Dynamic Analysis of Oligopolistic Behavior in the U.S. Airline Industry

LEOLA B. ROSS

The recent history of the airline industry has exhibited relentless price wars of national proportion begun by failing airlines desperate to fill their planes. However, price reductions and sporadic discounting are often observed intermittently on scattered routes from time to time. If substantial discounts are offered, these episodes may also be classified as less publicized (or covert) price wars. An arbitrary rule is described that classifies the most traveled routes between the second quarter of 1990 and the third quarter of 1992 as experiencing or not experiencing a price war on the basis of distribution of prices. The classification scheme is helpful in characterizing market behavior during price wars and normal periods. The causes and effects of price wars are assessed, and special attention is given to the relationship between price wars and concentration. The analyses are conducted in the context of an economic theory that depicts price wars as a normal reaction to changing market conditions when a specific type of equilibrium characterizes an industry. The most profound result is that price wars do not increase market concentration as successfully as more cautious price reductions taken during normal periods.

The recent history of domestic airlines has been marked by mergers, takeovers, failed airlines, volatile ticket prices, and price wars. Whereas the airline industry is among the most studied in the past decade, domestic airline price wars have not been the central focus of economic research. Examination of these price wars during the early 1990s is timely and significant with regard to both the economic literature and the political arena.

Past economic studies focused largely on static models aimed at describing airline industry behavior at a point in time. For example, Borenstein (*1*) links airport dominance and route concentration to high fares and argues that increased concentration of this nature should lead to even higher fares. The General Accounting Office (*2*) published a similar, more detailed static model seeking to capture the effects of certain barriers to entry, market share, and congestion on airfares. It found that a single variable does not a have a large effect on prices but that in combination the factors studied can significantly increase airfares. That study enjoyed the contribution of a tremendous amount of data, which enriched the explanatory power of the results substantially. A recent study, which was more parsimonious in its use of data, was done by Evans and Kessides (*3*). They found evidence that airport concentration was a strong determinant of fares on a given route. They further concluded that for the quarter they studied route dominance was relatively unimportant in explaining higher prices. The contrasting results of these studies affirm the need for a dynamically based model to explain pricing behavior. In a later section of the paper, reference is made to a Chow test of structural change across time periods. This test confirms that pricing behavior has not been the same across time, which suggests a possible explanation for differing results in previous papers.

Department of Economics, Southern Methodist University, Dallas, Tex. 75275-0496.

Economic studies focusing on the evolving nature of the airline industry are less numerous than single-period studies. Morrison and Winston (*4*) study entry and exit patterns as affected by hubbing and route fares. They find that airlines tend to shy away from airports where other airlines have hubs because of limited gates. They, like Evans and Kessides, find a strong correlation between airport concentration and high prices. However, they predict that hubbing should eventually decrease fares, since hubs allow increased airline connectedness and contact with competitors so that airlines should be able to compete with each other more effectively. Kim and Singal (*5*) examined the dynamic nature of prices during the merger wave of the mid-1980s. They identify the price changes on routes affected by specific mergers, compare them with price changes on routes unaffected by those mergers, and find that the elimination of the noncooperative failing airline allows the remaining airlines to collude more successfully. Furthermore, they suggest that multimarket contact helps airlines maintain a less-than-competitive arrangement and that the competition observed shortly after deregulation is less likely under the evolving market structure. However, since 1988, the airlines seem to have entered a new era of short-term price wars and collusive periods, in contrast to the predictions of Kim and Singal. Why has the stability they predicted broken down? Or does this recent trend actually reflect a different kind of equilibrium that has until now not been considered?

The model described here will show that pricing behavior varies not only over time but over routes. The causes and effects of price wars are modeled and evaluated to demonstrate that the airlines reflect both competitive and collusive behavior at various times and on various routes. It is shown that, regardless of hub and route dominance, lagging demand can trigger destructive competition and that certain types of routes will be more prone to price wars than others. Furthermore, there are clear winners and losers from price wars, and the toughest battles are fought on the routes with the most at stake.

