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Fare determination in airline hub-and-spoke networks

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This article provides the first evidence linking airfares to the structure of airline hub-and-spoke networks. The hypothesis tested is that any force that increases traffic volume on the spokes of a network will reduce fares in the markets it serves. This effect arises because of economies of density on the spokes. For example, since a large network (as measured by the number of city pairs that it connects) is expected to have low costs per passenger as a result of high traffic densities, fares in the individual markets served should be low, other things equal. Similarly, holding size fixed, a network that connects large cities should have higher traffic densities on its spokes (and thus lower fares in individual markets) than one serving small cities. Our empirical analysis supports these predictions. We find that network characteristics are important determinants of fares in 4-segment city-pair markets (these are markets requiring a connection at the hub). Furthermore, our empirical model predicts that the TWA-Ozark and Northwest-Republic mergers should have reduced fares in the 4-segment markets served by the hubs at St. Louis and Minneapolis.

1. Introduction

■ Airline deregulation has led to profound changes in the structure of the industry. In addition to giving airlines the freedom to set fares, deregulation removed restrictions on entry and exit, allowing the carriers to expand and rationalize their route structures. This flexibility led in the 1980s to a dramatic expansion of hub-and-spoke networks, where passengers change planes at a hub airport on the way to their eventual destinations.[1] By

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[1] For discussion of the impact of the new regulatory environment on airline operations, see Bailey and Williams (1988), Bailey, Graham, and Kaplan (1985), Levine (1987), Moore (1986), and Morrison and Winston

funnelling all passengers into a hub, such a system generates high traffic densities on its "spoke" routes. This allows the airline to exploit economies of density, yielding lower cost per passenger. These economies arise in part because higher traffic density on a route allows the airline to use larger, more efficient aircraft and to operate this equipment more intensively (at higher load factors).[2]

Restructuring of the industry in response to deregulation has also led to renewed interest among economists in the determinants of airfares in individual city-pair markets. This new line of research contains notable contributions by Bailey, Graham, and Kaplan (1985), Berry (1990), Borenstein (1989), Call and Keeler (1985), Graham, Kaplan, and Sibley (1983), Hurdle et al. (1989), and Morrison and Winston (1989, 1990). These studies typically explore the connection between airfares and market-specific measures of demand (city populations and incomes, tourism potential), cost (flight distance, load factors), and competition (number of competitors, market share). However, even though the airline industry has undergone a hub-and-spoke revolution, the impact of network characteristics on fares in individual markets has received little attention in this literature.[3] Given that networks play a critical role in lowering airline costs, this may be a serious omission. When a hub-and-spoke network successfully raises traffic densities, ticket prices are likely to reflect the resulting lower cost per passenger. Fare regressions that omit network variables may fail to capture such effects.

The purpose of the present article is to fill this gap in the literature by providing the first evidence linking airfares to the structure of airline hub-and-spoke networks. Our central hypothesis is that any force that increases traffic volume on the spokes of a network will reduce fares in the markets it serves. This effect arises because of economies of density on the spokes. For example, since a large network (as measured by the number of city pairs that it connects) offers many potential destinations to the residents of an endpoint city, its spokes should have higher traffic densities than the spokes of a small network. With costs correspondingly lower, fares in the individual markets served should be lower in the large network, other things equal.[4] Similarly, holding size fixed, a network that connects large cities should have higher traffic densities on its spokes (and thus lower fares in individual markets) than one serving small cities. Our emphasis on network variables, which include measures of network size and "population potential," distinguishes the present fare study from earlier research.

Despite this difference, the article follows the existing literature by estimating quasi-reduced-form fare equations, where the principal explanatory variables are exogenous. Estimation of a structural model, which would reveal the parameters of the airline cost function and thus directly indicate the strength of economies of density, is left for subsequent research.[5]

(1986). A measure of the increase in "hubbing" is provided by McShan and Windle (1989), who show that the total enplanements of each carrier became increasingly concentrated at selected airports over the 1980s. (Bailey, Graham, and Kaplan (1985) provide similar data for departures.)

[2] For discussion of these efficiency gains, see Bailey, Graham, and Kaplan (1985), especially Tables 3.4 and 3.5. Another reason for economies of density is that higher traffic density on a route allows more intensive use of fixed ground facilities and personnel as well as more effective aircraft utilization (more flight hours per day). Caves, Christensen, and Tretheway (1984) provide evidence on the magnitude of economies of density. They estimate an airline cost function that includes both network size (cities served) and output (essentially revenue passenger-miles). They find that, holding network size fixed, total costs increase less rapidly than output, with the associated elasticity equal to .80. Cost per passenger-mile therefore falls as traffic density in the airline's network rises.

[3] Borenstein (1989) and Morrison and Winston (1989, 1990) include measures of the carrier's airport dominance at the endpoints of a market. Although this variable provides some information about the network, it does not capture the type of network effects studied in this article. Using an approach somewhat similar to ours, Berry (1990) includes the numbers of routes served out of each endpoint city as explanatory variables. These variables, however, are not grounded in an explicit model of network effects.

[4] Lower marginal costs are associated with lower prices in most oligopoly models.

[5] For attempts to estimate structural models, see Berry (1989) and Reiss and Spiller (1989).

It should be noted that estimation of such a model would require the use of traffic-density data, which is not needed in the present framework. Instead, exogenous network characteristics serve as proxies for traffic density in a traditional reduced-form specification.[6]

Given our network emphasis, we do not consider fares for all types of travellers, but instead analyze the fare paid by the typical passenger who uses a hub airport. This is the *connecting* passenger, whose round trip requires a change of plane at the hub and thus consists of four flight segments. Fares for trips where travel requires no change of plane (e.g., New York-Chicago, Los Angeles-San Francisco, where the round trip has two flight segments) are thus not considered in the fare equation (the previous literature focuses mainly on such fares). While 4-segment passengers obviously play a critical role in hub operations, there are also two reasons why 4-segment fares are especially likely to reveal a density effect. First, unlike the endpoints of many nonstop markets, 4-segment endpoints are typically smaller nonhub airports where no carrier exercises market power. Therefore, the tendency of airport dominance to raise fares above costs, which may obscure any density effect, is not present in the data (Borenstein (1989) analyzes the impact of airport dominance). Second, because of the smaller size of 4-segment endpoints, we expect that 4-segment passengers typically travel on lower-density network spokes than nonstop passengers. Since economies of density are more likely to be unexhausted (and thus observable) on low-density spokes, the density effect may be revealed most clearly in 4-segment fares.

Our focus on 4-segment markets also bears on the current concern regarding excessive concentration at certain hub airports. As a result of recent mergers, TWA and Northwest now dominate the hubs at St. Louis and Minneapolis-St. Paul, respectively. As explained above, this domination makes higher fares likely for passengers originating or terminating at these airports, a prediction that has been partly confirmed by Borenstein (1990), U.S. General Accounting Office (1988), U.S. Department of Transportation (1989), and Werden, Joskow, and Johnson (1989). Although concern about the effects of concentration is certainly warranted, discussions of the issue have overlooked the fact that local traffic accounts for just part of the enplanements at the dominated hubs, with connecting traffic making up the rest. Given that connecting passengers often have a choice of hubs through which to make their trips, concentration at a particular hub does not mean elimination of competition in the 4-segment markets. Moreover, the larger hub network created by a merger is likely to have lower costs per passenger than the original networks as a result of higher traffic densities. These lower costs may partly or completely offset the effect of reduced competition, leading to lower 4-segment fares on average.[7] The magnitude of such effects, which offer a counterweight to fare increases for hub-originating or hub-terminating passengers, is computed using the fare equations estimated below.

One implication of our merger analysis may have relevance for the evaluation of mergers in other industries. In particular, our results show that a TWA-Ozark–type merger unambiguously lowers fares in city-pair markets served by only one of the merger partners (in this case, the gains from higher traffic density are not reversed by a loss of competition). Generally, a similar outcome is likely when a multiproduct firm with cost complementarities across product lines merges with a single-product competitor. Increased output in the affected product line lowers production cost for the firm's other outputs, reducing prices in these

[6] Hurdle et al. (1989) use a measure of traffic density on the route segment serving a city-pair market (which includes passengers travelling beyond the endpoints of the market) in a regression explaining fares. However, under their specification, this variable has no significant impact on fares. In a similar vein, Borenstein (1989) uses the airline's load factor on the route segment serving a market to capture density effects. Bailey, Graham, and Kaplan (1985) and Graham, Kaplan, and Sibley (1983) include the city-pair (as opposed to route-segment) traffic level on the right-hand side of their fare equation (this variable, however, may not always be a good density measure). The last three studies undertake appropriate simultaneity corrections.

[7] This point is also made by Levine (1987).

markets (where competition is unchanged). If the regulatory authorities ignore such welfare gains, which occur outside the market where the merger's direct effects are felt, some socially desirable mergers may be blocked. See Brueckner and Spiller (1991) for further discussion.

The data for this study are drawn from Databank 1A of the U.S. Department of Transportation's *Origin and Destination Survey* (the sample period is the fourth quarter of 1985). The article is organized as follows. Section 2 discusses the comparative-static properties of a simple theoretical model of a hub-and-spoke system, which are used to generate empirical hypotheses. Section 3 explains how the network characteristics are computed and shows the key features of the major networks operating in 1985. Section 4 describes the market-specific variables, while Section 5 describes the regression dataset. Section 6 presents the empirical results, and Section 7 simulates the estimated equation to predict the effect of the TWA-Ozark and Northwest-Republic mergers. Section 8 offers conclusions.

