# Airline price wars with multi-market carrier contacts and low-cost carrier entrants

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**Abstract**

Recent studies of airline price wars have raised interesting questions about the measurement of this phenomenon (Busse, 2002; Ross, 1997). We apply the rank dominance criterion for airlines in more than a thousand major route markets from 1996-1999 and find that the method appears to over-predict the frequency of fare wars. Progress in understanding causes and consequences depend on meaningful diagnosis of when and where fare wars are actually occurring (Morrison and Winston, 1996). Adopting higher thresholds for price war events, we proceed to explore the impact of multi-market contacts and other market structure variables. We adapt an index of assortativity, described by Newman (2002) in another context, of carrier route systems in each route that measures the extent of common routes ties among all local carriers. The index proves highly significant in explaining the probability of fare war occurrences in the data and seems to outperform other multi-market indicies that have been suggested.

## Section 1. Introduction

Price wars in airlines have been extensively examined in the literature. For recent examples, see Busse, 2002 and Ross, 1997. The phenomenon was once thought to be so pervasive as to make competition unworkable for this industry, requiring an extensive system of regulation (For a critical view, Keeler, 1978). Later, opponents of deregulation argued that price competition among major carriers would lead to so many bankruptcies that the industry would be perennially sick. Even years after deregulation, the pricing dynamics in the industry was described by some economists as a contributing factor in the wave of bankruptcies and financial distress observed among major carriers. (Morrison and Winston, 1996).

Prospects are good for tacit collusion in concentrated markets typical of many airline routes. But airlines face market conditions that can cause breakdowns in coordination and lead to price wars. In particular, airlines face high fixed costs and are often stuck with excess capacity during down turns in the economy that dampen the demand for air travel. (Levenstein and Suslow; 2002) In a repeated game framework, it is possible show that economic booms can work either way to make fare wars less likely or more likely than in busts. (Busse, 2002; Rotemberg and Saloner,1986; Ellison, 1994). In addition, the heterogeneity of firms traced to cost differences among the carriers has been an important factor in price determination in recent years.

A particularly interesting feature of airline markets is the extent of multi-market contacts among major carriers. The theory of mutual forbearance would seem to be particularly promising because of the network structure of airline routes. With mutual forbearance, having many points of contact might lead to greater cartel cohesion. In contrast, Morrison and Winston (1996) describe an alternative explanation for how the extent of multi-market contact could be

positively correlated with the occurrence of price wars in airlines. That is, in periods where there is a breakdown in cartel cohesion in one or more airline routes, fare wars may more easily spill over to other markets where the same carriers compete. Thus, the empirical effect on the probability of a fare war is positive. This effect was confirmed in their study, and there is some (albeit insignificant) evidence in the study by Ross (1997).

Unsettled measurement issues plague the existing literature. Empirical methods for identifying the occurrence of fare wars and the quantification of the degree of multi-market contacts are two that demand further attention before the determinants of price wars in airlines are can be understood with confidence. Section two discusses these issues and proposes some additional refinements for empirical tests. Section three and four present our empirical analysis.

**Section 2. Some measurement issues in fare war analysis**

Previous studies have used a number of different criteria when constructing a fare war index. Morrison and Winston (1996) assume that a fare war begins when average fares on a route drop by 20 percent or more from one quarter to the next. One difficulty with using changes in the market-wide sample mean of fares is that an airline may cut fares to its elastic customers while simultaneously raising fares to its inelastic customers. The start of a fare war might result in little change in mean fares with a simultaneous increase in price dispersion. This is illustrated in Morrison and Winston (1996, pg.111, fn. 62), who find that the percentage of routes classified as subject to a fare war increases from 5 percent, to 9.7 percent, to 11.9 percent as the sample mean is constructed from all 5 quintiles, the lowest 4 quintiles, and the lowest quintile. More than twice as many fare wars are found when attention is focused on the lowest quintile of the distribution of fares. A second concern is the presence of seasonality in airline fares. Morrison

and Winston (1996, pg. 88, fn. 5) are aware of this problem. Their probit model allows for seasonal differences in the probability of a fare war, but they do not control for seasonality when constructing their fare war indicator.