PRICE WAR EQUILIBRIUM

A growing theoretical literature has been devoted to explaining the dynamic nature of imperfect markets. It has been recognized since Stigler (*6*) that the static models of collusive cartel, Cournot-Nash equilibrium, or Bertrand competition do not sufficiently explain the behavior of firms existing in such markets. Whereas we know that a cartel is an unstable arrangement at best, empirically we observe that highly concentrated industries are likely to behave like any one of these classic models (including cartel) at some time. In the past decade, game theorists have developed dynamic models to portray more realistically the actions of oligopolists

who learn from the past and plan for an uncertain future. The Green and Porter model (*7*) is particularly applicable to recent airline behavior, since it describes an oligopoly that goes through periods of sustained collusion and intense competition. They describe a "Nash equilibrium" (the most profitable choice for a firm, given the most likely reactions of its competitors) of strategies that determine a firm's behavior over an infinite time horizon. In their model each firm will price at a normal (or collusive) level unless sales drop too low. If this happens, the firms will assume that some other firm is cheating (or discounting too much) and will respond by dropping prices to punish the cheating firm for some time. Thus, the dynamics of the industry will be characterized by firms bouncing back and forth between normal behavior and price wars. Green and Porter point out that a drop in sales need not be the result of a cheating party; it could be caused by a drop in consumer demand or some other factor. Thus, the price wars recently exhibited by the airlines could be based on the pricing practices of various airlines (perhaps, for example, the value pricing scheme of American Airlines) or simply a shrinking consumer demand for travel.

The primary difference between the Green and Porter model and the structure of the airline industry is the multimarket nature of the airlines. Recall that Kim and Singal suggested that such multimarket contact should allow the airlines to maintain collusive behavior without the threat of excessive competition, whereas Morrison and Winston indicated that this multimarket countact should, in fact, increase the competitiveness of the airlines. Adding multimarket contact to the Green and Porter model complicates matters somewhat. If an airline lowers prices on one route, what is to prevent the other airlines from abandoning that route altogether and lowering prices on some other route where it has a comparative advantage? Such behavior would lead to market segmentation, and then both firms would emerge as monopolists (or at least dominant carriers) in their respective markets. Casual empiricism suggests that this does not frequently occur, or does it? Southwest Airlines has successfully carved a niche by forcing other carriers to lower prices substantially or drastically reduce service on Southwest's routes. Whereas it is not clear that every airline could be a Southwest, it is curious that more have not tried to copy the success of their most profitable adversary.

A rigorous examination of the Green and Porter model, extended to multiple markets, reveals that though each airline could be more profitable as a monopolist, the lure of invading other routes may be too strong for a segregated market to be sustained. This is true if the markets still show some evidence of contestability in this industry and the only defense against an invasion by a competitor is limit pricing. Therefore, once a price war erupts, a spillover into another market only serves to extend the price war rather than to segregate the market or drive out competitors. The resulting equilibrium (not unlike the one described above) is a sequence of normal prices occasionally interrupted by an industrywide price war.

Since this theory predicts that price wars are not likely to disappear, where they are likely to occur and how they affect market structure are important issues in developing public policy or assessing market performance.

FREQUENCY ANALYSIS

The previously described theoretical model does not indicate whether price wars should lead to increased or decreased market concentration. It might seem counterintuitive that a price war would leave a market in the same condition in which it began. If no airline gains customers at the expense of a competitor, then one might question the rationality of starting a price war. To motivate the empirical model and to make explicit the effects of a price war on market concentration, consider a simple comparison of changes in concentration in price wars and in "normal" periods.

To analyze the frequency of anything concerning price wars, one must first define a price war. A price war may be characterized by public announcements by the airlines and newspaper headlines, or they may be more obscure. In fact, a price war may occur on only one or two routes for several time periods or half of the domestic routes for a single time period. With this in mind, the nature of the distribution of prices for a particular route should be analyzed to confirm or deny that a price war is occurring. Unfortunately, to ask this of the data, a "rule" must be imposed as to the inclusion or exclusion of a particular route at a particular time, and this rule will be unavoidably arbitrary. The rule chosen is as follows:

1. Calculate, by route and date, the maximum price charged and divide by 5 to determine the percentage of tickets sold below 20 percent of the maximum price.
2. Compare this percentage in each period with the percentage in the previous period to determine the percent change in the percentage.
3. Conclude that a price war is in effect if the percent change is more than 25 percent.
4. Conclude that the price war is still in effect if there was a price war last period and the percent change this period does not "substantially" change (does not decrease any more than 10 percent).
5. Call the period "normal" if a price war is not in effect by the preceding two steps.