2. A simple network model

■ This section sketches Brueckner and Spiller's (1991) model of a hub-and-spoke network in order to develop empirical hypotheses.[8]

□ **Theoretical framework.** Suppose that a monopoly airline operates the four-city network depicted in Figure 1, where city H is the hub. Residents of each city have a demand for air travel to every other city of the network, including the hub. Demand is symmetric across city pairs, with $D(Q)$ giving the inverse demand function for round-trip travel in each market. Q is total traffic in both directions in the market, so that Q_{AB}, for example, equals the number of passengers making round trips from A to B and back plus passengers making round trips from B to A and back. Letting $R(Q) = QD(Q)$ be the revenue function, total revenue from the network is then

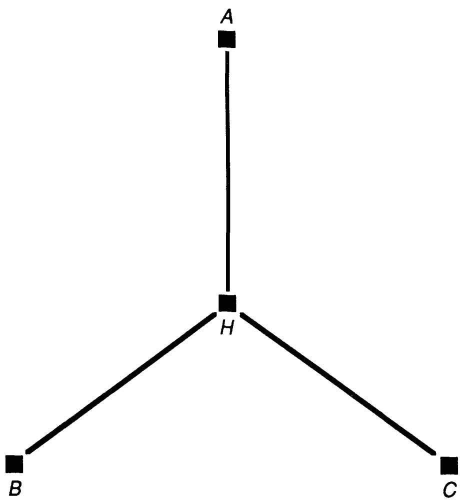
$$R(Q_{AB}) + R(Q_{AC}) + R(Q_{BC}) + R(Q_{AH}) + R(Q_{BH}) + R(Q_{CH}). \tag{1}$$

The last three terms are revenues in city-pair markets that include the hub.

Costs are represented by the function $c(Q)$, which gives the total cost of carrying a

FIGURE 1

A SIMPLE HUB-AND-SPOKE NETWORK



[8] For another network model, see Spiller (1989).

round-trip traffic volume of Q on a particular spoke of the network. With economies of density, c satisfies $c' > 0$ and $c'' < 0$ (the spoke cost function thus reflects increasing returns to scale). As noted above, the reason for the density effect is that higher traffic on a spoke allows the airline to operate larger, more efficient aircraft at higher load factors. Given that each spoke of the network carries traffic in three city-pair markets, total network cost is equal to

$$c(Q_{AB} + Q_{AC} + Q_{AH}) + c(Q_{AB} + Q_{BC} + Q_{BH}) + c(Q_{AC} + Q_{BC} + Q_{CH}). \qquad (2)$$

To maximize profit [(1) minus (2)], the monopolist sets marginal revenue in each city-pair market equal to the marginal cost of a passenger in the market. In a hub-inclusive city-pair market such as AH, marginal cost is simply c' for the AH spoke, so that the first-order condition is

$$R'(Q_{AH}) = c'(Q_{AB} + Q_{AC} + Q_{AH}). \qquad (3)$$

In a nonhub market such as AB, marginal cost is the sum of the c' expressions for the two spokes connecting the cities, so that the first-order condition is[9]

$$R'(Q_{AB}) = c'(Q_{AB} + Q_{AC} + Q_{AH}) + c'(Q_{AB} + Q_{BC} + Q_{BH}). \qquad (4)$$

Since the solution to the monopolist's problem is symmetric across markets, the model is easily extended to a network containing n nonhub cities in addition to the hub. Let Q_{NH} be traffic in each nonhub market and Q_H be traffic in each hub-inclusive market. Profit from the network is then

$$(n(n-1)/2)R(Q_{NH}) + nR(Q_H) - nc(Q_H + (n-1)Q_{NH}). \qquad (5)$$

Note that there are $n(n-1)/2$ nonhub markets, n hub-inclusive markets, and n spokes. The monopolist's first-order conditions have the same form as (3) and (4).[10]

□ **Comparative statics.** Using the above model, we can explore the effects of changes in the monopolist's environment via comparative-static analysis. In particular, if marginal revenue and cost are both linear, with $R'(Q) = \alpha - Q$ and $c'(Q) = 1 - \theta Q$, where $\alpha, \theta > 0$, then the following results can be established. First, an increase in n, the number of cities served by the network, raises traffic and lowers fares in all markets. As explained in the introduction, the reason is that the resulting higher traffic densities allow more effective exploitation of increasing returns.

Second, higher demand (a larger α) raises traffic in all markets while changing fares in a direction that depends on the strength of economies of density. Fares in the nonhub markets fall when the density effect is strong (when θ is large) and rise otherwise, an outcome familiar from standard monopoly models.[11] This result shows that the high demand associated with large city populations, for example, will lead to lower fares as long as economies of density are strong.

The effect of competition within the network is analyzed by Brueckner and Spiller (1991) using the simple four-city version of the model. Although the effects vary somewhat across the cases they analyze, the typical outcome is that competition leads to lower fares

[9] To avoid the possibility of arbitrage by passengers, fares in the nonhub markets should be less than the sum of the fares for the separate hub legs (otherwise, passengers could benefit by purchasing the leg tickets separately). This condition is satisfied in the solution to the linear model described below.

[10] Fixed costs of network operation, which presumably rise with the number of endpoints served, are ignored in this formulation. However, such costs have no effect on the monopolist's first-order conditions and thus no effect on fares under the model.

[11] Fares in the hub-inclusive markets fall as α rises.

in the market where it occurs while raising fares in all other markets in the network. The intuitive explanation of this result is straightforward. Introducing competition in a market (AB, for example) lowers traffic on the network spokes (AH and BH) that serve the market (total market traffic, including the competitor's share, rises). With economies of density, this traffic leakage raises the marginal cost of a passenger on each spoke. While competitive pressure in AB counteracts the higher marginal costs, reducing fares in the market, other markets that use the affected spokes (markets AC, BC, AH, and BH) lack competition. As a result, fares in these markets rise and traffic levels fall.[12] This outcome is a consequence of economies of density together with the cost complementarities inherent to a hub-and-spoke network. In such a setting, competition generates negative externalities outside the market where it occurs.

□ **Empirical hypotheses.** The above model depicts a monopoly hub-and-spoke system, none of which exist. However, since the comparative-static results are likely to apply more generally, they can be used to motivate an empirical study of the effects of network characteristics on fares. The results suggest the following empirical hypotheses: (i) a market served by a large hub-and-spoke network should have lower fares than a market served by a small network; (ii) when economies of density are strong, a market served by a network facing high travel demand should have lower fares than a market served by a low-demand network; (iii) a market where competition occurs should have lower fares than a market without competition; and (iv) a market served by a network facing widespread competition (and thus a large traffic leakage) should have higher fares than a market served by a network facing little competition. In the next section we discuss some of the network variables used to test these hypotheses.

3. Network characteristics

■ Our goal is to relate the fare paid by a 4-segment passenger, whose trip requires a change of planes at a hub airport, to the characteristics of the network in which he travels. The first step in this exercise is to compute network characteristics. This is done using data from Databank 1A (DB1A) of the U.S. Department of Transportation's *Origin and Destination Survey* for the fourth quarter of 1985. The DB1A databank is generated quarterly from a 10% sample of all airline tickets written in the United States. Each record contains an airline itinerary (a route flown on a given carrier, with the direction of travel specified), a dollar fare, and the number of passengers observed on the itinerary at the given fare over the quarter. The distance of the trip and the fare class are also shown.

To reconstruct the routes flown by the carriers, we use DB1A records containing the typical types of itineraries used by passengers: 2- and 4-segment round trips flown on a single airline.[13] After imposing several other restrictions,[14] we observe 23,428 4-segment

[12] The reduction in traffic in the AC and BC markets in turn raises marginal cost on the CH spoke, which leads to a higher fare and lower traffic in the CH market.

[13] Note that the directional routing for a 2-segment round trip lists three airports (e.g., LAX-SFO-LAX), while a 4-segment routing lists five airports (e.g., LAX-DFW-JFK-DFW-LAX). Along with 1-segment trips, 2- and 4-segment records cover the vast majority of airline travel in the United States. Moreover, 4-segment travel is quantitatively significant. Of the 1,356,000 passengers observed making 2- or 4-segment trips in our sample, somewhat less than a third (405,000) made 4-segment trips (recall that these numbers represent a 10% sample).

[14] The hub airport for the 4-segment itineraries must be the same in both directions. In addition, records whose itineraries contain travel outside the continental United States are excluded, as are records with a fare of less than \$10 (this follows Borenstein (1989)). Finally, only those DB1A records showing two or more passengers during the quarter (for a predicted quarterly traffic of 20) are used (one-passenger records are excluded). It is likely that the dataset embodying these restrictions captures the vast majority of routes operated by the carriers during the sample period.

itineraries and 6,319 2-segment itineraries from among a chosen set of 267 airports.[15] This route information is used to compute the characteristics of hub-and-spoke networks in operation during the sample period. As explained above, we seek variables measuring a network's size, the populations of the cities it serves, and the extent of competition within it from other carriers. Ultimately, the computed network characteristics are combined with the 4-segment DB1A fare data to show how network structure affects fares.

From the discussion in Section 2, we expect the fare in an individual market to be a decreasing function of network size. Although size was represented by n (the number of endpoints served) in the simple model of the last section, that model was based on the assumption that travel occurred in each possible city-pair market. Since this will not be true in real networks, n is not necessarily a good predictor of traffic flows on the network spokes (and thus of cost per passenger). A better measure of these flows is total 4-segment city pairs connected by the network, denoted *NTWCITP4*.[16] When the spokes of the network are symmetric, the 4-segment portion of total traffic on each spoke will be proportional to *NTWCITP4*.[17]

Based on the earlier analysis, we also expect fares in the market to depend on the populations of cities served by the network, with larger cities leading to lower fares when economies of density are sufficiently strong. To capture this effect, we compute the variable *NTWAVGPP*, which equals the average "population potential" of 4-segment markets in the network. A market's population potential equals the square root of the product of the city populations (this follows Graham, Kaplan, and Sibley (1983) and Call and Keeler (1985)). Population potential for city-pair market *AB*, for example, equals $(POP_A POP_B)^{1/2}$, where *POP* denotes population.[18] This quantity is summed across 4-segment city pairs and divided by *NTWCITP4* to arrive at *NTWAVGPP*. We expect fares to be inversely related to *NTWAVGPP* when the density effect is strong.[19]

The previous analysis also showed that competition in both 4-segment markets (e.g., *AB*) and 2-segment markets (e.g., *AH*) raises fares elsewhere in the network. The first effect is captured by the variable *NTWCOM4*, which equals the fraction of the network's 4-segment markets where at least one competing carrier is present. Competing carriers could provide service through the same hub or a different hub, or they could provide direct (non-

[15] As in previous research, each airport is treated as a different endpoint, so multiple-airport cities contain several distinct endpoints (see, for example, Borenstein (1989)). Another point to note is that the above figures overstate the number of (nondirectional) city-pair markets observed in the data. This is true because itineraries are directional and because different itineraries can be used within one market (i.e., different carriers, or different routes on a given carrier). The total number of nondirectional 4-segment markets is in fact 8,179, and the number of nondirectional 2-segment markets is 2,170. Traffic is not always observed in both directions in a market (this is often true in thin markets).

