Market Conduct in the Airline Industry: An Empirical Investigation

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Market conduct in the airline industry: an empirical investigation

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This article calculates conduct parameters (or "conjectural variations") for a set of duopoly airline routes. We estimate the mean conduct parameter for each airline and draw inferences about whether Bertrand, Cournot, or cartel models are supported by the data. Some sensitivity analysis with respect to underlying parameters is also carried out. In general we find that the Cournot model seems much more consistent with the data than either the Bertrand or cartel model.

1. Introduction

■ The airline industry is an important industry at the public policy level (and is personally important to the many economists who consume its services). In the aftermath of deregulation, there has been much discussion in the popular press on whether the industry is subject to "excessive competition" or, conversely, is becoming excessively concentrated. (For example, the June 1988 issue of *Consumer Reports* raised concerns about the large number of monopoly and duopoly routes in U.S. markets.) In this article we attempt to assess the competitiveness of a set of duopoly airline routes so as to shed light on whether high levels of route-specific concentration should be viewed as a cause for concern.

Our second objective is to add to the empirical evidence on the relative descriptive usefulness of certain simple oligopoly models: the Cournot model, the Bertrand model, and the cartel model. In other words, we hope to contribute to the empirical investigation of general principles of market behavior. Our method is to formulate and estimate a "conjectural variation" model of industry structure, using 33 duopoly airline routes as the data set under study. We find that our "base case" estimates of airline conduct are reasonably close to Cournot behavior. This finding is in contrast to most earlier attempts to estimate or calibrate conjectural variation models (see Iwata (1974), Gollop and Roberts (1979), Appelbaum (1982), and Dixit (1988)), which find behavior that is more competitive than the Cournot model would suggest, although less competitive than implied by the Bertrand model. It is

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worth noting, however, that the markets analyzed in these studies are less concentrated than the airline markets we examine. We also do some sensitivity analysis and present some explicit Bayesian calculations indicating how Bertrand, Cournot, and cartel priors might reasonably be updated given our data.

The airline industry has already been the subject of considerable empirical study in economics. Significant effort has been expended in the estimation of costs (see, for example, Caves, Christensen, and Tretheway (1984)) and the estimation of airline demand (see Oum, Gillen, and Noble (1986), Anderson and Kraus (1981), and Straszheim (1978)). Pricing behavior in the airline industry has been studied by, among others, Bailey, Graham, and Kaplan (1985), Borenstein (1989a and 1989b), and Borenstein and Rose (1989). Several authors, including Morrison and Winston (1987), Whinston and Collins (1988), Berry (1989), and Hurdle *et al.* (1989) investigate whether airline markets are "contestable" (as defined by Baumol, Panzar, and Willig (1982)). These pricing and contestability studies are, like ours, concerned with market conduct (at least implicitly). What distinguishes our article is the explicit estimation of conduct parameters and the attempt to isolate a single strategic setting by focusing only on duopoly routes. Other useful general references on the airline industry include Douglas and Miller (1974), Panzar (1979), Graham, Kaplan, and Sibley (1983), O'Connor (1985), and Levine (1987).

The structure of the article is as follows. In Section 2 we provide an overview of our theoretical methodology, which is devoted largely to a discussion of how the "conjectural variation" model can be interpreted for use in empirical investigations of market conduct. Section 3 discusses our statistical methodology. Section 4 describes the data, Section 5 describes the construction of marginal cost estimates, and Section 6 presents and interprets the estimates of conduct parameters. Section 7 presents a Bayesian analysis of market conduct, and Section 8 contains concluding remarks.

2. Theoretical structure

■ Our analysis is focused on duopoly, so we discuss the duopoly version of the conjectural variation model, although the analysis and conceptual issues extend immediately to the n-firm case. We have two firms, referred to as firms 1 and 2, producing (homogeneous) outputs x_1 and x_2 respectively. Total output, denoted X, is the sum of x_1 and x_2, and inverse demand is represented by $p(X)$. Costs for firm i, $i = 1, 2$ are denoted C^i, and profits, π^i, can be written

$$\pi^i = x_i p(X) - C^i(x_i). \tag{1}$$

If we regard output, x_i, as the choice variable, and if we restrict attention to a single period (i.e., to a single choice of x_1 and x_2), then the Nash equilibrium is represented by first-order conditions

$$\pi^i_i = p + x_i p' - c^i = 0, \tag{2}$$

where subscripts on π represent derivatives and c^i represents marginal cost. This Nash quantity (or "Cournot") solution might fail to hold for a variety of reasons. For example, if price rather than quantity is the choice variable, then the Nash equilibrium (in prices) will not satisfy (2), or if the firms manage to collude and maximize combined profits, then (2) will not be satisfied. In general we can write

$$p + x_i p' - c^i = \delta^i(x_1, x_2). \tag{3}$$

Equation (3) is purely definitional; it contains no theoretical restrictions. The variable δ^i is simply defined as the difference between the left-hand side of (2) and zero. In general we can expect δ^i to vary with x_1 and x_2, and possibly with other variables or parameters as well.

The conjectural variation model arises by assuming that each firm views industry output X as a function of its own output x_i, yielding first-order condition

$$\pi_i^i = p + x_i p' dX/dx_i - c^i = 0, \tag{4}$$

which, after noting that $dX/dx_i = dx_i/dx_i + dx_j/dx_i$, can be rewritten as

$$\pi_i^i = p + x_i p'(1 + v^i) - c^i = 0, \tag{5}$$

where $v_i \equiv dx_j/dx_i$. Variable v_i is referred to as the "conjectural variation." If $v^i = 0$, then equation (5) is the same as (2) and therefore yields the Cournot solution.

There has been extensive consideration of the appropriate interpretation of the conjectural variation model. (Influential articles include Bresnahan (1981), Perry (1982), Kamien and Schwartz (1983), and Boyer and Moreaux (1983).) It has been argued by Friedman (1983), among others, that the conjectural variation, as it arises in a static or "one-shot" model, cannot be taken as a literal expectation of future strategic reactions. At best it is some sort of static approximation to the real-time action and reaction that arises in a dynamic setting. The interesting question is whether this approximation is useful. Many game theorists prefer to use explicit repeated game models, but that approach has its own weaknesses.