To measure route concentration, the Theil coefficient (an entropy-based measure), $TC = \Sigma_a s_a \ln s_a$, is calculated for each route at each time period in the sample (where the market share of Airline a on a route is s_a). TCs were calculated with all the data for the 100 most traveled airports. The measure more commonly used for industry case studies is the Herfindahl index, $HI = \Sigma_a s_a^2$, since it is more widely known and understood. Both of these indices possess some properties relating them to economic theory. For example, HI may be linked to a firm's ability to price above marginal cost in a particular setting, and TC may be used to draw some conclusions about the detachment of upper management from the actual production process [a more detailed description of these properties is given by Hannah and Kay (*8*, p. 27)]. However, both of these relationships are shaky at best, and neither lends itself to a reduced form regression. From a practical perspective, the difference between the two measures is that HI places most of its weight on the largest firm share on the route or airport or industry in question, whereas TC places its emphasis on the dispersion of the firm's respective shares. [For a description of these properties see Theil (*9*).]

TC is distinguished from an arbitrary index such as the Herfindahl by virtue of its origins in statistics and information theory [for a discussion of these origins see Slottje (*10*, pp. 63–66)]. The entropy class of indices measures the deviation of a particular

distribution (in this case the distribution of firm shares) from a hypothesized null distribution (in the case of concentration the implied null is a symmetric market). If market shares are insignificantly different from the null distribution, TC will be distributed χ^2 with number of firms less two degrees of freedom (*11*). Hence, divergence of a TC from its null is governed by a well-known distribution, so that statistical inference is possible and its usefulness is maximized. Further, Hayes and Ross (*12*) show that these properties may also be used to construct a directed divergence statistic for conducting inference test of the similarities of concentration among routes and time periods.

The calculated frequency of increased concentration during price wars and normal periods is given in Table 1. In the first column, restrictions are placed on the percent increase in concentration. We begin by considering the event of any increase at all during and after price wars and find that an increase occurs in or out of a price war with almost equal probability. As we tighten our definition (requiring from a 5 to a 50 percent increase in concentration), it is clear that the occurrence of a price war does not increase the probability of large changes in concentration either but exhibits a consistent difference. Clearly, this analysis is based on our arbitrary price war rule, and we have no confidence intervals to substantiate these conclusions. However, the similarities in percentages between price wars and normal periods appear to be robust to the percent increase in concentration. These similarities can be easily observed in Figures 1 and 2.

DATA

The data used for the construction of this frequency analysis and the model to follow have been extracted from two data banks maintained by the Department of Transportation—the *Origin and Destination Survey* (Data Bank 1A or DB1A) and the *T100 Do-*

TABLE 1 Frequency Analysis of Price Wars and Increases in Concentration by Route

	Frequency of Increased Concentration (this periods behavior)		Frequency of Increased Concentration (last periods behavior)	
% Increase in Concentration	During Price War (%)[a]	Normal Period (%)[b]	After Price War (%)[a]	Normal Period (%)[b]
0	3039	3724	2336	4427
	(53.86)	(47.48)	(49.97)	(50.25)
5	2159	2555	1611	3103
	(38.27)	(32.57)	(34.46)	(35.22)
10	1610	1812	1193	2229
	(28.54)	(23.10)	(25.52)	(25.30)
15	1217	1361	894	1684
	(21.57)	(17.35)	(19.12)	(19.11)
22	992	1080	714	1358
	(17.58)	(13.77)	(15.27)	(15.41)
25	817	887	583	1121
	(14.48)	(11.31)	(12.47)	(12.72)
50	382	404	234	552
	(6.77)	(5.15)	(5.01)	(6.27)

[a] Percent based on routes exhibiting a price war.
[b] Percent based on routes not exhibiting a price war.