[16] It could be argued that an increase in the fixed costs of operating the hub, which presumably rise as *NTWCITP4* grows, is passed on in higher fares. If this were true, an increase in *NTWCITP4* would generate opposing effects on fares, one operating through spoke traffic density and the other through rising fixed costs. However, as argued in footnote 10, fixed costs have no effect on the first-order conditions for fare determination in a network model, which implies that the second effect would not materialize.

[17] Referring to (5), total nonhub market traffic along each spoke will be proportional to *NTWCITP4* divided by n. In the more realistic case where the network spokes are asymmetric, this divisor will differ from n, being larger (smaller) when the spoke is heavily (lightly) travelled. Such asymmetry is taken into account below by the introduction of two additional variables indicating the fraction of network city pairs that include the market's origin city and the fraction that include the destination. These variables are discussed below in the section dealing with market-specific variables.

[18] Population is measured in 10,000s. In the case of big cities, the population of the entire metropolitan area containing the airport is used (the actual city population is used for small urban areas). Details are available on request.

[19] Alternatively, enplanements at the endpoint airports could be used in place of city populations to measure traffic generation at the endpoints. Since enplanements may be endogenous, however, we prefer the population measure.

TABLE 1 **Variable Definitions**

Variable	Definition
NTWCITP4	The number of 4-segment city-pair markets connected by the network
NTWAVGPP	The average population potential of the network's 4-segment city-pair markets, where population potential equals the square root of the product of the market city populations
NTWCOM4	The fraction of the network's 4-segment city-pair markets where at least one competitor is present
NTWCOM2	The fraction of the network's 2-segment markets where at least one competitor is present
ORIGSHR	The fraction of the network's 4-segment city-pair markets that include the origin city
DESTSHR	The fraction of the network's 4-segment markets that include the destination city
DIST	One-way flight distance for the market
MKTPP	The market's population potential (see *NTWAVGPP*)
INCORIG	Per capita income for the origin city
TEMPDIF	The mean January temperature at the destination minus the mean temperature at the origin
MKTCOM	The number of carriers competing with the given carrier in the market
MKTPCOM	The number of carriers serving both endpoints of the market without serving the market itself
FARE	The dollar fare
ORD, LGA, JFK, DCA	Dummy variables taking the value one if origin or destination is one of the given airports
ORIGCONC	A dummy variable taking the value one if the origin is a concentrated hub airport
DESTCONC	A dummy variable taking the value one if the destination is a concentrated hub airport
POINTS	The number of nonhub cities served by the network
U4	The network's 4-segment utilization rate, equal to *NTWCITP4* divided by $POINTS*(POINTS - 1)/2$
U2	The network's 2-segment utilization rate, equal to the number of 2-segment markets divided by *POINTS*
NTWCOM4S	The fraction of the network's 4-segment markets with same-hub competition
NPASS	Number of passengers on a record

stop) service. The second effect is captured by *NTWCOM2*, which equals the fraction of the network's 2-segment markets experiencing competition (2-segment markets are those where one endpoint is the hub). Competitors could offer either 2- or 4-segment service. Our analysis suggests that fares in a given market should be increasing in both *NTWCOM4* and *NTWCOM2* (for future reference, variable definitions are given in Table 1).

Table 2 shows the values of the above variables for the major networks along with some other variables of interest (networks with *NTWCITP4* values below 60 are not shown). *POINTS* equals the number of endpoints connected to the hub.[20] *U4* is the network's 4-segment "utilization rate," which equals *NTWCITP4* divided by the number of possible 4-segment markets, $POINTS*(POINTS - 1)/2$. *U2* is the network's 2-segment utilization rate, equal to the number of 2-segment markets (not shown) divided by *POINTS*. Finally, *NTWCOM4S* equals the fraction of the network's 4-segment markets experiencing "same-hub" competition (where the competitor uses the same hub).

Table 2 shows a large range of network sizes in 1985. The largest system is American's Dallas-Ft. Worth network, which serves 1,564 city pairs. The Atlanta networks of Delta and Eastern are close behind in size, followed by the networks of USAir at Pittsburgh and United at Chicago-O'Hare. The population potential of networks also varies considerably. The Denver/Frontier, Minneapolis/Republic, and Phoenix/America West networks show low values of *NTWAVGPP*, indicating service to small cities, while the high *NTWAVGPP* values for the Denver/Continental, Kansas City/Eastern, Chicago/Midway, and St. Louis/TWA networks indicate that these systems tend to connect large cities.

[20] Since *POINTS* is computed as the number of cities from among our 267 that appear in 2- or 4-segment itineraries, it may understate the number of points actually served by the carrier (our list may exclude actual endpoints, or traffic may not be observed to some cities on our list that are in fact served).

TABLE 2 Network Characteristics (Fourth Quarter 1985)

Hub/Carrier	*NTWCITP4*	*POINTS*	*U4*	*U2*	*NTWCOM4*	*NTWCOM2*	*NTWCOM4S*	*NTWAVGPP*
Atlanta/Delta	1368	86	.374	.884	.701	.921	.476	113.1
Atlanta/Eastern	1306	91	.319	.879	.779	.962	.498	131.5
Baltimore-Wash./Piedmont	214	47	.198	.787	.692	.568	.005	130.2
Charlotte/Piedmont	716	59	.418	.949	.588	.661	.053	127.4
Dayton/Piedmont	158	33	.299	.788	.665	.462	.000	135.4
Denver/Continental	307	44	.325	.886	.932	1.000	.554	204.4
Denver/Frontier	498	50	.407	1.000	.673	.900	.407	75.2
Denver/United	635	82	.191	1.000	.800	.927	.426	140.6
Dallas-Ft. Worth/American	1564	101	.310	.990	.650	.870	.227	134.7
Dallas-Ft. Worth/Delta	402	55	.271	.982	.948	.944	.868	152.4
Detroit/Republic	528	61	.289	.852	.642	.769	.013	156.2
Houston/Continental	325	44	.344	.909	.794	.950	.052	170.2
Kansas City/Eastern	125	39	.169	.949	1.000	.946	.064	291.1
Chicago (Midway)/Midway	64	19	.374	1.000	.984	.053	.000	252.7
Memphis/Republic	668	57	.419	.947	.704	.704	.058	134.2
Minneapolis/Northwest	242	42	.281	1.000	.740	.952	.368	183.4
Minneapolis/Republic	480	59	.281	.966	.429	.754	.185	81.7
Chicago (O'Hare)/American	758	78	.252	1.000	.815	.962	.506	174.1
Chicago (O'Hare)/United	1033	116	.155	.931	.754	.963	.372	151.4
Philadelphia/USAir	144	42	.167	.738	.507	.903	.000	113.0
Phoenix/America West	140	22	.606	1.000	.700	.682	.014	86.7
Pittsburgh/USAir	1243	81	.384	.914	.526	.568	.000	135.2
San Francisco/United	133	37	.200	.973	.398	.750	.030	97.7
Salt Lake City/Western	537	52	.405	1.000	.611	.692	.000	115.6
St. Louis/Ozark	445	54	.311	.926	.544	.800	.247	111.4
St. Louis/TWA	756	63	.387	.938	.952	.967	.146	196.0

The *U2* and *U4* variables indicate how successful a network is in generating traffic among the cities that it serves. A relatively low value of *U4*, for example, indicates that service is observed in a small fraction of the 4-segment markets in which connections are feasible. On this criterion, relatively unsuccessful networks include Baltimore-Washington / Piedmont, Denver / United, Kansas City / Eastern, Chicago-O'Hare / United, and Philadelphia / USAir, all of which have *U4* values below .200. Successful networks, on the other hand, include Atlanta / Delta, Charlotte / Piedmont, Denver / Frontier, Chicago / Midway, Memphis / Republic, Phoenix / America West, Pittsburgh / USAir, Salt Lake City / Western, and St. Louis / TWA, all of which have *U4* values above .350.[21] The underlying reasons for variation in *U4* are not immediately apparent. A low value of *NTWAVGPP* might be expected to lead to a low *U4*, but Table 2 shows numerous counterexamples. Similarly, network size is not a good predictor of *U4*, as inspection of the table shows.[22] The variable *U2*, which

[21] A network with a low *U4* value might, of course, have many dense spokes despite the low frequency of connections between endpoints. For this reason, the utilization rate is not a perfect indicator of network success. In addition, like all of the network calculations in this article, the utilization rates do not capture flight frequency, which ideally would be taken into account in appraising the success of a network.