Ross (1997) proposes the use of the "rank dominance" method when constructing a fare wars indicator. This method is a statistical test for differences in mean fares from the current quarter to the same quarter in the previous year. Taking annual differences in this manner controls for well-known seasonality of fares. Rather than using the sample mean of all fares on a route, the distribution of fares is divided into quintiles, and evidence of a decrease in fares is considered separately for each quintile. This method is capable of detecting a decrease in fares in the lower quintiles even when fares are increasing in the upper quintiles. Ross considers measures based on the lowest, two lowest, and three lowest quintiles. The percentage of routes classified as subject to a fare war in her sample varies from 48 to 38 percent for these three measures.[1]

Busse (2002) does an extensive search of the *Wall Street Journal* to find media reports of fare wars. She finds a much lower percentage of markets subject to fare wars.[2] The fact that this is a purely subjective method based on the opinion of airline officials and journalists does not diminish its potential validity. One explanation for the relatively high frequency of fare wars found in Ross (1997), relative to Morrison and Winston (1996) and Busse (2002), might be provided by the relatively large passenger volume found in the major markets. Large samples may provide very precise estimates of fare differences, allowing the rank dominance method to detect statistically significant fare decreases that are not economically significant.

Episodes of fare wars are problematical to identify because the severity of the fare decrease can vary continuously. Yet, in an episodic study of fare wars it is preferable not to

include instances of modest price cuts within the normal bounds of market fluctuations.

The unexpectedly high incidence reported by Ross may suggest that the rank dominance method is detecting statistically significant fare decreases that are too small in dollar terms to be economically relevant. To examine this possibility, we employ a modified rank dominance method to construct a measure of the presence of a fare war on a route. Specifically, we impose minimum thresholds of 10% and 20% fare decreases as additional constraints in selecting among the set of markets meeting the rank dominance criterion. This is the qualitative standard adopted by Morrison and Winston (1996), who found a 75 percent correlation between a fare war measure based on this standard and the number of references to fare wars found in *Aviation Week*, the *Wall Street Journal*, and the *New York Times*.

A second issue dealt to be considered here is the effect of overlaps in the network structure of major carriers on the probability of a fare war on specific routes where major carriers are jointly competing. Multi-market contacts have been measured with a variety of indicators. We adopt a measure of multi-market contact that was developed in the literature on assortative mixing in social networks (Newman,2002; Newman, Watts, and Strogatz, 2002).[3] The assortativity index measures the degree of interaction among two groups by comparing the degree of contact within groups and between groups. In the current context, if we let $J_A$ and $J_B$ denote a pair of binary variables that indicate the presence of airlines A and B on each route, and form the matrix $X=[J_A \;\; J_B]$, then the 2x2 matrix $V=X'X$ summarizes the degree of overlap in the route structures of the two airlines. The diagonal elements of V are the number of routes served by A and B respectively, and the off diagonal elements are the number of routes in common. Letting $\|V\|$ denote the sum of the elements of V, and normalize V as $Z=(\|V\|)^{-1}V$, then the index of multi-market contact may be defined as:

$$MMC=[1-tr(Z)] / (1-\|ZZ'\|)$$

where tr(Z) is the sum of the diagonal elements of Z. It may be shown that this measure: a) varies on the unit interval, b) increases as the number of common routes increases, c) increases as the scale of the airlines equalize, d) takes the value zero if there are no common routes, and e) takes the value one if the route structures are identical. Given these properties, greater multi-market contact is reflected as larger values of the index.[4]

A few examples may help illustrate the properties of the MMC measure. First consider a pair of airlines of equal scale but disjoint route structures. The matrix V is diagonal, with equal diagonal elements.

$$V = \begin{bmatrix} 200 & 0 \\ 0 & 200 \end{bmatrix} \qquad \text{where } \|V\| = 400$$