A middle-of-the-road view, described, for example, in Brander and Spencer (1985) and Dixit (1988), is that the conjectural variation is simply a useful and intuitive summary measure of market conduct. This follows from a comparison of equations (3) and (5). As mentioned, equation (3) is a fully general description of behavior. If we let $v^i = -\delta^i/p'x_i$, then expression (5) is equivalent to expression (3). The departure of v^i from 0 can then be seen as a logically consistent test of whether the "one-shot" Cournot model is a good description of a particular industry or set of industries. Similarly, the estimated magnitude of v^i can be used to address the question of whether the industry is consistent with the Bertrand model or with the cartel model.

Specifically, if the two firms have the same costs and can be described by the Bertrand model, then both should have conduct parameters of -1. (This can be seen by recalling that the Bertrand model requires, in the homogeneous product case, that price equal marginal cost. From (5) this arises if $v = -1$.) If the two firms have different costs, then the firm with the higher marginal cost at the solution will have a conduct parameter of -1, while the other firm has a conduct parameter greater than -1. As already shown, the Cournot case arises (for any costs) if $v = 0$. The cartel solution arises, under identical costs, if the conduct parameter equals 1. (If $v = 1$, then first-order condition (5) is equivalent to the monopoly first-order condition, since $X = 2x$.) These tests are independent of whether the conjectural variation is regarded as an expectation. We prefer to think of the conjectural variation as an indicator of the strategy variable, or as an indicator of the degree of collusion, and therefore refer to v^i simply as a "conduct parameter" for the rest of this article.

Our principal objective here is to estimate conduct parameters for a set of duopoly airline routes and consider whether the results support Bertrand, Cournot, or cartel outcomes. We rewrite first-order condition (5) as

$$v^i = (p - c^i)\eta(X)/(ps^i) - 1, \tag{6}$$

where $\eta(X)$ is the (positive) elasticity of market demand, $-(dX/dp)(p/X)$, and s^i is the market share of firm i. Strictly speaking, this is a deterministic equation. Conduct parameter v^i can be calculated (for each route) if one knows the elasticity of demand at the observed point, the market share of firm i, and marginal cost at the observed point.

3. Statistical methodology and data requirements

■ Our principal statistical assumption is that each airline route in our data set represents a similar strategic situation. After conduct parameters are calculated, using equation (6) for each firm and for each route, we then treat each of these calculated values as an "observation" consisting of a common element and an "error." We therefore convert equation (6) to the stochastic specification

$$v_k^i = v^i + \epsilon_k^i, \qquad (7)$$

where v_k^i is the calculated value of the conduct parameter for firm i on route k, v^i is the expected value of the conduct parameter for firm i, and ϵ_k^i is a random deviation of v_k^i from its expected value (with mean 0). We estimate the mean and standard deviation of the conduct parameter and infer whether the data favor the Bertrand, Cournot, or cartel models. We also carry out the Bayesian exercise of seeing how our evidence would change certain particular priors. Specifically, we are interested in seeing whether this data would induce someone who believed in the Cournot model, in the Bertrand model, or in the cartel model to revise his or her opinion significantly. (This approach is similar in spirit to Leamer's (1986) investigation of whether certain macro data could influence Keynesian or Monetarist priors.)

We use a cross-section data set of Chicago-based duopoly airline routes involving American Airlines and United Airlines. Working with duopoly routes reduces the market conduct problem to its purest form, and restricting the routes to Chicago-based routes reduces the importance of variations in route-specific idiosyncratic factors, such as airport delays, climate, and whether or not the route involves a hub city for a particular airline. (Chicago is a hub for both American Airlines and United Airlines, while most of the connecting cities are hubs for neither airline.) Dealing with the same two airlines on every route corrects for many firm-specific effects, and restricting the observations to one particular time period eliminates the problem of structural change over time, although at the cost of forgoing potential expansion of the data set.

The data requirements are as follows (as implied by equation (6)):

(1) price (fare) information for each airline and route

(2) marginal cost per passenger for each airline and route

(3) elasticity of demand for each airline and route

(4) market shares for each airline on each route.

The theoretical structure in Section 2 assumes that the firms produce a single homogeneous product. In fact, airlines offer different products, such as first class and economy, and, as reported by Borenstein and Rose (1989), price dispersion is very important in airline fares: the expected difference in prices paid for two passengers selected at random from a given route is about one-third of the average fare. Most analysis of the airline industry divides airline fare classes into three general categories, first class, regular economy, and discount, but it is fairly difficult to draw a strict distinction between the latter two. We therefore combine discount and regular economy into a single category, called "economy," and use that as the basic data. The analysis was also done using just the strict discount category, which makes only a small difference, as the vast majority of the traffic is in the discount category in any case. We make the approximation that the economy category can be treated as a homogeneous product, using, for each route, a carrier's weighted average regular economy/discount price as the product price for that carrier.

4. The data

■ Quantity and price data were obtained from I.P. Sharp Associates. The I.P. Sharp data derive from Databank 1A of the U.S. Department of Transportation (DOT) *Origin and Destination Survey*. This data set is a 10% sample of all tickets that originate in the United

States on significant domestic carriers. I.P. Sharp "filters" the DOT data in an effort to remove obvious errors and misleading observations (such as passengers cashing in "frequent flyer" points being mistakenly classified as "discount" passengers). In addition, we used only "one-coupon" passengers, which effectively restricts attention to passengers on direct flights between the two cities in question.

The data set consists of 33 Chicago-based airline routes for the third quarter of 1985. The 33 routes were selected by taking all Chicago routes on which American Airlines and United Airlines together had a market share exceeding 75%, and on which each carrier had at least 100 passengers in the 10% sample.[1] (The average combined market share over the 33 routes is 96%.) The implicit assumption about other carriers, if any, is that their outputs are exogenous to the two major firms. Chicago is a major hub for both airlines.