[22] Another possibility is that *U4* is a decreasing function of the population of the hub city (a large hub city generates substantial local traffic, reducing the need to rely on connecting traffic to exploit economies of density in the network). To test this hypothesis as well as those listed above, we regressed *U4* on *NTWCITP4*, *NTWAVGPP*, *NTWCOM4*, and the population of the hub city, denoted *POPHUB*, using information for the networks in Table 2. The regression, which had an R^2 of .2417, yielded a negative coefficient for *POPHUB*, confirming the above hypothesis (the coefficient, however, was insignificant, with a t-statistic of 1.54). The coefficients of *NTWCITP4*, *NTWAVGPP*, and *NTWCOM4* were respectively positive, negative, and positive, but all were insignificant (note

naturally takes higher values than *U4*, also shows some variation across networks.[23]

The *NTWCOM4* numbers show that networks experience varying degrees of competition in their 4-segment markets. At one extreme, competition is present in all of the 4-segment markets served by the Kansas City/Eastern network. At the other extreme, United faced at least one competitor in just 40% of the 4-segment markets served out of its San Francisco hub. Other networks facing relatively low levels of 4-segment competition are Charlotte/Piedmont, Dayton/Piedmont, Denver/Frontier, Dallas-Ft. Worth/American, Detroit/Republic, Minneapolis/Republic, Philadelphia/USAir, Pittsburgh/USAir, and St. Louis/Ozark. Interestingly, three of the carriers in this list (Frontier, Republic, and Ozark) were acquired in mergers shortly after 1985. Values of *NTWCOM2* show similar variation, with the Chicago-Midway/Midway and Dayton/Piedmont networks noteworthy for the small amount of competition in their 2-segment markets.[24]

Low values of *NTWCOM4S* indicate that few of the network's 4-segment markets experience same-hub competition, implying that the hub airport does not support another carrier's hub-and-spoke network. This, of course, does not preclude competition in the 4-segment markets, which occurs through other hubs or in direct service. Table 2 shows that low (or zero) values of *NTWCOM4S* are often accompanied by high values of *NTWCOM4*, as in the case of Philadelphia/USAir.[25]

4. Market-specific variables

■ The fare for a particular 4-segment trip is assumed to depend on the characteristics of the network within which it occurs, as represented by the variables *NTWCITP4*, *NTWAVGPP*, *NTWCOM4*, and *NTWCOM2*. In addition, the fare will depend on market-specific variables measuring demand, the cost of serving the market, and the level of competition.

We use three demand variables representing market size, income, and tourism potential. Market size is measured by *MKTPP* (market population potential), which equals the square root of the product of the city populations. From Section 2, the effect of this demand variable should be negative when economies of density are strong. Another demand measure is *INCORIG*, per capita income of the origin city. We do not use a composite measure of income at both endpoints of the market on the belief that observed fares will depend on the direction of travel even though published fares are nondirectional. High income at the origin city, for example, is likely to result in reduced sensitivity to the cost of travel and thus greater willingness to use less restrictive (and more expensive) directional tickets. At the same time, high traffic flows out of a high-income endpoint lead to lower cost per passenger on the spoke between the endpoint and the hub, which is expected to reduce fares via the density effect. The net effect of *INCORIG* on fares is thus hard to predict. The final

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that *NTWAVGPP*'s negative effect on *U4* contradicts the hypothesis in the text). Explaining variation in network utilization thus appears to require more data than we have at our disposal.

[23] A *U2* value below one indicates that some cities that are endpoints of 4-segment trips are *not* observed as endpoints for 2-segment trips. Apparently, this outcome can occur when the hub is close to the endpoint cities (the distance to the hub is then so short that air travel is uneconomical). Alternatively, some cities may be so small that they generate too little traffic in the hub-inclusive market to be observed (when traffic is low, the city has a better chance of showing up in one of many nonhub markets than in the single hub-inclusive market). A combination of these factors may explain the low *U2* values for the Baltimore-Washington/Piedmont, Dayton/Piedmont, and Philadelphia/USAir networks. Finally, note that use of one-passenger DB1A records, which we excluded, might reveal traffic in very thin 2-segment hub-inclusive markets, leading to higher *U2* values.

[24] The Midway figure highlights the fact the Midway is treated as a different destination than Chicago-O'Hare.

[25] In addition to those shown in Table 2, a number of small networks (with *NTWCITP4* values between 10 and 60) appear in the regression dataset. These are Indianapolis/USAir, Denver/Aspen, Memphis/Delta, Charlotte/Eastern, Houston/Eastern, Tampa/Northwest, Washington-Dulles/New York Air, San Francisco/Air Cal, John F. Kennedy/TWA, Syracuse/Empire, Los Angeles/Western, Orlando/Florida Express, and Chicago-O'Hare/Air Wisconsin.

demand variable is another directional measure, *TEMPDIF*, which equals the mean January temperature at the destination minus the mean temperature at the origin. A large value of *TEMPDIF*, which indicates that origin residents are likely to engage in vacation travel in the market, is expected to lead to lower observed fares as origin residents select the most restrictive (and thus cheapest) tickets.[26,27]

To control for the cost of serving the market, the fare regression includes the distance variable *DIST*, equal to the one-way distance of the trip. Fares are expected to increase with distance. Following earlier research, we also include dummy variables to represent the four slot-controlled airports: Chicago-O'Hare (*ORD*), Washington-National (*DCA*), La Guardia (*LGA*), and John F. Kennedy (*JFK*). A given variable assumes the value one if either the origin or destination for the market is the airport in question.[28] Since slot control raises the cost of providing airline service, the dummy coefficients are expected to be positive.

To measure the effects of competition, we compute the total number of carriers competing with the observed carrier in the market, denoted *MKTCOM*.[29] While it is possible to use the *MKTCOM* variable directly in the regressions, more insight is gained by following Morrison and Winston (1989) and constructing a set of variables that allows the effect of extra competition to depend on the initial number of competitors. Accordingly, we created the variables *MKTCOM*1, *MKTCOM*23, and *MKTCOM*4+, defined as follows:

$$MKTCOM1 = \begin{cases} MKTCOM & \text{if} \quad MKTCOM = 0, 1 \\ 1 & \text{otherwise} \end{cases}$$

$$MKTCOM23 = \begin{cases} 0 & \text{if} \quad MKTCOM = 0, 1 \\ MKTCOM - 1 & \text{if} \quad MKTCOM = 2, 3 \\ 2 & \text{otherwise} \end{cases}$$

$$MKTCOM4+ = \begin{cases} 0 & \text{if} \quad MKTCOM = 0, 1, 2, 3 \\ MKTCOM - 3 & \text{otherwise} \end{cases}$$

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[26] We also experimented with Borenstein's (1989) tourism variable, city hotel receipts as a fraction of personal income, but it performed poorly.

[27] Directional fare differences may also be due to yield management by the carriers. In particular, even though published fares are nondirectional, the allocation of seats across ticket categories may depend on whether a flight serves primarily residents of one endpoint or the other. To see this, consider a simple example for a 2-segment city-pair market. Let the endpoint cities of the market be R, a rich city, and P, a poor city, and suppose the carrier wishes to charge higher fares to residents of R despite the fact that published fares are nondirectional. Suppose further that the carrier operates morning and evening flights from R to P as well as morning and evening flights from P to R, and assume that passengers prefer to depart from their origin city in the morning and return in the evening. To achieve its goal of price discriminating against R residents, the carrier allocates few seats to the cheapest fare categories on the morning flight from R to P and on the evening flight from P to R. R residents, who primarily use these flights, are thus forced to pay relatively high fares. By allocating a greater number of seats to the cheapest fares on the morning flight from P to R and on the evening flight from R to P, the residents of P end up paying lower fares, consistent with their low incomes.

[28] We tried Borenstein's (1989) approach of including dummies for a large number of congested airports. The results were largely unaffected by this alteration, and moreover, many airport variables had insignificant or significantly negative coefficients, contrary to the rationale for their use.

[29] The same carrier is counted as a competitor more than once if it offers several routings in the market. For example, if a carrier offers both connecting and direct service, it is counted as two competitors. Since the availability of several routings yields greater scheduling convenience, a carrier offering such flexibility provides more effective competition in the market than a carrier that offers a single routing. (Note that a carrier is not counted as competing with itself when multiple routings are offered.) Also, it should be noted that *MKTCOM* is computed jointly with the network characteristics, which use the two-passenger DB1A records. Therefore, a carrier is counted as a competitor if it is observed carrying two or more passengers in either direction in the city-pair market. While other researchers (see Borenstein (1989)) require an airline to carry more traffic to be counted as a competitor, an airline in our regression dataset can carry as few as four (observed) passengers (see below). The two-passenger criterion for counting a competitor thus appears appropriate.

*MKTCOM*1's coefficient gives the effect on fares of increasing *MKTCOM* from 0 to 1; *MKTCOM*23's coefficient gives the effect of increasing *MKTCOM* from 1 to 2 or from 2 to 3; *MKTCOM*4+'s coefficient gives the effect of increasing *MKTCOM* from 3 to 4 and beyond. We expect the coefficients of these successive variables to be negative and declining in absolute value, indicating diminishing returns to competition.

We again follow Morrison and Winston (1989) by including a variable to measure potential competition in the market. This variable, denoted *MKTPCOM*, is equal to the number of carriers that serve both endpoints of the market but do not provide service in the market itself. Finally, in order to capture carrier fixed effects, we include a set of carrier dummy variables in the estimating equation (American is the default carrier). In addition to controlling for differences in the airlines' cost structures, these variables partly net out the effect of frequent-flier programs (carriers with attractive programs can charge higher fares; see Borenstein (1989, 1991)). It should be noted that failure to include the airline dummies could lead to biased coefficients of the network variables, which could then be contaminated by carrier fixed effects.

Two additional variables that are jointly market- and network-specific are also computed to account for the fact (noted above) that the origin and destination cities may not be equally connected to the network. *ORIGSHR* is equal to the share of the network's 4-segment city-pair markets that include the observation's origin city, and *DESTSHR* is defined analogously for the destination city. A large value of *ORIGSHR* means that traffic is observed between the origin and many other points in the network. This means that traffic density should be high on the spoke between the origin city and the hub, leading to low cost per passenger over a portion of the route and thus to low fares in the market (a similar argument applies to *DESTSHR*). Holding *ORIGSHR* and *DESTSHR* constant, an increase in *NTWCITP4* simultaneously increases the number of cities connected to origin and destination, lowering costs on both spokes simultaneously and thus reducing fares in the market.

It is important to realize that the issue of airport dominance, which figures prominently in the articles of Borenstein (1988, 1989) and Morrison and Winston (1989, 1990), does not arise in the present setting. The reason is that our focus on 4-segment trips means that no carrier exercises airport dominance at the endpoints of a market where it is observed. It is interesting, however, to consider what happens to a carrier's fares when a market endpoint is dominated by *another* carrier (such markets are in fact present in the data). To address this issue, we construct dummy variables *ORIGCONC* and *DESTCONC*, which take the value one when the origin or destination airport is a concentrated hub (with a single carrier accounting for more than 60% of total enplanements). These airports are Charlotte, Dayton, Dallas-Ft. Worth, Chicago-Midway, Memphis, Salt Lake City, and Pittsburgh. On the one hand, the high fares charged by the airport's dominant carrier should allow fringe competitors to charge similarly high fares, implying positive coefficients for the concentration dummies. On the other hand, fringe competitors attempting to gain a foothold at the airport may be forced to charge lower fares than the dominant carrier in order to attract passengers.[30] With the dominant carrier's fares already high, the result may be an average fare level for the competitor, implying insignificant dummy coefficients.