The normalized value of V is

$$Z = \begin{bmatrix} 1/2 & 0 \\ 0 & 1/2 \end{bmatrix} \qquad \text{where tr(Z)=1 and } \|ZZ'\| = 1/2$$

Consequently, the value of the multi-market contact index is

$$MMC = \frac{1 - tr(Z)}{1 - \|ZZ'\|} = 0$$

This index will always be zero when the route structures are disjoint. That is, when there is no multi-market contact. At the other extreme, consider a pair of airlines with identical route structures. Assume that they both serve the same 200 routes. The matrix V is

$$V = \begin{bmatrix} 200 & 200 \\ 200 & 200 \end{bmatrix} \qquad \text{where } \|V\| = 800$$

The normalized value of V is

$$Z = \begin{bmatrix} 1/4 & 1/4 \\ 1/4 & 1/4 \end{bmatrix} \qquad \text{where tr(Z)=1/2 and } \|ZZ'\| = 1/2$$

Consequently, the value of the multi-market contact index is

$$MMC = \frac{1 - tr(Z)}{1 - \|ZZ'\|} = 1$$

The index will always be one for airlines with coincident route structures.

As the scale of the airlines diverge, the off diagonal elements of V cannot exceed the smaller of the two diagonal elements. That is, if one airline serves 400 routes, and the other serves 200 routes, at most, they can have 200 routes in common. In this case,

$$V = \begin{bmatrix} 400 & 200 \\ 200 & 200 \end{bmatrix} \qquad \text{where } \|V\| = 1000$$

The normalized value of V is

$$Z = \begin{bmatrix} 2/5 & 1/5 \\ 1/5 & 1/5 \end{bmatrix} \qquad \text{where tr(Z)=3/5 and } \|ZZ'\| = 13/25$$

Consequently, the value of the multi-market contact index is

$$MMC = \frac{1 - tr(Z)}{1 - \|ZZ'\|} = 5/6$$

In general, differences in the scale of the airlines will decrease the degree of multi-market contact.

Finally, consider a pair of airlines of equal scale, whose route structures overlap randomly. From among the routes served by the first airline, the probability that the route is common with the second airline is one half. On average, half their routes in common.

$$V = \begin{bmatrix} 200 & 100 \\ 100 & 200 \end{bmatrix} \qquad \text{where } \|V\| = 600$$

The normalized value of V is

$$Z = \begin{bmatrix} 1/3 & 1/6 \\ 1/6 & 1/3 \end{bmatrix} \qquad \text{where tr(Z)=2/3 and } \|ZZ'\| = 1/2$$

Consequently, the value of the multi-market contact index is

$$MMC = \frac{1 - tr(Z)}{1 - \|ZZ'\|} = 2/3$$

The multi-market contact index increases as the number of common markets increases, and as the scale of the airlines equalize. This measure is easily generalized to the case of more than two airlines on a route, by simply adding the appropriate market presence binaries to the original matrix X. One limitation of this measure is that it is based on the number of markets served, and does nothing to account for potential differences in the value of the markets served. A second measure of multi-market contact will be constructed using market revenues rather than market counts, **mmc_$**. Specifically, the matrix V will be redefined with the market value of routes served by carriers A and B on the diagonal, and the market value of common routes off diagonal.

**Section 3. Data Used in this study**

This study uses the Bureau of Transportation Studies' quarterly *Origin and Destination*

*Survey* (*O&D*) for the period 1996 through 1999 to construct fare war indicators for selected airline routes. The analysis includes origin-destination routes chosen from among the largest one hundred airports in the U.S., based on passenger emplanements. After screening the data to ensure enough sample points to obtain a reliable observation of the fare quintiles, the final sample comprises 1131 routes over the full 16 quarters. For the first set of models, fare wars were identified by the RD criterion alone, and in addition, the models were fit on indicators with added constraint that the fare decrease be at least 20%.