We use "local traffic" as the measure of volume or output. That is, for the Chicago-Albany route we include passengers who originated in Chicago and flew to Albany, not passengers who, for example, originated in Los Angeles, had a stopover in Chicago, then continued to Albany. The output for a route, such as Chicago-Albany, consists of all directional trips between the two cities (i.e., those originating in Chicago destined for Albany, and those originating in Albany destined for Chicago). A round-trip ticket is considered to be two directional trips on the route, and the fare paid for each directional trip is taken to be half the round-trip fare. A one-way ticket is simply one directional trip. Our basic unit of price data is the directional fare. Table 1 lists the city name and distance (in miles) for each route, along with the directional fare (in dollars) and the number of directional passengers in the 10% sample for each airline and for each route. Estimated actual volumes would be about ten times the figures given below. Routes are listed in ascending order of distance.

Equation 6 also calls for the elasticity of demand, which requires that some elasticity estimate be obtained. We could obtain a demand elasticity from our own data set by assuming a common demand structure across routes, imposing a particular functional form, then estimating a demand elasticity. However, as the data set has only 33 observations, we believe it to be unlikely that we could obtain reasonable estimates of a sufficiently flexible demand structure. Our preferred approach is to take elasticity estimates from the most carefully done demand study we could find and use them in equation (6). We have, accordingly, taken elasticity estimates from Oum, Gillen, and Noble (1986), who used 1978 data from 200 routes and subdivided fare classes into the three categories first class, regular economy, and discount. Their estimated elasticities for discount travel range from 1.5 to 2.0, and the range for regular economy is from 1.2 to 1.4. (In a study of North Atlantic routes, Mutti and Murai (1977) found a discount price elasticity of 1.4.).

It should be noted that equation (6) does not impose any functional form on demand, but estimation of demand will normally involve the specification of a particular functional form. Oum, Gillen, and Noble used the translog function as the parametric specification of demand. This allows elasticities of demand to vary according to output level and therefore across routes. The actual estimates are, however, quite similar across routes. Furthermore, their data set does not fully nest ours, so there is little we can do except use the average elasticity as the assumed elasticity for each route in our data set. We take 1.6 as our "base case" elasticity, reflecting the Oum, Gillen, and Noble estimates and the relative proportions of discount and regular economy passengers in our data set. We also report results using demand elasticities of 1.2 and 2.0, which probably covers the reasonable range.

As for costs, the basic data we use are from Department of Transportation Form 41, which consists of financial and operating data for U.S. airlines. There are several difficulties

[1] There was one additional route in this category, Chicago-Cincinnati, but we were unable to obtain price information for it.

TABLE 1 Price and Volume Data, Third Quarter 1985

Route	Distance	AA Fare	UA Fare	AA Passengers	UA Passengers
Grand Rapids	134	101	102	751	688
Indianapolis	167	78	86	1488	517
Columbus	286	136	135	1524	2678
Des Moines	306	125	142	827	1746
Omaha	423	129	137	721	2131
Buffalo	467	134	132	1261	1309
Rochester	522	161	155	1160	872
Tulsa	587	149	146	1091	521
Wichita	591	162	163	731	496
Syracuse	601	147	155	926	759
Baltimore	612	146	154	1764	2716
Oklahoma	692	163	174	934	665
Albany	717	150	154	1172	622
New York	721	153	174	18104	18103
Charleston	750	109	113	223	429
Hartford	778	162	166	1505	2844
Dallas	800	148	128	6223	1163
Providence	842	145	161	945	824
Austin	972	130	104	742	152
San Antonio	1041	161	147	491	435
Albuquerque	1122	132	134	453	190
Phoenix	1440	185	147	2304	2592
Tucson	1441	148	159	818	391
Las Vegas	1521	148	129	1842	2653
Reno	1680	154	156	351	474
Ontario, CA	1707	183	175	819	1034
San Diego	1729	189	168	1441	1546
Seattle	1730	183	201	1042	1969
Los Angeles	1740	203	211	6592	6270
Portland	1749	154	198	643	1204
Sacramento	1790	192	202	371	616
San Jose	1837	237	238	744	993
San Francisco	1848	219	217	2398	3827

associated with converting this accounting data into route-specific marginal cost per passenger. Estimation of marginal cost is described in Section 5.

5. Estimation of marginal cost

■ Our theoretical structure calls for route-specific marginal cost data. Unfortunately, the appropriate operational definition of marginal cost is far from obvious. One reasonable specification of route-specific total cost is the linear form used by Douglas and Miller (1974) and Panzar (1979),

$$C^i(x_i) = a_i x_i + b_i f_i(x_i) + F_i, \tag{8}$$

where x_i is the number of passengers served by the ith airline, f_i is the number of the airline's flights, a_i is the cost of serving a passenger, b_i is the cost of a flight, and F_i is fixed cost. (The parameters a, b, and F would vary from route to route depending on distance.)

The associated marginal cost of carrying a passenger on a given route is

$$c^i(x_i) = a_i + b_i f_i'(x_i). \tag{9}$$

If an extra passenger could be accommodated without adding a flight, then the marginal cost of that passenger would be a. At capacity, however, an extra passenger would require an extra flight, so the marginal cost would be $a + b$. In a stochastic world, we would want to attribute some fraction of extra flight costs to each additional passenger, suggesting that in general marginal cost consists of the direct cost of passenger service (in-flight meals, extra fuel, etc.) plus a share of the cost incurred to make flights and seats available. Thus, using this formulation, marginal cost is simply taken to be average variable cost.

Even if one accepts this cost structure as a reasonable representation of the costs of serving a particular route, there are (at least) two further problems to consider. First, it is not entirely clear which costs should be taken as variable costs and which should be taken as fixed costs. Secondly, airlines report overall costs, not route-specific costs. Some way of assigning route-specific marginal costs must be found.