5. The regression dataset

■ The regression dataset is based on the 4-segment DB1A records already used in generating network characteristics. Observations on the market and network-characteristics variables are added to each record, and two exclusion criteria are then applied. First, records repre-

[30] Beyond the effect of entry barriers, the dominant carrier is presumed to exercise market power because airport dominance enhances the attractiveness of its frequent-flier program and also leads local travel agents to favor its computer reservation system over those of competitors (see Borenstein (1989)).

senting very thin markets or unusual fares are dropped.[31] In addition, records are excluded if the fare class is not YD (coach discount) for all segments of the trip (this eliminates about a quarter of the data). YD fares should be most closely linked to costs, and they also should be least contaminated by the effects of frequent-flier programs, which have been discussed at length in the literature. As a result, the YD records should most clearly reveal the effect of traffic density (as represented by network characteristics) on a carrier's cost per passenger.[32]

A problem with this exclusion criterion is that the YD fare class is not defined consistently across carriers: some carriers designate most of their tickets as discount, while others apply the classification to a minority of fares.[33] Carriers of the latter type are thus under-represented in the data under the YD criterion. While this outcome is clearly undesirable, adding non-YD fares to the dataset would introduce a large number of tickets with high fares that may bear very little relation to airline costs. With the addition of this new data, the cost-reducing effect of traffic density (as captured by network characteristics) is less likely to be revealed in fares.[34]

The round-trip fare for each observation, denoted *FARE*, is the dependent variable for the regression. Because each observed fare for a given 4-segment trip generates an individual DB1A record, there are typically multiple records corresponding to a given itinerary (carrier/route combination), each with a different fare. Thus, while the regression dataset contains 9,964 observations, the number of distinct itineraries is smaller, equal to 6,054 (3,888 of these itineraries have a single fare, 1,236 have two observed fares, 505 have three, and the balance (7%) have four or more observed fares). In performing the regressions, we take two alternative approaches. One uses all the data, treating each fare observation as distinct.[35] The other approach treats each itinerary as a single observation, setting the fare value for those itineraries that are repeated equal to the passenger-weighted mean of the multiple fares. While the latter approach throws away information, we present it for purposes of comparison and as a sensitivity test. Finally, it should be noted that since our specification allows fares in a market to vary directionally, itineraries in opposite directions within one market are not viewed as the same.[36]

Table 3 shows the variable means as well as minimum and maximum values for the non-dummy variables.[37] Note that the means of the carrier dummies give the frequency

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[31] This is done by excluding records with fewer than four passengers (corresponding to quarterly traffic of less than 40 passengers). In addition, records showing travel within a small network (where *NTWCITP4* is less than 10) are excluded, as are records where the origin or destination is a hub for the carrier (since such a trip involves travel between two of the carrier's hubs, it in effect occurs within two networks). The earlier restriction to round trips means that one-way change-of-plane itineraries are not included in the regression dataset. Such trips could not be used because the origin (home) city of the traveller cannot be identified. This means that the demand variables that depend asymmetrically on characteristics of the origin and destination cities cannot be evaluated.

[32] Recall that network characteristics are computed using a dataset that is not restricted by fare class.

[33] Among records satisfying the restrictions described in footnote 31, 98% of American's observations have YD designations for all four flight segments, compared with only 3% of Delta's. Among other major carriers, USAir's YD share is 63%, Continental's is 47%, Eastern's is 87%, Northwest's is 79%, and United's is 80%.

[34] As expected, the performance of the network variables does not consistently support our empirical hypotheses in regressions that include non-YD data.

[35] In this respect, our dataset differs from that of Borenstein (1989). By focusing on thick markets, Borenstein had enough fare variation in each market to estimate separate equations for various fare quantiles (20%, median, etc.).

[36] Calculation of the network variables described above is not sensitive to the direction of observed travel in a market.

[37] With the exception of *FARE*, these values are computed on the "mean-fare" dataset, which has a single fare per carrier on each itinerary (the mean *FARE* is computed using all 9,964 observations). The variables *MKTCOM* and *MKTPCOM*, which have large ranges, are distributed as follows: *MKTCOM* equals zero for 21% of the observations (indicating no competition in the market). It equals 1 for 16%, 2 for 15%, 3 for 11%, 4 for 9%, 5 for 7%, and 6 or more for the remaining 21% of the observations (the median value is 2). *MKTPCOM* equals zero

TABLE 3 Summary Statistics

Variable	Mean	Minimum	Maximum
NTWCITP4	785	11	1564
NTWAVGPP	144.6	8.2	335.5
NTWCOM4	.706	.000	1.000
NTWCOM2	.813	.053	1.000
ORIGSHR	.053	.001	.385
DESTSHR	.052	.001	.385
DIST	1296	157	3471
MKTPP	167.3	2.0	1191.8
INCORIG	10160	5001	19411
TEMPDIF	3.8	−55.9	55.9
MKTCOM	3.39	0	22
MKTPCOM	2.32	0	11
NPASS	11.41	4	270
FARE[a]	269	34	1380

Dummy Means

Carriers		Other	
USAIR	.082	*ORD*	.039
ASPEN	.002	*LGA*	.034
CONTINENTAL	.056	*DCA*	.040
DELTA	.005	*JKF*	.004
EASTERN	.100	*ORIGCONC*	.041
FRONTIER	.030	*DESTCONC*	.044
AMERICA WEST	.030		
MIDWAY	.014		
NORTHWEST	.017		
NEW YORK AIR	.001		
AIR CAL	.001		
OZARK	.017		
PIEDMONT	.105		
REPUBLIC	.102		
TRANS WORLD	.089		
UNITED	.094		
EMPIRE	.003		
WESTERN	.053		
FLORIDA EXPRESS	.008		
AIR WISCONSIN	.001		

[a] *FARE*'s mean value is computed using all 9,964 observations. Other means are computed from the mean-fare dataset, where repeated itineraries are dropped (it has 6,054 observations).

with which the carriers appear in the mean-fare dataset.[38] The variable *NPASS*, which gives total passengers per itinerary, is shown although it is not used in the regressions.

Before turning to the empirical results, it should be noted that our procedures are based on the implicit assumption that network characteristics, which are under the control of the airline, are determined independently of fares. The exogeneity of network characteristics is a reasonable assumption given that a carrier's fares can be adjusted much more easily than

for 14% of the observations (indicating no potential competition). It equals 1 for 22%, 2 for 22%, 3 for 19%, and 4 or more for the remaining 23% of the observations (the median value is again 2).

[38] American accounts for 19% of the itineraries. The low frequency of Delta observations is due to Delta's infrequent use of the YD fare class.

the characteristics of its network. If this assumption were violated, the estimated coefficients in the fare equation would contain simultaneity bias. In addition, the merger simulations performed below, which analyze the impact of exogenous merger-induced changes in network characteristics, would be inappropriate.

6. Empirical results

■ **Basic findings.** Table 4 contains the main regression results. In the regressions, the dependent variable *FARE* and distance are used in log form (the latter is denoted *LDIST*), while all other explanatory variables are untransformed. The first column of the table shows the coefficients for an equation estimated on the entire dataset (described as *ALL*). The dummy coefficients for this equation are presented in Table 5. (The equation does not include the variables *ORIGCONG* and *DESTCONC*, which are added later.)

The results in the first column provide strong support for the analytical framework developed in this article. The coefficient of *NTWCITP4* is negative and significant, indicating

TABLE 4 **Regression Results**

Variable/ Sample	*ALL*	*ALL*	*MEAN-FARE*	*MEAN-FARE*	*ALL*	*MEAN-FARE*
INTERCEPT	3.005	2.920	3.126	3.041	3.008	3.184
	(33.36)	(32.53)	(29.31)	(28.54)	(33.40)	(28.02)
NTWCITP4	−0.0000489	−0.0000666	−0.0000234	−0.0000399	−0.0000495	−0.0000410
	(3.08)	(4.22)	(1.24)	(2.11)	(3.12)	(2.31)
NTWAVGPP	−0.000460	−0.000482	0.00000448	−0.0000115	−0.000466	−0.000362
	(2.47)	(2.58)	(0.02)	(0.05)	(2.50)	(1.75)
NTWCOM4	0.191	0.188	0.133	0.128	0.192	0.173
	(3.31)	(3.25)	(1.94)	(1.86)	(3.32)	(2.63)
NTWCOM2	0.015	0.00663	0.112	0.0939	0.0145	0.111
	(0.24)	(0.11)	(1.47)	(1.23)	(0.24)	(1.44)
ORIGSHR	−0.854	−0.925	−0.885	−0.962	−0.861	−0.821
	(7.10)	(7.68)	(6.28)	(6.81)	(7.14)	(6.52)
DESTSHR	−0.929	−0.996	−1.031	−1.105	−0.921	−0.937
	(7.57)	(8.10)	(7.16)	(7.66)	(7.50)	(7.40)
LDIST	0.373	0.390	0.337	0.356	0.373	0.334
	(47.93)	(51.98)	(37.20)	(40.67)	(47.93)	(32.36)
MKTPP	−0.0000625	−0.000101	−0.0000465	−0.0000934	−0.0000651	−0.000144
	(2.06)	(3.38)	(1.29)	(2.62)	(2.15)	(2.71)
INCORIG	0.00000994	0.00000831	0.0000111	0.00000928	0.00000978	0.0000111
	(3.67)	(3.06)	(3.51)	(2.92)	(3.60)	(3.90)
TEMPDIF	−0.000818	−0.000825	−0.000899	−0.000908	−0.000794	−0.000656
	(5.98)	(6.01)	(5.44)	(5.54)	(5.79)	(4.96)
MKTCOM1	−0.0766	−0.0844	−0.0707	−0.0797	−0.0764	−0.0730
	(7.75)	(8.56)	(6.22)	(7.02)	(7.74)	(5.49)
MKTCOM23	−0.0344	−0.0405	−0.0414	−0.0481	−0.0341	−0.0438
	(7.19)	(8.53)	(7.21)	(8.46)	(7.14)	(6.03)
MKTCOM4+	−0.00625	−0.00524	−0.00583	−0.00454	−0.00622	−0.00356
	(4.30)	(3.60)	(3.22)	(2.51)	(4.27)	(1.20)
MKTPCOM	−0.0156	—	−0.0172	—	−0.0157	—
	(8.17)		(7.47)		(8.22)	
ORIGONC	—	—	—	—	−0.0158	—
					(1.06)	
DESTCONC	—	—	—	—	0.0370	—
					(2.45)	
R^2	.3610	.3567	.3836	.3779	.3615	—

Note: *t*-statistics in parentheses; estimation is by OLS except for last column, which is GLS.