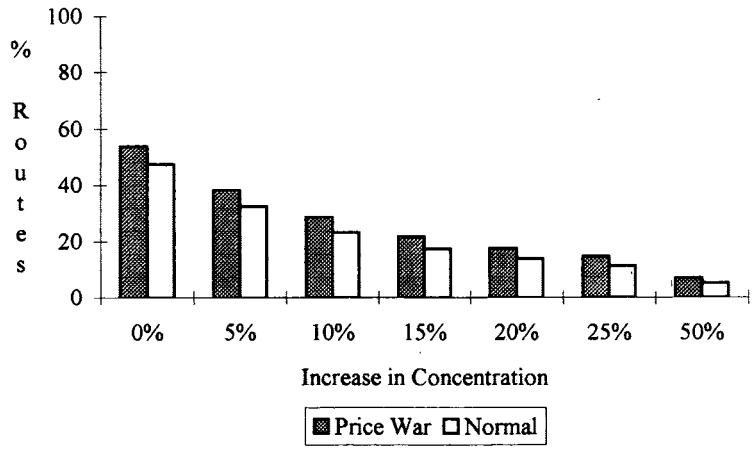

FIGURE 1 Frequency of increased concentration during a price war.

mestic Segment Data (Data Bank 28DS or T100). These data banks are available from the Volpe National Transportation Systems Center in Cambridge, Massachusetts, or from the National Archives in Washington, D.C., for older data. The DB1A is a random 10 percent survey of all tickets issued for flights within the United States and is published on a quarterly basis. The T100 contains data reported by U.S. carriers operating nonstop service within the United States and is published monthly. The following types of tickets are removed from the sample:

1. Any ticket with one or more segments of first-class travel,
2. Any tickets that are not either one-way or round-trip,
3. Any tickets with more than one change of plane per direction of travel,
4. Tickets with any origin or destination outside the United States,
5. Interline tickets (tickets where services are provided by more than one carrier), and
6. Any tickets that were less than $10 or more than $750 each way (or $20 and $1,500 round-trip, respectively) (these are assumed to be frequent flier tickets, chartered flights, or input errors).

There are 1,226 routes selected from these two data sets to use for these analyses. These are the only routes that are present in both data sets for all the time periods among the top 100 airports in the United States and represent roughly 30 percent of all tickets in the DB1A. The use of the T100 somewhat restricts the choice set of routes since it is a segment-based data source. For an observation to occur on T100 there must be a nonstop flight between the endpoints. The use of the hub-and-spoke system by most major carriers has reduced the number of airports having nonstop flights between them. Thus, to ensure a balanced panel of routes, the data set is reduced. Conversely, the DB1A has observations on almost any combination of segments imaginable between various endpoints. If the statistical tests were restricted to variables extracted from DB1A, the number of routes in the sample would be considerably larger. However, information such as number of flights scheduled and load factor is only available from the T100. These variables enlarge the set of independent variables and should not be ignored when analyzing pricing behavior. However, inconsistencies in the interpretation of the variables extracted from these data sets may arise, given their differences.

The most recent 11 quarters of data were used for the analysis (1990:1 through 1992:3). The price equation below was estimated by route pair and time. (A route pair is listed in alphabetical order such that, for example, flight DFW-LGA is the same as LGA-DFW and is called DFWLGA. This is common in the literature and is necessary to prevent duplication of observations in light of the high percentage of round-trip tickets purchased.)

EMPIRICAL MODEL

The frequency analysis gave insight into the effects of price wars on some minimum change in concentration. To more thoroughly examine the influence of route characteristics on market behavior, a system of equations describing changes in the bottom quintile of prices, changes in concentration, and the absolute price level is defined. All three of these may be determined by the characteristics of the route and market. Price levels are defined by a reduced form of demand and supply conditions. Price changes are often responses to slackening demand or the behavior of competitors (both are suggested by our theory). Finally, route concentration changes may be the result of price changes, shifts in consumer demand, or the concentration of the endpoints of travel. Therefore, the following system of equations is suggested:

$$\begin{aligned} \text{PERCHANG}_{it} = {} & \beta_{10} + \beta_{11}\text{LNSCHED}_{it} + \beta_{12}\text{LNPRICE}_{it} \\ & + \beta_{13}\text{ROUTHEIL}_{it} + \beta_{14}\text{APTHEIL}_{it} \\ & + \beta_{15}\text{LFLAG}_{it} \end{aligned} \tag{1}$$

$$\begin{aligned} \text{ROUCHANG}_{it} = {} & \beta_{16} + \beta_{17}\text{PERCHANG}_{it} + \beta_{18}\text{APTHEIL}_{it} \\ & + \beta_{19}\text{LFLAG}_{it} + \beta_{21}\text{LNPASS}_{it} \\ & + \beta_{22}\text{LNSCHED}_{it} \end{aligned} \tag{2}$$

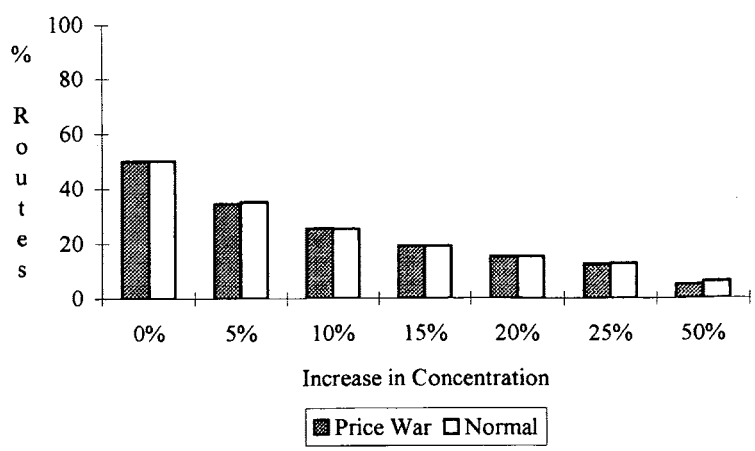

FIGURE 2 Frequency of increased concentration after a price war.

$$LNPRICE_{it} = \beta_{23} + \beta_{24}LNPASS_{it} + \beta_{25}PERSTOP_{it} + \beta_{26}PERROUND_{it} + \beta_{27}\ ROUTHEIL_{it} + \beta_{28}APTHEIL_{it} + \beta_{29}LOADF_{it} + \beta_{30}LNDIST_{i} \quad (3)$$

The endogenous variables are as follows:

- $PERCHANG_{it}$ = ($PERCENT_{it}$ − $PERCENT_{it-1}$)/$PERCENT_{it-1}$, where $PERCENT_{it}$ is the percentage of tickets sold at 20 percent or less than the maximum price, is a measure of price volatility and is expected to increase ROUCHANG in price wars and normal periods (source DB1A).
- $ROUCHANG_{it}$ = ($ROUTHEIL_{it}$ − $ROUTHEIL_{it-1}$)/$ROUTHEIL_{it-1}$ is a measure of market structure volatility (ROUTHEIL is defined later) (source DB1A).
- $LNPRICE_{it}$ is the natural logarithm of the average price of a ticket on route i at time t. The predicted effect of this variable on PERCHANG is positive in normal periods and negative during price wars (source DB1A). (Since all variables henceforth, except LNDIST, are indexed over route and time, the subscripts will be dropped from the following descriptions.)

The exogenous variables are as follows:

- LNSCHED is the natural logarithm of the total number of nonstop flights scheduled for a route. This variable is related to the frequency of fights and thus reflects the possibility that a route may be rather competitive and, thus, exhibit more activity over time. It is expected to increase both PERCHANG and ROUCHANG during normal periods and price wars (source T100).
- ROUTHEIL is the Theil concentration index of the route traveled, $\Sigma_a\ s_a \ln s_a$, where s_a is the proportion of passengers Airline a serves on the route. This is a measure of route concentration and is expected to positively affect LNPRICE and decrease PERCHANG at all times (source DB1A).
- APTHEIL = (AP1THEIL + AP2THEIL)/2, where AP1THEIL is the Theil concentration index of the airport first listed in the route pair and AP2THEIL is the Theil concentration index of the airport listed second in the route pair, measures concentration and is expected to increase LNPRICE and ROUCHANG and decrease PERCHANG at all times (source DB1A).
- LFLAG = $LOADF_{t-1}$, where LOADF (load factor) is the percentage of available seats occupied on nonstop flights. This variable reflects both past and current demand. The lagged load factor is expected to be instrumental in stirring activity when planes are empty, thus decreasing both PERCHANG and ROUCHANG in normal periods, but it might have an opposite effect on ROUCHANG during price wars. The effect of the current load factor on LNPRICE should be negative during normal periods and price wars (source T100).
- LNPASS is the natural logarithm of the total number of passengers in the sample flying the route. This is an indicator of highly established routes thus decreasing ROUCHANG; newer, less-traveled routes are likely to be more contestable. However, since it might also imply economies of scale, it might decrease LNPRICE (source DB1A).
- PERSTOP is the percentage of passengers experiencing a change of planes. This indicates a route that is starting or ending at a nonhub airport and, thus, is expected to increase costs and LNPRICE as well (source DB1A).
- PERROUND is the percentage of passengers flying round-trip on a route. A large percentage of round-trip tickets might imply more pleasure travel as opposed to business travel and a more elastic price resulting in lower LNPRICE at all times (source DB1A).
- LNDIST is the natural logarithm of the great circle distance in official statute miles between the origin and destination of airports. Greater distance is expected to increase both costs and LNPRICE for both models (source T100).

A monotonic logarithmic transformation of the variables (such as distance, total passengers, average price, and number of scheduled flights) with magnitudes out of line with the other variables is taken.

There exists explicit simultaneity in the system of equations, and therefore three-stage least squares estimation is appropriate. The time-series nature of the data is ignored in the error structure for three reasons. Since the cross section (1226) is far greater than the time series (10 after lagging some variables), it is likely that the pooled sample closely resembles a cross-sectional data set. Whereas it is possible that some autocorrelation exists in the error structure of the LNPRICE equation, as prices are expected to have some inertia, it is doubtful that this is a problem in the first two equations, since a change in concentration or a price war in this period does not imply similar behavior next period. And finally, as will be explained shortly, the data set is split into two subsets that are independent of time and route. Therefore, to draw comparisons between the entire data set and the two subsets, one regression technique must be used, and it is not possible to treat the two subsets as panel data when they are completely unbalanced. The balanced nature of the original data set, however, is essential for determining the values of lagged variables (PERCHANG, ROUCHANG, and LFLAG) and is instrumental in assessing the importance of dynamic change in the market structure.

RESULTS

The system of equations from the previous section was estimated three times. Initially, the model was estimated allowing for no variation in parameters across routes or periods. This is referred to as the combined model. Next, the data set was segregated by time period so that a general test for time-invariant behavior could be conducted. It is clear that this is not the case. Therefore, the conflicting results of previous studies, which where discussed earlier, may be partially explained by differences in the time periods used by the authors. Since this model was only estimated to demonstrate this point and is not the focus of this research, the parameter estimates are not reported. However, the by-equation Chow test results are reported in Table 2. (This test for structural change is done by-equation since there is no Chow test defined for a system of equations. The residuals used for these tests are from the two-stage least squares step of the three-stage least squares procedure.)

In the final estimation the pooled data set was separated into two categories: price war and normal. This separation disregards the panel nature of the data set since each route/period observation is categorized by the price war rule described in an earlier section of this paper. The regression results for these two models are reported with the combined model in Table 3. Again, a Chow test was conducted confirming that separating the data in this way

TABLE 2 Results of Chow Tests of Structural Change

	H_0: Time Invariant Structure	H_0: Price War Invariant Structure
	F-Statistic (DF-num, DR-den, Critial Value)	F-Statistic (DF-num, DR-den, Critial Value)
Equation (1)	4.48	119
	(54, 12200, 1.32)	(6, 12248, 2.10)
Equation (2)	6.65	4.64
	(54, 12200, 1.32)	(6, 12248, 2.10)
Equation (3)	43.38	52.88
	(72, 12180 ,1.22)	(8, 12244, 1.94)

significantly improves the fit of the model. The *F*-statistics are also reported in Table 2. Since it is shown that the combined model is incorrect, a discussion of the results is unnecessary. They are reported so that one can observe how a model ignoring the effects of price wars can give results contrary to the segregated models.