One proxy for variable cost is operating expenses. The DOT reports operating expenses for each carrier, based on its Form 41. There are eight cost items in operating expenses: flying operations, maintenance, passenger service, aircraft and traffic servicing, promotion and sales, general and administrative, depreciation and amortization, and transport-related expenses. A convenient way of summarizing cost data is to report operating cost per "passenger-mile," where passenger-miles is total passengers times average miles per passenger. Table 2 shows costs per passenger-mile for each of the two carriers for 1985.

The first row of Table 2 is the base case and includes general and administrative expenses in the calculation. The second row, "low" cost, omits general and administrative expenses. We report results based on both possibilities. We believe that including general and administrative expenses is no less reasonable than including many of the other elements in operating expenses. However, using two values of cost has the advantage of indicating the sensitivity of the results to differences in costs. One point to note is that the cost data include first class passengers as well as regular economy and discount passengers. If first class passengers entail higher costs than other passengers, then using the overall average cost as the cost for discount passengers will involve a slight upward bias in the cost numbers. Fortunately, only a very small fraction of all passengers are in the first class category, so this bias is not likely to be very large.

We need to convert this overall cost per passenger to a route-specific cost. The simplest procedure would be to take the cost per passenger-mile and multiply by flight length to obtain the cost per passenger for any particular route. There are, however, strong *a priori* reasons to believe that cost is not linear in distance. A lot of crew time is used in boarding and deplaning, and fuel consumption is highest during take-off and landing, suggesting that costs are strictly concave in distance rather than linear. Figure 1 illustrates this point clearly, by showing in bar graph form the implied relationship between the price-cost margin ratio and distance under the assumption that costs per passenger-mile are constant. The figure shows that the assumption of linear costs would imply a strong negative correlation between the price-cost margin ratio and distance. While it is possible that there is some systematic relationship between the margin ratio and distance, it is unlikely to be as strong as it appears in Figure 1. Furthermore, the implied negative margins on long routes would appear to be inconsistent with any reasonable notion of profit maximization. It seems clear that some other adjustment to costs is required to get plausible estimates of route-specific costs.

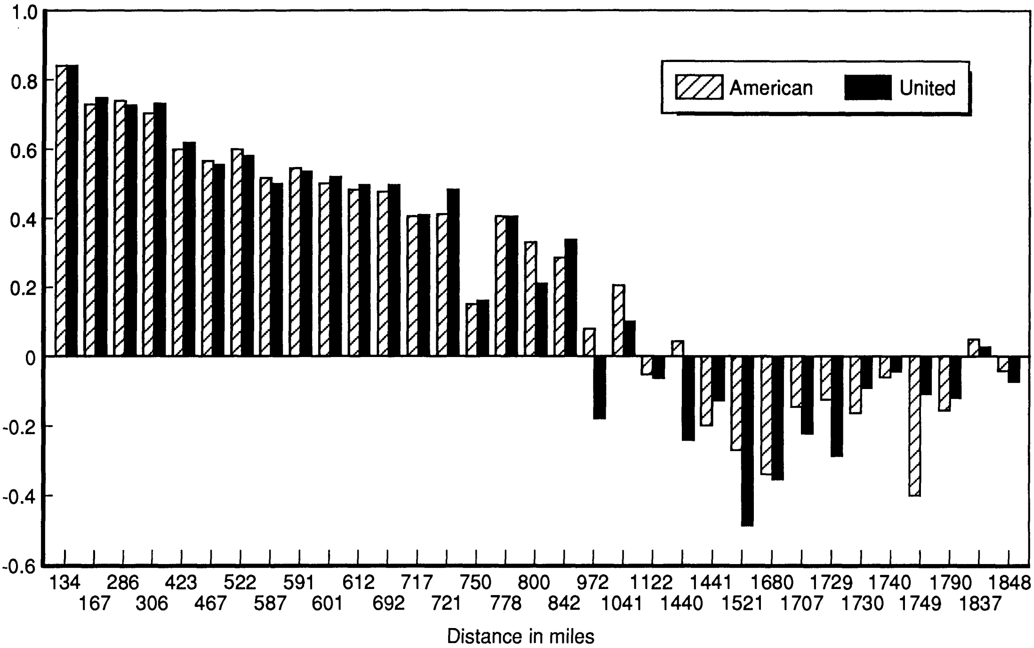
The sensitivity of cost per passenger-mile (cpm) to distance flown is measured by the elasticity of cpm to distance, D. If costs per passenger are concave in distance, then this elasticity will be negative: cost per passenger-mile will decrease with distance. We redefine

TABLE 2 Costs per Passenger-Mile (Cents) 1985

	American	United
Base	12.33	12.61
Low	11.62	12.07

FIGURE 1

MARGIN [(P-C)/P] VS. DISTANCE (Assuming costs are linear in distance)



this elasticity to be positive and represent it using the variable $\theta = -(dcpm/dD)(D/cpm)$. One method of obtaining θ is to estimate an explicit cost function. Caves, Christensen, and Tretheway (1984) used 1970–1981 data to estimate a cost function that included both an elasticity of operating cost per passenger-mile with respect to stage length (nonstop distance) and an elasticity with respect to volume, obtaining results (in their preferred regressions) of .15 and .20 respectively. Volume is the product of flight length and number of passengers. To the extent that apparent "economies of volume" are really due to flight length, that effect should be included in the adjustment to cost per passenger for our purposes. This suggests that the appropriate adjustment based on this work would be substantially more than 15%, but probably less than 35%. Applying just the 15% correction to our data moderates the relationship between the percentage price-cost margin and distance to some extent, but the relationship is still strongly negative, suggesting that this correction is not enough.