TABLE 5 **Airport and Carrier Dummy Coefficients**

ORD	0.0466 (2.95)	MIDWAY	−0.0611 (0.96)
LGA	0.00214 (0.13)	NORTHWEST	0.0454 (1.68)
JFK	−0.654 (1.13)	NEW YORK AIR	0.0201 (1.52)
DCA	0.0978 (6.73)	AIR CAL	−0.0163 (0.12)
USAIR	0.00907 (0.40)	OZARK	−0.0372 (1.16)
ASPEN	0.252 (2.83)	PIEDMONT	−0.0657 (2.71)
CONTINENTAL	−0.0994 (4.79)	REPUBLIC	0.0296 (1.48)
DELTA	0.146 (2.88)	TRANS WORLD	0.00370 (0.24)
EASTERN	0.0531 (4.07)	UNITED	0.0802 (5.48)
FRONTIER	−0.0918 (3.23)	EMPIRE	0.099 (1.64)
AMERICA WEST	−0.106 (3.39)	WESTERN	0.124 (5.25)
		FLORIDA EXPRESS	0.118 (3.47)
		AIR WISCONSIN	0.638 (5.84)

Note: Estimates are for the first equation of Table 4; *t*-statistics in parentheses.

that fares are low, as predicted, when the market is served by a large network. The strength of this effect is indicated in Table 6, which shows that fares in a market fall by half a percent when the network grows in size by 100 city pairs.[39] The coefficients of *ORIGSHR* and *DESTSHR* are also negative and significant, indicating that, holding *NTWCITP4* fixed, fares are low when the origin and destination are well connected to the rest of the network (recall that spoke traffic will be high and cost per passenger low in this case). Table 6 shows that when *ORIGSHR* (*DESTSHR*) increases by one standard deviation (.04 for both), fares fall by 3.4% (3.7%). Since the coefficients of these variables are not significantly different from one another, these effects are indistinguishable.

The coefficient of *NTWAVGPP* is also negative and significant as expected, indicating that when the network serves large cities, fares in any given market are low. Table 6 shows that increasing *NTWAVGPP* by 41 (one standard deviation) lowers fares in a given market by 1.9%. The network competition variables *NTWCOM4* and *NTWCOM2* both have positive coefficients, although only *NTWCOM4*'s is significant. Thus, as predicted, a network with pervasive competition in its 4-segment markets has high fares as a result of the cost-increasing leakage of traffic to competitors. A one-standard-deviation increase in *NTWCOM4* (an increase of .15) raises fares by 2.9%. Although 2-segment competition was also expected to raise fares, the insignificant effect of *NTWCOM2* could be due to the relatively small variation in this variable across networks.

Taken as a group, the above network variables are strongly significant, with the *F*-statistic for the joint test of zero coefficients significant at the .0001 level. Our results thus

[39] Since the dependent variable is in log form, this number comes from multiplying *NTWCITP4*'s coefficient by 100. The same principle applies to other calculations in Table 6.

TABLE 6 Impacts of Variables on Fares

Variable Change	Percentage Change in Fare
Network 4-segment city pairs increases by 100	−.5%
Network average population potential increases by 41 (one std. dev.)	−1.9%
Fraction of network 4-segment markets with competition increases by .15 (one std. dev.)	+2.9%
Fraction of network 4-segment markets that include origin increases by .04 (one std. dev.)	−3.4%
Fraction of network 4-segment markets that include destination increases by .04 (one std. dev.)	−3.7%
Distance increases by 1%	+.4%
Market population potential increases by 143 (one std. dev.)	−.9%
Per capita income of origin city increases by $1,210 (one std. dev.)	+1.2%
January temperature differential increases by 22 degrees (one std. dev.)	−1.8%
Number of market competitors increases from zero to one	−7.7%
Number of market competitors increases from one to two or from two to three	−3.4%
Number of market competitors increases from three to four	−.6%
Number of potential competitors increases by one	−1.6%
Origin or destination is Chicago-O'Hare	+4.7%
Origin or destination is Washington-National	+9.8%

provide the first concrete evidence linking a detailed set of network characteristics to airfares. This evidence indirectly confirms the importance of networks in lowering airline costs. Furthermore, our results suggest that fare equations that omit network variables are misspecified.[40]

Turning to the market-specific variables, distance has the expected positive effect on fares, with *LDIST*'s highly significant coefficient indicating an elasticity of 0.4. *MKTPP*'s significantly negative coefficient shows that fares are low when the market contains large cities, with a one-standard-deviation increase in this variable (equal to 143) lowering fares by .9%. While this effect follows that of *NTWAVGPP*, it is interesting to note that the network variable's coefficient is seven times as large in absolute value as *MKTPP*'s. This suggests that network population potential is more important in reducing fares than market potential, a finding that makes sense given that the network spokes connecting the cities in a particular market carry traffic bound for many other destinations.

The significantly positive coefficient of *INCORIG* shows that residents of high-income cities pay high fares. This suggests that any tendency of higher-income origins to generate more traffic (thus lowering fares via the density effect) may be overshadowed by a tendency to purchase less restrictive (and thus more expensive) tickets.[41] Whatever the explanation, Table 6 shows that a $1,210 increase (one standard deviation) in per capita income raises fares by 1.2%. *TEMPDIF*'s coefficient is negative and significant, indicating that markets where the destination's January temperature is high relative to the origin's have low fares. The magnitude of this tourism effect is indicated in Table 6, which shows that a 22-degree increase in *TEMPDIF* lowers fares by 1.8%.

The *MKTCOM* coefficients, all of which are negative and significant, show diminishing returns to market competition, as expected. The magnitude of *MKTCOM1*'s coefficient shows that addition of the first competitor to a monopoly market lowers fares by 7.7%. Addition of a second or third competitor reduces fares by a further 3.4%, while the addition

[40] If the estimated fare equation controls for traffic densities on the spokes, then network variables could be omitted.

[41] As noted above, it may also be true that carriers price discriminate against high-income cities through yield management.

of an extra competitor beyond three lowers fares by a further 0.6%.[42] Also, the addition of a potential competitor to the market (a unit increase in *MKTPCOM*) lowers fares by 1.6%.[43] It is interesting to note that the percentage impact on fares of adding the first competitor to a monopoly market is larger than any other effect listed in Table 6.

Turning to the dummy coefficients shown in Table 5, we see that slot control leads to higher fares at only two of the four controlled airports (the coefficients of *LGA* and *JFK* are insignificant). Fares are higher by 4.7% when the origin or destination is Chicago-O'Hare, while a Washington-National origin or destination raises fares by 9.8%. The airline dummies also show many significant carrier effects. Among the major carriers, those charging fares significantly higher than American's for a given trip are Delta (+14.6%), Eastern (+5.3%), United (+8.0%), and Western (+12.4%). Some regional carriers also charge higher fares than American: Aspen (+25%), Air Wisconsin (+64%), Empire (+12%), and Florida Express (+12%). Carriers charging lower fares than American are Continental (−9.9%), Frontier (−9.2%), America West (−10.6%), and Piedmont (−6.6%).

□ **Variations on the basic regression.** The next step is to explore whether the empirical results are robust with respect to the type of sample data used. The equation is reestimated on the mean-fare sample, where repeated itineraries are collapsed into a single observation (the fare value is set equal to the passenger-weighted mean of the multiple fares). While there is no good reason to prefer this approach to use of the entire sample (fare information is thrown away and aggregation bias may arise), we present the results for comparison. The results, shown in the third column of Table 4, are somewhat different from those in the first column. In particular, the coefficients of *NTWCITP4*, *NTWAVGPP*, and *MKTPP* coefficients are now insignificant. However, the fourth column of Table 4 shows that when *MKTPCOM* (the potential competition variable) is deleted, the *NTWCITP4* and *MKTPP* coefficients are again statistically significant (for comparison, the second column shows the results of running the same regression on the entire sample). The results in columns three and four thus lend further support to our basic hypotheses. However, lack of a good justification for the mean-fare approach makes the results based on the complete sample more credible.

The fifth column of Table 4 shows the effect of adding the airport-concentration dummies *ORIGCONC* and *DESTCONC* to the equation of column one. This change has little effect on the other coefficients. The dummy coefficients show that a concentrated origin has no significant effect on fares, while a concentrated destination raises fares by 3.7%. Evidently, in competing for passengers at a concentrated origin, fringe firms keep their fares below those of the dominant carrier (leaving fares at an average level, as explained above). Since this competitive motive is absent when the destination is the concentrated endpoint (passengers are then collected at an unconcentrated origin), carriers are free to exploit the "umbrella" effect generated by the dominant carrier, which leads to high fares. These results provide an interesting extension to previous findings on airport dominance (see Borenstein (1989)).

The estimates presented so far ignore potential correlation between the error terms for different observations. In fact, observations corresponding to multiple fares for a given carrier on a particular route are likely to have correlated errors, as are observations for different carriers on the same route. In addition, observations corresponding to travel in different directions within a market may have correlated errors (this is true within and across carriers). While such correlation has no effect on the consistency of the parameter

[42] The *MKTCOM* coefficients are significantly different from one another in pairwise tests.