The results of the normal period and price war models are often conflicting and for some variables are counterintuitive. First, consider the PERCHANG equation. LNSCHED leads to increases in price volatility during normal periods, thus indicating a push toward price wars. However, during a price war LNSCHED takes the opposite sign, indicating that price wars on frequently departing flights may be less severe. ROUTHEIL and APTHEIL are associated with decreasing PERCHANG in normal periods, indicating an ability to sustain prices more effectively when concentration is higher. Conversely, the positive coefficients during price wars indicate that if a price war breaks out it will be more severe. Perhaps this is an indication that these routes are contestable; this

TABLE 3 Three-Stage Least Squares Estimation Results

	Expected (PW,N)	During a Price War	Normal Period	Combined Model
(1) PERCHANG				
INTERCEPT		40.99[b]	0.85[b]	16.94
LNSCHED		-0.30[a]	0.02[b]	-0.21[b]
LNPRICE		-4.26[a]	-0.33[b]	-1.47[b]
ROUTHEIL		0.77	-0.11[b]	0.48[a]
APTHEIL		6.71[b]	-0.14[b]	3.07[b]
LFLAG		-4.89[b]	0.08[b]	-2.27[b]
(2) ROUCHANG				
INTERCEPT		2.36[b]	1.43[b]	0.29
PERCHANG		-0.06[b]	0.51[a]	0.09[b]
APTHEIL		0.39[a]	0.27[b]	-0.22
LFLAG		-0.35	0.17	0.39[a]
LNPASS		-0.23[b]	-0.13[b]	-0.17[b]
LNSCHED		0.04	0.002	0.04[b]
(3) LNPRICE				
INTERCEPT		4.68[b]	4.63[b]	4.62[b]
LNPASS		-0.05[b]	-0.11[b]	-0.09[b]
PERSTOP		0.11[b]	0.03[b]	0.19[b]
PERROUND		0.07[a]	0.44[b]	0.32[b]
ROUTHEIL		-0.12[b]	-0.19[b]	-0.16[b]
APTHEIL		0.11[b]	0.19[b]	0.17[b]
LOADF		-0.16[b]	-0.61[b]	-0.43[b]
LNDIST		0.13[b]	0.20[b]	0.18[b]
Cross Model Correlation				
(1) & (2)		0.245	-0.098	-0.343
(1) & (3)		-0.014	0.233	-0.233
(2) & (3)		-0.050	-0.019	-0.019

[a]Significant at the 5% level.
[b]Significant at the 1% level.

is consistent with the theory described above. The positive coefficient on LFLAG is counterintuitive because it suggests that fuller planes exhibit more discounted fares during normal periods. However, we intuitively observe that empty planes increase the severity of a price war should it erupt. Again, this is consistent with the theory in the second section. LNSCHED and LFLAG exhibit similar effects on ROUCHANG.

The negative coefficient on PERCHANG in the ROUCHANG equation is curious. This seems to indicate that price wars slightly increased market shares for smaller airlines at the expense of the larger airline, creating a more symmetric market. The positive coefficient during normal periods suggests that covertly discounting some fares without starting a price war gives more market share to the larger airlines. Put simply, price wars do not increase market concentration. This is consistent with the simple frequency analysis described earlier, but the relationship is not revealed so explicitly. These results suggest that if a relatively small airline tries to increase its market share by starting a price war, it may have some minimal success, and these price wars may be a useful market mechanism for keeping the dominant carriers in check.

The most surprising results, from an economic perspective, are in the LNPRICE equation. For example, PERROUND was expected to decrease prices because of pleasure travel. However, we show that an increase is actually the case. Perhaps one-way tickets are dominated by lower-priced commuter flights (consider the New York, Boston, Washington shuttles as an example). Further, the negative impact of ROUTHEIL on prices seems unusual. Is it possible that this is an indication of limit pricing on highly concentrated routes? This explanation is consistent with the theory given earlier.