It is also possible to infer the effect of flight length on cost per passenger from the price-distance relationship. This is done, for example, by Bailey, Graham, and Kaplan (1985). They assume that route-specific cost per passenger, c, is a function of several variables, including distance:

$$c = c(D, z), \tag{10}$$

where D is distance and z is other variables. Price is taken to be the product of costs and a markup function, $M(ms)$, where ms represents "market structure": $p = M(ms)c(D, z)$. Dividing through by passenger-miles and letting ppm denote price per passenger-mile then yields the equation

$$ppm = M(ms)cpm(D, z). \tag{11}$$

Taking the derivative of this function and forming elasticities indicates that θ equals the (negative of the) elasticity of ppm with respect to distance, minus any elasticity of the markup with respect to distance.

Bailey, Graham, and Kaplan (1985) regress the log of price per passenger-mile against the log of distance and against other variables that might influence cost or the markup and obtain an elasticity with absolute value .483. If market structure is uncorrelated with distance, this implies a value for θ of .483. Similar results are obtained by Morrison and Winston (1986) and Hurdle *et al.* (1989), whose work implies estimated elasticities of price per passenger-mile to distance with (absolute) values of about .50.[2] Based on these studies, we take .50 as our base case value for θ. This substantially reduces but does not eliminate the negative correlation between the price-cost margin ratio and distance. In our sensitivity analysis we also report the results obtained using elasticities of .25 and .75.

American Airlines and United Airlines have different average flight lengths for the U.S. market as a whole: 831 miles and 765 miles respectively. Letting average flight length for airline i be represented by AFL^i and cost per passenger-mile by cpm^i, the formula for cost per passenger for airline i on route k is given by

$$c_k^i = cpm^i(D/AFL^i)^{-\theta}D. \qquad (12)$$

Using the value $\theta = .50$ makes all but two of 66 price-cost margins positive, with the two negative values being very close to zero. We conclude that the base case adjustment we have made for flight length appears plausible, while recognizing that the range of reasonable adjustments is fairly large.

An additional concern is that marginal cost may vary across routes on the basis of other factors aside from distance. It might be argued that the marginal opportunity cost of a passenger depends on how well the route fits into the airline's overall network, on average load factors, on the type of aircraft used, etc. It is difficult to know how to account for these factors in the absence of route-specific cost data. This problem should not greatly affect the estimation of average conduct parameters, however, provided that the routes we have selected are representative (from the cost point of view) of each carrier's total traffic, and provided that Chicago plays a similar role in each airline's network. We believe both these conditions to be met.

6. Results

■ The first set of results is the calculation[3] of route-specific conduct parameters using equation (6). Table 3 reports cost per passenger estimates and the calculated conduct parameters for the base configuration ($\eta = 1.6$, $\theta = .50$, and costs including general and administrative expenses). It also reports calculated conduct parameters for the case with $\eta = 1.6$ and $\theta = .75$. As in Table 1, routes are listed from shortest to longest.

Looking first at the cost columns in Table 3, we see that the two airlines have very similar, but not identical, implied costs per passenger. (The table shows just the base case costs, but this is true for all cases.) As described earlier, if two firms in a duopoly have slightly different costs, then, strictly speaking, the less costly firm will have a Bertrand conduct parameter that is slightly larger (i.e., less negative) than -1, while both firms may have cartel conduct parameters that differ slightly from 1 (depending on how the cartel is assumed to operate). The costs here are sufficiently close, however, that these adjustments are negligible compared to the overall precision of the data, so we continue to treat the values -1 and 1 as representing the Bertrand and cartel solutions. The Cournot conduct parameter is 0, even if costs differ.

Perhaps the most striking implication of Table 3 is that in the base case (as shown by columns 4 and 5), the longer routes appear to be more competitive (i.e., have lower conduct

[2] Hurdle *et al.* (1989) regress yield per passenger-mile on the log of distance (and other variables), obtaining a coefficient of $-.11$. Algebraic manipulation of their specification implies an elasticity of price per passenger-mile with respect to distance (evaluated at the mean of our sample) of about $-.50$.

[3] All calculations were programmed in version 2.0 of GAUSS.

TABLE 3 **Costs and Conduct Parameters**

Route	AA Cost $\theta = .50$	UA Cost $\theta = .50$	AA CP $\theta = .50$	UA CP $\theta = .50$	AA CP $\theta = .75$	UA CP $\theta = .75$
Grand Rapids	41.14	40.37	.82	1.02	.09	.30
Indianapolis	45.93	45.07	−.11	1.95	−.74	.45
Columbus	60.11	58.98	1.46	.41	.87	.11
Des Moines	62.18	61.01	1.50	.34	.80	.08
Omaha	73.10	71.73	1.74	.02	1.08	−.16
Buffalo	76.81	75.37	.39	.35	.10	.11
Rochester	81.21	79.69	.39	.81	.21	.62
Tulsa	86.12	84.50	−.00	1.08	−.13	.89
Wichita	86.41	84.79	.25	.90	.13	.76
Syracuse	87.14	85.50	.19	.59	.04	.47
Baltimore	87.93	86.28	.62	.16	.42	.08
Oklahoma	93.50	91.75	.17	.82	.09	.77
Albany	95.18	93.39	−.10	.82	−.16	.77
New York	95.44	93.65	.20	.48	.13	.45
Charleston	97.34	95.52	−.50	−.62	−.61	−.63
Hartford	99.14	97.28	.79	.01	.75	.02
Dallas	100.5	98.65	−.39	1.33	−.40	1.42
Providence	103.1	101.2	−.14	.28	−.13	.33
Austin	110.8	108.7	−.72	−1.43	−.65	−.86
San Antonio	114.7	112.5	−.13	−.20	−.01	−.01
Albuquerque	119.1	116.8	−.78	−.31	−.63	.12
Phoenix	134.9	132.4	−.08	−.70	.24	−.30
Tucson	134.9	132.4	−.79	−.17	−.51	.43
Las Vegas	138.6	136.0	−.75	−1.15	−.24	−.70
Reno	145.7	143.0	−.80	−.77	−.22	−.31
Ontario, CA	146.9	144.1	−.28	−.49	.19	−.06
San Diego	147.8	145.0	−.28	−.58	.16	−.09
Seattle	147.8	145.1	−.11	−.32	.51	.01
Los Angeles	148.3	145.5	−.16	.02	.23	.44
Portland	148.6	145.9	−.84	−.35	−.09	−.02
Sacramento	150.4	147.6	−.08	−.31	.50	.05
San Jose	152.3	149.5	.33	.04	.77	.39
San Francisco	152.8	149.9	.26	−.20	.78	.16

parameters) than the shorter routes. Since the demand elasticity is assumed to be the same for all routes, this is a consequence of the fact that the longer routes have lower percentage price-cost margins than the short routes.