[43] The fact that fares depend both on actual and potential competition suggests that airline markets are at best imperfectly contestable (under perfect contestability, the presence of actual competitors should have no effect on fares). This argument is developed by Call and Keeler (1985) and Morrison and Winston (1987).

TABLE 7 **Two-Stage Least Squares Results**

Variable	OLS	2SLS
INTERCEPT	2.954	2.214
	(32.75)	(17.74)
NTWCITP4	−0.0000737	−0.0000712
	(4.63)	(4.19)
NTWAVGPP	−0.000259	0.000246
	(1.38)	(1.18)
NTWCOM4	0.0834	0.135
	(1.44)	(2.17)
NTWCOM2	0.00415	0.0933
	(0.07)	(1.41)
ORIGSHR	−0.946	−0.996
	(7.79)	(7.68)
DESTSHR	−0.990	−0.963
	(7.98)	(7.27)
LDIST	0.385	0.457
	(51.01)	(40.96)
MKTPP	−0.0000884	0.000465
	(2.93)	(6.88)
INCORIG	0.00000551	0.0000143
	(2.02)	(4.68)
TEMPDIF	−0.000862	−0.000475
	(6.22)	(3.09)
MKTCOM	−0.0149	−0.0592
	(12.51)	(12.04)
R^2	.3446	—

Note: Based on entire sample: *t*-statistics in parentheses.

estimates, it may bias the standard errors, leading to potentially incorrect conclusions about the statistical significance of coefficients. To address this issue, we applied the estimation method for random effects models with unbalanced panels suggested by Greene (1990) and used by Evans and Kessides (1991), which takes error correlation into account via a generalized least squares (GLS) procedure. The GLS procedure was applied to the mean-fare sample, and the results are shown in the last column of Table 4 (see the Appendix for details). Comparing these results to the ordinary least squares (OLS) mean-fare estimates in column 4, only one previously significant coefficient becomes insignificant under GLS. Point estimates are also similar in magnitude.[44] These results suggest that ignoring error correlation across observations does not lead to serious bias in the standard errors of estimated coefficients. (Evans and Kessides (1991) reached a similar conclusion.)

The preceding discussion has also ignored the possibility that the number of carriers competing in the market is an endogenous variable. Morrison and Winston (1989), who use similar competition variables, recognize this drawback but argue that a proper correction for endogeneity would require a complete structural model of the airline's fleet allocation process within its network.[45] While proper handling of endogeneity would be difficult, we experimented with a crude simultaneity correction to see how it affected the results. The three market-competition variables are replaced by the single (endogenous) variable *MKTCOM*, equal to the number of carriers competing with the observed carrier in the

[44] The R^2 for the equation, which is estimated without a constant term under GLS, is not meaningful and thus is not reported.

[45] For analyses of entry in airline markets, see Berry (1989), Reiss and Spiller (1989), and Morrison and Winston (1990).

market (endogeneity corrections using the three separate competition measures would have been impractical). After adding a number of instruments, the fare equation is then estimated using two-stage least squares.[46]

Table 7 shows the 2SLS results along with OLS results for this new specification.[47] The OLS results are similar to the first-column results from Table 4, although the *NTWAVGPP* and *NTWCOM4* coefficients are insignificant and the *MKTCOM* coefficient shows a small effect from addition of a competitor (fares fall by only 1.5%). In the 2SLS equation, the *NTWAVGPP* and *MKTPP* coefficients unexpectedly change sign from negative to positive (the latter is significant), and *MKTCOM*'s coefficient shows a stronger 5.9% fare reduction from an extra competitor.[48] Most importantly, the coefficients of *NTWCITP4*, *ORIGSHR*, *DESTSHR* and *NTWCOM4* are significant and have magnitudes similar to their Table 2 values, which shows that our main findings are robust to a crude simultaneity correction. The differences between the Table 7 estimates and those in Table 4 may result from collapsing the separate market-competition variables into one, which leads to a misspecified equation.

7. Merger simulations

■ By 1987, the acquisitions of Ozark by TWA and of Republic by Northwest were complete, leading to larger consolidated hub-and-spoke networks at St. Louis and Minneapolis. These mergers created monopolies on many 2-segment routes out of St. Louis and Minneapolis, leading to concern about higher fares. Borenstein (1990), U.S. General Accounting Office (1988), U.S. Department of Transportation (1989), and Werden, Joskow, and Johnson (1989) investigated actual fare changes in the 2-segment markets, with mixed results. Fare increases did occur, but some markets experienced little fare change or saw decreases.

In contrast, there has been little study of fare changes in the 4-segment markets served by the St. Louis and Minneapolis hubs. As explained above, mergers are less likely to create a monopoly in such markets because competition can continue through other hubs. For this reason, efficiency gains from the merger are less likely to be offset by anticompetitive effects, making it more likely that the 4-segment markets enjoy welfare gains.

The impact of the mergers on 4-segment fares can be studied using the equation estimated above. There are four sources of fare change in a given market when networks are blended as a result of a merger: competition in the market may be reduced; the new network is larger than either of the previous networks (*NTWCITP4* rises); the network has different average population potential (*NTWAVGPP* changes); and it has a different level of 4-segment competition (*NTWCOM4* changes). Recall from above that we view these merger-induced changes in network characteristics as exogenous. This assumption is likely to be appropriate in evaluating the short-run impact of the mergers on fares.

The first part of Table 8 shows how the post-merger networks differ from the original networks of the four merger partners. *NTWCITP4* rises in each case, but population potential and competition fall for the large (acquiring) carriers and rise for the small carriers. The latter changes push fares in opposite directions (higher population potential lowers fares, while higher competition raises them); a larger network reduces fares.[49]

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[46] The following instruments are added to identify the equation: *INCDEST*, per capita income at the destination; *CHINORIG*, *CHINDEST*, percentage changes in per capita incomes at the origin and destination over the period 1979–1983; *CHPORIG*, *CHPDEST*, percentage changes in populations at the origin and destination over the period 1980–1986; *HOTLDEST*, *HOTLORIG*, hotel receipts as a fraction of total personal income at the origin and destination; *CAPORIG*, *CAPDEST*, dummy variables indicating whether the origin or destination is a state capital.

[47] As in the mean-fare regressions of Table 4, the potential-competition variable is omitted from the equation. In addition, the coefficients for the slot-control and carrier dummies are not reported.

[48] It should be noted that a standard endogeneity test indicates that *MKTCOM* is indeed endogenous.

[49] These calculations are based on network characteristics computed for the fourth quarter of 1988. The *NTWAVGPP* and *NTWCOM4* values for the merged networks were set equal to the 1988 St. Louis/TWA and

TABLE 8 Merger Simulations

Pre-Merger Carrier/Hub	Change in *NTWCITP4*	Change in *NTWAVGPP*	Change in *NTWCOM4*
TWA/St. Louis	+532	−34.9	−.143
Ozark/St. Louis	+843	+49.7	+.265
Northwest/Minneapolis	+557	−84.1	−.247
Republic/Minneapolis	+319	+17.6	+.064

St. Louis Network Fare Changes	
Fare changes on original TWA routes under different competitive conditions	
TWA without Ozark (.59)	−3.7%*
TWA and Ozark with no competitors	+3.9%*
TWA and Ozark with 1 or 2 competitors	−0.3%
TWA and Ozark with 3 or more competitors	−3.1%*
Fare changes on original Ozark routes under different competitive conditions	
Ozark without TWA (.31)	−1.3%
Ozark and TWA with no competitors	+6.3%*
Ozark and TWA with 1 or 2 competitors	+2.1%
Ozark and TWA with 3 or more competitors	−0.7%*
Weighted-average fare changes on routes served by both TWA and Ozark	
TWA and Ozark with no competitors (.01)	+4.7%*
TWA and Ozark with 1 or 2 competitors (.02)	+0.5%
TWA and Ozark with 3 or more competitors (.07)	−2.3%*
Minneapolis Network Fare Changes	
Fare changes on original Northwest routes under different competitive conditions	
Northwest without Republic (.20)	−3.6%*
Northwest and Republic with no competitors	+4.1%*
Northwest and Republic with 1 or 2 competitors	−0.1%
Northwest and Republic with 3 or more competitors	−3.0%*
Fare changes on original Republic routes under different competitive conditons	
Republic without Northwest (.62)	−1.1%**
Republic and Northwest with no competitors	+6.5%*
Republic and Northwest with 1 or 2 competitors	+2.3%*
Republic and Northwest with 3 or more competitors	−0.5%
Weighted-average fare changes on routes served by both Northwest and Ozark	
Northwest and Republic with no competitors (.06)	+5.2%*
Northwest and Republic with 1 or 2 competitors (.03)	+1.0%
Northwest and Republic with 3 or more competitors (.09)	−1.8%*

* Fare change significantly different from zero at the 5% level.
** Fare change significantly different from zero at the 10% level.
Note: Numbers in parentheses give relative frequency of each type of market.

The fare impacts of the mergers are computed taking account of these sources of change.[50] Computations are done separately for each of the four carriers under different assumptions about initial competition in the market. Referring to Table 8, we see that on

Minneapolis/Northwest values. However, instead of setting *NTWCITP4* equal to the 1988 numbers, we took into account the fact that all networks grew in size between 1985 and 1988 (this growth presumably reflects the general increase in traffic). The 1988 TWA and Northwest *NTWCITP4* values were deflated by average growth of all networks over 1985–1988 to arrive at estimates of the size of the TWA and Northwest networks immediately after the merger.

[50] The calculations are based on the coefficients in the first column of Table 4. Recall that since the model is estimated using coach-discount (YD) fares, these impacts apply only to this fare class (recall, however, that the YD class includes most of the DB1A data).

an original TWA route where Ozark was not present, the merger reduces fares by a statistically significant 3.7%. Since there is no loss of competition on such a route, the merger's impact is found by aggregating the effects on fares of a larger network (−2.6%), lower 4-segment competition (−2.7%), and lower population potential (+1.6%), which lead to the net change of −3.7%. The same combination of forces yields a 3.6% reduction in fares on original Northwest routes where Republic was not present (see the second half of Table 8). For the smaller carriers, the merger has the reverse effects on *NTWAVGPP* and *NTWCOM4* (see the top of Table 8), and fare reductions are smaller. Fares on original Ozark routes without TWA fall by 1.3% (a value not significantly different from zero), while fares on original Republic routes without Northwest fall by 1.1% (significant only at the 10% level).

