for all carriers on the observed route other than the observed carrier, where the weight for each carrier is its *RUTSHARE*. For very small carriers for which cost per ASM data were not available, the *COST* variable was assumed to be 0.08. *Source: Air Carrier Traffic Statistics and Air Carrier Financial Statistics,* USDOT, and DB1A for route shares.

TRIX—Tourism index for a metropolitan area = hotel income from group/tourist customers divided by total personal income. *Source: Census of Service Industries,* 1977 for proportion of hotel revenues from group/tourist; *Census of Service Industries,* 1982 for metropolitan area hotel revenues; *State and Metropolitan Area Data Book,* 1985 for total personal income.

TOURIST—The weighted average of the *TRIX* across the two endpoints of the observed route, where the weight for one endpoint is the proportion of travelers on the route who originated their travel (origination point of the ticket, not of the observed directional trip) at the other endpoint of the route. *Source:* DB1A for proportion of travel on the route that originates at each endpoint of the route.

APT_i—scarcity rent variable for airport i, defined in text. *Source:* DB1A.

References

BAILEY, E.E., GRAHAM, D.R., AND KAPLAN, D.P. *Deregulating the Airlines.* Cambridge, MA: MIT Press, 1985.

——— and WILLIAMS, R.J. "Sources of Economic Rent in the Deregulated Airline Industry." *Journal of Law and Economics,* Vol. 31 (1988), pp. 173–202.

BANERJEE, A. AND SUMMERS, L.H. "On Frequent Flyer Programs and Other Loyalty-Inducing Arrangements." Mimeo, Harvard University, 1987.

BORENSTEIN, S. "Price Discrimination in Free-Entry Markets." *RAND Journal of Economics,* Vol. 16 (1985), pp. 380–397.

———. "Hubs and High Fares: Airport Dominance and Market Power in the U.S. Airline Industry." Institute of Public Policy Studies Discussion Paper #278, University of Michigan, 1988a.

———. "On the Efficiency of Competitive Markets for Operating Licenses." *Quarterly Journal of Economics,* Vol. 103 (1988b), pp. 357–385.

———. "The Competitive Advantage of a Dominant Airline." Institute of Public Policy Studies Discussion Paper #280, University of Michigan, 1989.

BERRY, S.T. "Estimation of a Model of Entry in the Airline Industry." Mimeo, Yale University, 1989.

BRESNAHAN, T.F. "Empirical Studies of Industries with Market Power." In R.C. Schmalenesee and R. Willig, eds., *Handbook of Industrial Organization.* Amsterdam: North-Holland, 1989.

CALL, G.D. AND KEELER, T.E. "Airline Deregulation, Fares, and Market Behavior: Some Empirical Evidence." In A.F. Daughety, ed., *Analytical Studies in Transport Economics.* Cambridge: Cambridge University Press, 1985.

CARLTON, D.W., LANDES, W.M., AND POSNER, R.A. "Benefits and Costs of Airline Mergers: A Case Study." *Bell Journal of Economics,* Vol. 11 (1980), pp. 65–83.

DOUGLAS, G.W. AND MILLER, J.C. *Economic Regulation of Domestic Air Transport: Theory and Policy.* Washington, D.C.: Brookings Institution, 1974.

GRAHAM, D.R., KAPLAN, D.P., AND SIBLEY, D.S. "Efficiency and Competition in the Airline Industry. *Bell Journal of Economics,* Vol. 14 (1983), pp. 118–38.

LEVINE, M.E. "Airline Competition in Deregulated Markets: Theory, Firm Strategy, and Public Policy." *Yale Journal on Regulation,* Vol. 4 (1987), pp. 393–494.

MORRISON, S.A. AND WINSTON, C. "Empirical Implications and Tests of the Contestability Hypothesis." *Journal of Law and Economics,* Vol. 30 (1987), pp. 53–66.

PETERAF, M.A. "The Effects of Potential Competition on Market Performance in Monopoly Airline Markets." Mimeo, Northwestern University, 1986.

SHAPIRO, C. "Consumer Information, Product Quality, and Seller Reputation." *Bell Journal of Economics,* Vol. 13 (1982), pp. 20–35.

SPENCE, M. "Monopoly, Quality, and Regulation." *Bell Journal of Economics,* Vol. 6 (1975), pp. 417–429.

U.S. DEPARTMENT OF TRANSPORTATION. *Study of Airline Computer Reservation Systems.* Washington, D.C.: U.S. Department of Transportation, 1988.

U.S. FEDERAL AVIATION ADMINISTRATION. "Air Traffic Activity and Delays: Report for October 1987." Mimeo, November 1987.

"Airline Reservation Systems: Curse of the Mummy's Tomb." *Regulation,* Vol. 9 (1985), pp. 8–9, 55–56.

"Growing Giants: An Unexpected Result of Airline Decontrol is Return to Monopolies: Big Carriers Are Dominating Nation's Hub Airports; Legislators are Concerned." *Wall Street Journal,* July 20, 1987, p. 1, 6.

"The 1988 Louis Harris Survey." *Travel Weekly,* June 29, 1988, pp. 9–142.