One possible explanation is that our base case value of the elasticity of cost per passenger-mile to distance, θ, is insufficient. As suggested by columns 6 and 7, a value for θ of .75 eliminates the negative correlation between conduct parameters and distance (although it has the effect of concentrating negative conduct parameters in the middle-distance range). An alternative explanation is that demand might be more elastic on long routes than on short routes. Several observers, including Douglas and Miller (1974) and Levine (1987), have suggested precisely this, on the grounds that airfare is a larger share of total trip costs on long trips. If so, then by assuming the same elasticity of demand for all distances, we would induce the apparent negative correlation between distance and the conduct parameter evident in our results, even if the "true" conduct parameters were unaffected by distance. This does run counter to the alternative intuition that short routes have more substitutes (such as bus, car, and train) than long routes and might therefore have more elastic demand.

Perhaps it is also worth entertaining the interesting possibility that, holding market structure constant, long routes really are characterized by more competitive conduct than short routes. One interesting feature of our base case calculations is that the implied absolute price-cost margins are relatively uniform with respect to distance.

The final point to emphasize concerning Table 3 is that a large majority (57 out of 66) of the estimated base case route-specific conduct parameters are in the "reasonable range" of -1 to 1. Note that there is nothing that forces the estimated conduct parameters to be in this range. They can, from a purely computational point of view, quite easily be large negative or positive numbers. The apparent reasonableness of the calculated conduct parameters gives us some confidence in the methods used. However, the estimated conduct parameters are even more reasonable if the value $\theta = .75$ is used, with 64 out of 66 conduct parameters being in the range $[-1, 1]$. Once again, the fact that letting $\theta = .75$ gives "better" results could be an indication that we have erred in ignoring some positive correlation between demand elasticity and distance, or it could suggest that costs per passenger-mile decline more rapidly with distance than suggested by earlier studies. For our estimates of mean conduct parameters, whether $\theta = .50$ or $\theta = .75$ makes little difference. The estimated base case mean conduct parameters for both airlines, along with the standard error and 95% confidence interval for each mean, are reported in Table 4.

Table 4 shows that the base case yields estimated mean conduct parameters that are close to the Cournot value of 0 for both airlines, and are remarkably close to each other. Application of classical hypothesis tests would strongly reject both the cartel hypothesis ($v = 1$) and the Bertrand hypothesis ($v = -1$). A natural question to ask, however, is how sensitive these results are to various modifications in the underlying demand and cost parameter assumptions embodied in the estimation of conduct parameters. Ideally, one would want to have some idea of the errors associated with the estimates of the demand elasticity and the cost parameters, and to incorporate them in the calculation of standard errors and confidence intervals for the base case. In practice, of course, such an exercise is rarely feasible. A more practical alternative is to do sensitivity analysis over the range of plausible parameters in order to check on the fragility or robustness of the basic conclusions.

We carried out such a sensitivity analysis. The central parameters are η, θ, and whether general and administrative expenses are included in costs. The values of η considered are 1.2, 1.6, and 2.0, while the values of θ are .25, .50, and .75. There are therefore nine sets of results for each of the two cost levels. Part A of Table 5 reports the nine results for American Airlines, assuming the base cost level, and Part B reports the corresponding United Airlines conduct parameters. Each cell in the table contains the estimated mean conduct parameter followed by its standard error in parentheses. A 95% confidence interval can be constructed by multiplying the critical t-value of 2.036 by the standard error and adding and subtracting the result from the mean.

Perhaps the most significant feature of both parts of Table 5 is that none of the estimated conduct parameters approach either the Bertrand or cartel values of -1 and 1. Most of the values remain generally within range (i.e., within about two standard deviations) of the Cournot value of 0.

It is implied by equation (6) that the conduct parameter is increasing in the demand elasticity. If the demand elasticity were higher than we thought, then a given price-cost margin would be "explained" by less competitive (i.e., larger) conduct parameters. Reading down the base case column in Table 5, we see that an increase in the assumed demand elasticity of .4 induces an increase in the implied conduct parameter of about .25 to .30.

TABLE 4 **Estimated Mean Conduct Parameters: Base Case**

	American			United		
$\eta = 1.6$ $\theta = .50$	Mean	Standard Error	95% Confidence Interval	Mean	Standard Error	95% Confidence Interval
	.06	.11	(−.17, .30)	.12	.13	(−.14, .38)

TABLE 5 Part A: Sensitivity of American Conduct Parameters

	$\theta = .25$	$\theta = .50$	$\theta = .75$
$\eta = 1.2$	−.29 (.13)	−.20 (.09)	−.17 (.06)
$\eta = 1.6$	−.05 (.17)	.06 (.11)	.11 (.08)
$\eta = 2.0$	.19 (.21)	.33 (.14)	.39 (.10)

TABLE 5 Part B: Sensitivity of United Conduct Parameters

	$\theta = .25$	$\theta = .50$	$\theta = .75$
$\eta = 1.2$	−.26 (.14)	−.16 (.10)	−.11 (.06)
$\eta = 1.6$	−.02 (.19)	.12 (.13)	.18 (.08)
$\eta = 2.0$	.23 (.23)	.40 (.16)	.48 (.10)

As .4 is a fairly substantial variation in the assumed elasticity of demand, this does not seem to be an alarming degree of sensitivity. As for variation in θ, we see that the estimated conduct parameters are increasing as θ becomes larger, but that this effect is relatively modest. Table 6 shows the effects of using the low-cost values. Only the American Airlines results are reported. (The United Airline results are very similar.) The low-cost case implies a cost level about 5% below the base costs.