As a whole, the results of this regression are informative. Factors that reduce discounting in normal periods imply increased intensity when price wars occur. Similarly, factors that increase discounting in normal periods imply less intense price wars. It is also apparent that small, covert reductions in price during normal periods will increase route shares for the larger airlines better than rapid changes that set off price wars, whereas smaller carriers can gain some market share during price wars.

CONCLUSIONS

The use of a system of simultaneous equations is particularly instructive in evaluating the causes and effects of volatile prices in the airline industry. We have confirmed that what pushes a route into a price war, such as frequently departing flights that fill up quickly, may also act to reduce the severity of a price war. Characteristics that reduce normal-period price discounting, such as dominance of routes and at airports, may intensify a price war. Most significant, the advantages of covert price reductions by larger airlines are affirmed by the changing sign of PERCHANG when regressed on ROUCHANG. This demonstrates that the incentive to cheat in normal periods is very strong for small airlines seeking to improve their market share.

Many aspects of economic theory have been affirmed, indicating that perhaps the airlines are, in fact, in an equilibrium that is characterized by both collusive and competitive behavior. The suggestion that the multimarket contact can successfully reduce competition is as correct as the alternative. In this sense, past research that focused on dynamic change in the airlines is certainly superior to static reduced-form models that ignore the importance of change in this industry. However, one must appeal to economic theory to successfully interpret empirical results. The results of this research indicate that price wars are likely to occur for some time and that market concentration may go up or down on the basis of the frequency of these price wars and the ability of the airlines to stay in the game. Since this industry is so sensitive to demand conditions, price wars may become less common if consumer demand becomes stronger. If demand improves, the traveling population will look forward to higher fares and a less competitive market.

ACKNOWLEDGMENTS

The author expresses gratitude to FAA for its sponsorship of the Graduate Research Awards Program and to Southern Methodist University for its support. The author is indebted to Herman Beriens, Joseph Hirshberg, Esfandier Maasoumi, Daniel Slottje, and especially Kathy Hayes of Southern Methodist University and to John Fischer, Larry Jenney, and Francis Mulvey of the Transportation Research Board for many helpful comments and suggestions. Any errors are the responsibility of the author.

REFERENCES

1. Borenstein, S. Hubs and High Fares: Dominance and Market Power in the U.S. Airline Industry. *RAND Journal of Economics*, Vol. 20, No. 3, Autumn 1989.
2. *Airline Competition: Effects of Airline Market Concentration and Barriers to Entry on Airfares.* GAO/RECD-91-101. General Accounting Office, April 1991.
3. Evans, W. N., and I. N. Kessides. Localized Market Power in the U.S. Airline Industry. *Review of Economics and Statistics*, Vol. 75, No. 1, Feb. 1993.
4. Morrison, S. A., and C. Winston. Dynamics of Airline Pricing and Competition. *American Economic Review*, Vol. 80, No. 2, May 1990.
5. Kim, E. H., and V. Singal. Mergers and Market Power: Evidence From the Airline Industry. *American Economic Review*, Vol. 83, No. 3, June 1993.
6. Stigler, G. J. A Theory of Oligopoly. *Journal of the Political Economy*, Vol. 72, No. 1, 1964.
7. Green, E. J., and R. H. Porter. Noncooperative Collusion Under Imperfect Price Information. *Econometrica*, Vol. 52, No. 1, Jan. 1984.
8. Hannah, L., and J. A. Kay. *Concentration in Modern Industry: Theory, Measurement and the U.K. Experience.* The Macmillan Press Ltd., London, 1977.
9. Theil, H. The Development of International Inequality. *Journal of Econometrics*, Vol. 42, No. 1, Sept. 1989.
10. Slottje, D. J. *The Structure of Earnings and the Measurement of Income Inequality in the U.S.* Elsevier Science Publishers, Amsterdam, Netherlands, 1989.
11. Read, T. R. C., and N. A. C. Cressie. *Goodness-of-Fit Statistics for Discrete Multivariate Data.* Springer-Verlag, New York, 1988.
12. Hayes, K. J., and L. B. Ross. The Decomposition and Recomposition of the Theil Coefficient: An Application to Airline Industry Structure. Working Paper 9307. Southern Methodist University, Dallas, Tex.