While both mergers thus put downward pressure on fares in markets where there was no reduction in competition, a different picture emerges in markets where the merging carriers competed. In such cases, the network effects are countered by the effect of reduced competition, which in turn depends on the number of competitors initially present. Table 8 shows that fares rise significantly in markets served only by the merging carriers. For example, fares on original TWA routes where Ozark was the only competitor rise by 3.9%, while fares on original Ozark routes where TWA was the only competitor rise by 6.3%. A weighted average of these fare changes (indicating average change in the market) is 4.7%.[51] These numbers, along with the analogous Northwest-Republic figures, show that complete elimination of competition swamps the network effects of the merger, leading to higher fares.

The outcome is different when the merger does not create a market monopoly. When one or two other competitors are present in a market served by the merging carriers, the loss of a competitor by itself does not lead to as large an increase in fares. In this situation, network and competition effects cancel, as can be seen in Table 8. Three of four individual fare changes, as well as both of the weighted-average changes, are insignificant in this case. When three or more airlines compete with the merging carriers in the market, reduction of competition has virtually no effect on fares. In this case, network effects dominate, and both of the weighted-average fare changes are significantly negative.[52]

These calculations show that competitive effects are strong relative to the network effects of a merger. However, since Table 8 shows that competition between the merging carriers occurred in relatively few markets, competitive effects play a minor role in determining the overall impact of each merger on 4-segment passengers. In the case of St. Louis, for example, markets served by TWA but not Ozark account for 59% of all markets served by one or both carriers, while markets served by Ozark but not TWA account for 31% of the total (the numbers in parentheses in Table 8 show the relative frequency of market types).[53] The balance of the markets (only 10%) have competition between TWA and Ozark (as seen in Table 8, 1% of the total have no other carriers aside from TWA and Ozark, 2% have one or two, and 7% have three or more additional carriers). Since the merger has no effect on competition outside this small number of markets, network effects dominate in determining its overall impact. As a result, fares in the 4-segment markets fall on average in response to the merger, with the weighted-average fare change across the different market types equal to −2.7% (this number is statistically significant).

[51] The weights in the weighted average calculation were derived from relative shares of total enplanements at the hub airports.

[52] If the specification is modified to follow Morrison and Winston (1989), with extra competitors beyond one treated identically, then the simulation results are different. In this case *MKTCOM23* and *MKTCOM4+* are replaced by a single variable, *MKTCOM2+*. Because *MKTCOM2+*'s coefficient is small in absolute value, fares fall in markets served by both TWA and Ozark and *at least one* additional carrier. Given that our *MKTCOM* coefficients are significantly different from one another (see footnote 42), Morrison and Winston's specification and the associated simulation results are inappropriate for our data.

[53] Since these numbers are based on the data used to construct network characteristics (DB1A records with two or more passengers), all actual service may not be captured.

A similar outcome emerges in the case of Minneapolis. Markets served by only one of the merger partners account for 82% of the total (20% of the markets are served by Northwest but not Republic, while 62% have Republic but not Northwest). With competitive effects present in only 18% of the markets (see Table 8 for details on their structure), network effects again dominate, reducing fares on average by a statistically significant 1.2% across markets. This number is smaller than the St. Louis figure because the increase in network size is smaller for each Minneapolis carrier and because competitive effects are present in a greater share of the markets.

Our Minneapolis prediction, and our general methodology, is buttressed by results reported in Borenstein (1992), who calculates actual 4-segment fare changes at Minneapolis in response to the Northwest-Republic merger. His results show an average fare decline of 1.5% (computed relative to a national average), a number close to our 1.2% figure.[54]

In contrast to the above procedures, it could be argued that each merger partner should be counted as a potential competitor in markets that it does not serve. Under this approach, Ozark would be counted as a potential competitor in markets served only by TWA and other carriers, and so on. When this is done, the merger has an anticompetitive effect in such markets, namely the elimination of a potential competitor (there is still no effect on actual competition). When this approach is implemented, the fare changes in the TWA-without-Ozark and Ozark-without-TWA cases become −2.2% and +.2% respectively (the latter change is not statistically significant). Similarly, the fare changes in the Northwest-without-Republic and Republic-without-Northwest cases become −2.0% and +.4% (neither is significant). The overall changes at St. Louis and Minneapolis become −1.3% and +.01% respectively (again, neither of these changes is significant). Although this approach undermines our previous conclusion, it does not adhere to our definition of potential competition, which requires that a carrier serve both endpoints of the market but not serve the market itself in order to be counted as a potential competitor. In particular, for Ozark to be a potential competitor (under our definition) in each market that it does not serve, it would have to serve both endpoints of the market without offering service *between the endpoints* through the St. Louis hub. This, of course, is virtually impossible given that all of Ozark's service was centered around the St. Louis hub. Similar observations apply to other carriers. As a result, this modification of our approach is not viable.

To complete the analysis of a merger's impact, the effects on hub-terminating and hub-originating passengers must be considered. However, since our analysis focuses on fare determination for 4-segment travel, we cannot simulate the impact of a merger on the fares paid by these passengers, most of whom presumably make 2-segment trips in travelling to the hub city. While there has been much study of actual 2-segment fare changes at the affected hubs, the results are mixed, showing that fare increases were by no means universal across markets (see above). A consistent set of predictions for all types of passengers, as well as overall welfare calculations, must therefore await estimation of a structural model of pricing in airline networks. The direction of the overall impact on passenger welfare from such a model, which balances gains for connecting passengers against (anticipated) losses for hub-terminating and hub-originating passengers, is unclear *a priori.*

8. Conclusion

■ This article has provided the first detailed evidence linking airline fares to the structure of hub-and-spoke networks. Our findings provide evidence of the importance of networks in reducing airline costs. More generally, the results provide support for the hypothesis that

[54] Dyer (1991) also studies actual fare changes in the 4-segment markets served through St. Louis and Minneapolis. Her results show no systematic effect of the merger on 4-segment fares, in contrast to the above predictions and to Borenstein's (1992) finding. Results in such an exercise are evidently sensitive to the construction of the sample used for the pre-merger/post-merger comparison, and this may explain the discrepancy.

forces leading to higher traffic densities on the spokes of a network reduce fares in the various markets it serves.

It should be noted that this last conclusion is based on a relation between traffic densities and network characteristics for which we provide no direct evidence. However, in subsequent research, Brueckner and Spiller (1992) find (among other things) that spoke traffic does vary with network characteristics in the manner hypothesized here (for example, spoke traffic levels for a given type of market are higher in a large network than in a small one). This finding supports our interpretation of the present results. Brueckner and Spiller (1992) also carry out different tests of our basic hypothesis by investigating the relation between fares and actual spoke traffic densities. They find that higher density reduces both fares and the marginal cost of carrying an extra passenger (indicating economies of density).

In addition to highlighting the role of networks, the present article also sheds new light on the issue of hub concentration. Our findings show that a merger leading to a concentrated hub also generates an efficiency gain by creating a larger network. The simulation results suggest that in the 4-segment markets, where the merger has little effect on competition, this efficiency gain is passed on to passengers in the form of lower fares. This effect cushions the losses from higher fares paid by hub-originating and hub-terminating passengers, who may experience a significant reduction in competition as a result of the merger. More generally, our analysis suggests that in a merger involving a multiproduct firm with cost complementarities across outputs, consumers in markets not directly affected by the merger may benefit (prices fall via the complementarity effect). This principle may be relevant for merger analysis in other industries.

Appendix

■ The GLS procedure is carried out as follows. First, use of the mean-fare sample eliminates the problem of within-carrier error correlation on a given route (which arises because of multiple fares). To understand the error structure in the mean-fare case, let f_{ijc} denote the mean fare charged by carrier c on the route from origin city i to destination city j and back. Let x_{ijc} denote the vector of network variables for carrier c on the route (note $x_{ijc} = x_{jic}$), let y_{ij} denote the vector of nondirectional market variables such as competition levels that are not carrier specific ($y_{ij} = y_{ji}$), and let z_{ij} denote the directional variables *INCORIG* and *TEMPDIF* ($z_{ij} \neq z_{ji}$). Then the fare equation can be written

$$f_{ijc} = \beta' x_{ijc} + \delta' y_{ij} + \gamma' z_{ij} + u_{ijc},$$

where β, δ, and γ are vectors of coefficients and where

$$u_{ijc} = \epsilon_{ij} + \nu_{ijc}.$$

ϵ_{ij} is a (directional) route-specific error term and ν_{ijc} is an error that is both carrier- and route-specific (these errors are uncorrelated and both have zero expectation). We assume that $E(\nu_{ijc}^2) = \sigma_\nu^2$, $E(\nu_{ijc}\nu_{stk}) = 0$ for $(i, j, c) \neq (s, t, k)$, $E(\epsilon_{ij}^2) = E(\epsilon_{ij}\epsilon_{ji}) = \sigma_\epsilon^2$, and $E(\epsilon_{ij}\epsilon_{st}) = 0$ for $(s, t) \neq (i, j), (j, i)$. Because of the common route-specific error, the u_{ijc} are correlated across carriers for a given route (i, j). In addition, since the route-specific errors corresponding to travel in different directions in a market are perfectly correlated, u_{ijc} and u_{jic} are correlated, as are u_{ijc} and u_{jik}. A superior approach would allow ν_{ijc} and ν_{jic} to be correlated, so that carrier-specific part of the error also exhibits directional correlation (in this case u_{ijk} and u_{jik} would exhibit greater correlation that u_{ijk} and u_{jih}, $h \neq k$, indicating that same-carrier errors in different directions are more correlated than errors for different carriers). However, this assumption would introduce severe additional complexity. For the details of the technique used to estimate this model, see Evans and Kessides (1991) and Greene (1990, pp. 500–501).

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