Comparing Table 6 with Part A of Table 5 illustrates the sensitivity of estimated conduct parameters to the level of costs. Given the base case elasticities, a reduction in costs of about 5% causes the American Airlines conduct parameter to rise from .06 to .20. While the Cournot solution is within a 95% confidence interval for both estimates, it is clear that a major error in costs could undermine the results substantially. Given concerns over the appropriate conceptual definition of marginal cost for this industry, the sensitivity of results to the level of costs is probably of more concern than sensitivity to η or θ. Our cost data are based on average operating costs per passenger. Presumably, marginal cost would not be expected to exceed average operating cost for this industry, suggesting that alternative measures of marginal cost would imply less competitive (more collusive) behavior than reported here.

Perhaps the final observation to make concerning this sensitivity analysis is to take note of the "extreme bounds." The highest estimated conduct parameter is .55, with a standard error of .11, while the lowest is −.29, with a standard error of .13. Even these extreme bounds would strongly reject the Bertrand and cartel outcomes.

As a "reality check" on our results, one might compare our implied profit levels with actual reported profit levels. The operating profit rate for firm i on a given route can be defined as $R^i = (p^i - aoc^i)x^i/p^ix^i$, where aoc represents average operating cost. If marginal cost equals average operating cost, then, using equation (5), we obtain $R^i = s^i(v^i + 1)/\eta$. If $\eta = 1.6$, this implies a profit rate of roughly 30% for a symmetric Cournot duopoly. Actual reported operating profit rates for American and United (over the U.S. market as a whole) are much less than this. For 1985 as a whole, American reported an operating profit of about 9%, while United reported a small operating loss. There is no necessary inconsistency

TABLE 6 Sensitivity of American Airlines Conduct Parameters: Low Costs

	$\theta = .25$	$\theta = .50$	$\theta = .75$
$\eta = 1.2$	−.18 (.12)	−.10 (.09)	−.07 (.06)
$\eta = 1.6$	.10 (.16)	.20 (.11)	.24 (.09)
$\eta = 2.0$	.37 (.21)	.50 (.14)	.55 (.11)

in this profit comparison, as our sample is only a small subset of total traffic for these two airlines, accounting for about 5% of total quarterly revenue. Our routes do appear to earn relatively high returns in the raw data, with revenues per passenger-mile (for the third quarter of 1985) of over 16 cents for each airline, compared with an overall 1985 average operating revenue per passenger-mile of abut 13.5 cents for American and just under 12 cents for United. This explains nearly the entire profit differential. It is also consistent with the 1987 data presented by Borenstein (1989a), which shows that United earned much higher yields on its Chicago routes than on its non-Chicago routes.

There are several good reasons why our sample might be more profitable than the average. First, our sample consists of duopoly routes and is therefore less competitive than the overall market average. Second, American and United are established firms in a stable long-run rivalry, and might therefore compete less vigorously with each other than a more recent entrant would. In addition, various factors relating to the importance of Chicago as a hub might be relevant. Finally, the implied profit rate is quite sensitive to various parameter estimates. (For example, a demand elasticity of 2.0 combined with a conduct parameter of −0.2 and three firms per route would yield an implied profit rate of 13%.) On the whole, while one should be alert to the possibility of data problems, especially involving the measurement of both profit and marginal cost, our findings do seem consistent with a plausible interpretation of profit comparisons.

7. Bayesian analysis of market conduct

■ The effect of statistical research in economics is not that investigators or readers will simply reject or fail to reject a particular model or parameter value on the basis of a new study. Rather, most readers will (slowly) update their priors in response to new information. In this section we undertake some illustrative Bayesian calculations designed to indicate how alternative prior beliefs might reasonably be influenced by the current data set. This should indicate the kind of prior one would need to seriously distrust the Cournot model.[4] The assumptions underlying this analysis are as follows.

(1) The population of conduct parameters is Normal with unknown mean μ and variance σ^2.

(2) Prior beliefs can be represented by the Normal-Gamma "natural conjugate" joint distribution of the mean conduct parameter and its precision. (The precision is the reciprocal of the variance.) Thus the prior marginal distribution of the precision is Gamma with parameters A^i and B^i, (where i represents the airline in question) and the prior conditional distribution of the mean conduct parameter is Normal with expected value v^{i0}.

(3) A natural interpretation of parameters A and B is that our prior beliefs are based on a prior sample with 2A observations in which the sum of squared deviations of the observations about the sample mean is 2B. We assume that the prior belief and the current data set are given "equal weight" in the formation of a posterior. This case is constructed by letting A equal half the current sample size and letting B equal half the sum of squared deviations of the current sample.

Under these conditions, the posterior marginal distribution of the mean conduct parameter is a generalized t-distribution whose expected value and variance can be easily calculated. (See Hey (1983) or Zellner (1971).) The results are reported in Table 7. One should not take these calculations too seriously for, as is typical of Bayesian calculations, they depend on precise but arbitrary assumptions about prior beliefs. (If we assume prior ignorance by setting A and B equal to zero, we simply get the estimates described in

[4] This approach is very similar in spirit to a study by Leamer (1986) on the question of whether inflation data could reasonably cause "Monetarists" and "Keynesians" to converge significantly in their posterior beliefs.

TABLE 7 **Bayesian Posteriors for American Airlines and United Airlines Conduct Parameters: Base Case**

	American		United	
Prior	Mean	95% Confidence Interval	Mean	95% Confidence Interval
Bertrand	−.47	(−.71, −.22)	−.44	(−.70, −.18)
Cournot	.03	(−.13, .19)	.06	(−.12, .24)
Cartel	.53	(.30, .76)	.56	(.32, .79)

Table 4.) They also depend on prior values of η and θ about which we might have considerable uncertainty. Nevertheless, one can sensibly say that a prior "believer" in the Cournot model would be comforted by our results. One needs fairly strong non-Cournot priors to seriously distrust the Cournot model for our data set.

8. Concluding remarks

■ Our main objectives in writing this article are to contribute to the understanding of the airline industry and to add to the store of empirical knowledge concerning general principles of oligopoly behavior. In our sample of United Airlines and American Airlines duopoly routes, we found strong evidence against the cartel hypothesis and against the highly competitive Bertrand hypothesis. Cournot behavior falls within what we take to be the plausible range for this set of markets, taking into account the various errors and approximations that underlie our reasoning.

We would generally expect different industries to behave differently: a Cournot approximation might be a useful approximation for one industry, while the Bertrand model might better describe another. The results obtained in this article are somewhat closer to the Cournot model than most attempts to estimate conduct parameters in other industries.

For the Bertrand model to be supported in the case of homogeneous or near-homogeneous products, prices have to be at or close to marginal costs. The main reason for the poor performance of the Bertrand model here is simply that revenues on these routes more than covered operating costs, and average operating cost was taken as our proxy for marginal cost. If marginal cost were taken to be something less than average operating costs, then the Bertrand model would be even more strongly rejected. As for the cartel model, markups of price over average cost were simply not large enough in 1985 to be consistent with cartel behavior on these routes, unless marginal cost was substantially less than average operating cost. Both the Bertrand and cartel models might be regarded by many economists as behavioral extremes that we would not observe very often in actual data, so our rejection of these models would not be surprising. The relatively strong performance of the Cournot model is perhaps more noteworthy.

We have used both classical and Bayesian inference. As is almost always the case in applied econometrics, however, our actual data generation process is at best a crude approximation to the pure repeated sampling process that underlies classical statistics, and the difficulty of determining plausible priors makes the Bayesian exercise more illustrative than definitive. Our analysis is probably best viewed as exploratory data analysis in combination with what Leamer (1978) refers to as a "Sherlock Holmes inference." Specifically, we are using data heuristically in an effort to construct a plausible interpretation of the data, trying, where possible, to be clear about the role of explicit and implicit prior information in our analysis. Claiming more than this would probably be overstating the case.

It could be argued that we have ignored some important determinants of market conduct. In particular, several studies (including Berry (1989) and Borenstein (1989a and

1989b)) discuss the role of "airport presence" as an influence on a carrier's ability to obtain high price-cost margins on a particular route. (Airport presence refers to an airline's share, or possibly total volume, of flights at a particular airport.) Thus a route joining two major hubs might have a lower marginal cost and a higher demand than an otherwise identical route joining a hub and nonhub. The lower cost effect, as described in the section on costs, implies that our calculated costs might be too high for connecting cities where a carrier has a high presence (and too low for other routes). This will affect route-specific conduct parameter estimates, but provided that our sample is reasonably representative of routes for both airlines, then the average conduct parameter estimates should not be affected.

On the demand side, airport presence effects introduce an element of product differentiation into the analysis. An airline with "high presence" at the two airports at each end of a route might be thought to offer a slightly different and more attractive product than an airline with "low presence" operating the same route. This would presumably lead to both higher fares and higher volumes for the high-presence carrier. The possibility of such differentiation does not greatly affect the calculation of conduct parameters, although some additional information about the structure of demand would have to be assumed, possibly leading to increased specification error.

Treating the product offered by American Airlines and United Airlines as homogeneous is certainly an approximation. However, because our data set is reasonably symmetric with respect to American and United, we believe this approximation is not unreasonable. A possible line of further inquiry would be to incorporate various sources of product differentiation, including airport presence effects, load factors, aircraft type, reliability, etc. into the analysis of airline conduct.

Another approximation in the analysis is that we abstract from intracarrier product differentiation. Strictly speaking, the airlines face a multiproduct duopoly problem, in which fairly complex theoretical issues arise. In effect, firms would take into account the effect of a change in quantity (or price) for one fare class on the competitive situation in other fare classes.[5] A complete method for dealing with the multiproduct problem, assuming profit maximization, is to write down the profit function inclusive of all products and solve the firm's maximization problem. It is still possible to solve for the conduct parameter for a particular product. This solution for the conduct parameter will have an algebraic form including the terms given by equation (6), but in addition there will be other terms involving cross-elasticities of demand across fare classes and cross-route "conjectural variations" of ambiguous sign. If these terms impart no systematic bias to conduct parameter v (i.e., if they have mean zero), then our estimates of v are unaffected. Alternatively, if the cross-elasticities of demand are small, then any bias will be small.

We repeated the analysis using just "discount" passengers, and found very similar results to those reported in Section 6. The base case conduct parameter estimates were even closer to the Cournot value of 0. Specifically (assuming an elasticity of 1.7), the estimated conduct parameters were .04 and .08 for American and United respectively (rather than .06 and .12).

One natural reaction to our analysis is to argue that to understand the performance of the airline (or any other) industry it is necessary to explicitly consider the repeated game aspect of firm interaction. (Interesting examples of empirical attempts to examine the temporal structure of industry conduct include Bresnahan (1987) and Porter (1983).) We would agree that looking at the time series behavior of the conduct parameter would be very interesting and could be used to draw inferences about dynamic interaction in duopoly, possibly shedding light on the empirical value of the large array of solution concepts that

[5] In fact, even the large airline firms (which are technically sophisticated by general commercial standards) do not understand very well how to optimize quantities across fare classes. As described in Kraft, Oum, and Tretheway (1986), the major airlines use a formal but essentially heuristic method of seat allocation across fare classes known as "airline seat management" rather than calculate solutions to explicit maximization problems.

have recently been suggested for sequential games. Casual empiricism suggests that airlines sometimes engage in "cutthroat" competition, perhaps resembling the Bertrand outcome, sometimes succeed in establishing very high price cost margins, and sometimes engage in what might be called normal competitive conduct. The third quarter of 1985 seems to be a case of the last of these possibilities. We see analysis of the dynamic pattern of (imperfectly) competitive pricing as a natural extension of the analysis presented here, although beyond the scope of the present article.

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