The models incorporate as explanatory variables market structure measures for each route. The model includes dummy indicators for the slot-constrained hubs,[5] **slots**, and for the hubs that are dominated, **domhub**, i.e. where a single major carrier has a majority share of the emplanements at the origin or destinations[6]. Herfindahl indexes, **Herf**, were also constructed based on the market share distribution in the *O&D* file. The entry of a new carrier on the route, lagged by a quarter is captured by **lgent**. Because of its unique importance in the later years of the sample, a second variable indicating the entry of a low-cost carrier, **lgent_lc**, such SouthWest Airlines, is also included

In addition to *O&D* data from the Bureau of Transportation Studies, *T100 Domestic Segment* and *T100 Market data* used to construct load factors at the route level, **lgloadf**, and nation-wide, **load_avg**, Two measures of assortativity or multi-market contact described in section two. The first one, **mmc_n**, is based on a count of the markets served, while the second, **mmc_$**, is a weighted index based on the value of passenger revenues in the markets served. To contrast with earlier papers, the multimarket contact measure in Ross(1997) was constructed, **mmc_R**. It is found by calculating the pairwise correlation coefficients of the route structure of any two carriers in the market, and summing over all pairs. Finally, a set of variables indicating

nationwide business conditions affecting the overall market for airline services included seasonal dummies, **q1** to **q3**, a time trend, **ltrend**, and the price index for jet fuel times route distance, **fuel_cos**. Full definitions and sample descriptive statistics on all the variables is provided in the appendix.

**Section 4. Results**

**Table 1** reports the effects of adopting alternate thresholds for identifying fare wars in our sample for 1997-1999. The RD criterion taken alone produces a large frequency of fare wars—almost 25% of the sampled markets over a three-year period! It seems incredible to assert that these are meaningful occurrences of fare wars. More likely, these reflect price variations within the bounds of normal changes in market conditions, such as cost and demand fluctuations. Indeed, in our data there was a substantial decline in the jet fuel index that would put downward pressure on fares as a cost-shifter. The imposition of modest fare change thresholds as a component of fare war research would help to draw a tighter focus to events where nontrivial price cuts have occurred. While there is nothing unambiguous about the choice of threshold, the results clearly demonstrate the potential sensitivity of empirical analysis to this design parameter. Indeed, we find that the interpretation of probit models explaining the determinants of fare wars can be affected by the method employed to flag these occurrences.[7]

In **Table 2**, three probit models are reported for fare war occurrences defined by the adjusted Rank Dominance criteria, using the threshold of a 20% change from the previous quarter. While the frequency of fare wars may be over-stated in the models reported here in **Table 2**, if we take these indicators as closer to the truth than those calculated from the RD criterion alone, there are a number of interesting results.

The models differ only by the choice the measure of multi-market contact (Model 1

contains our **mmc_n** measure, Models 2 uses the **mmc_R** variable, and Model 3 contains all measures), retaining the same set of other covariates. The results are largely robust across these three models, except for a one key difference. Our assortativity measure of multi-market contact, **MMC_n**, reported in Model 1, displays a significant and negative effect on the probability of a fare war. Recall that multi-market contact would reduce the chances of a fare war to the extent that carriers understand mutual forbearance and the potential costs of short-run unilateral price-cutting. On the other hand, close ties among competitors in many markets means that, when a fare war breaks out against a particular carrier, it would likely spill over into multiple routes where retaliation is being carried out. Using Ross's measure of multi-market contact, **mmc_R**, seems to give this result. When both measures are added to the model, as shown in the column for Model 3, the coefficient on our assortativity index remains negative and significant, but the result on the Ross measure is not sustained. This evidence suggests that when major carriers have strong assortativity in their service configurations across markets, the net effect is to decrease the probability of a fare war, other things the same.

Other variables in the model are also informative about the incidence of price wars. First, the entry of any carrier into a city-pair route market, **lgent**, seems to correlate strongly with the occurrence of a fare war. One should expect that the firm heterogeneity that results from the entry of a low-cost carrier would have an important destabilizing effect on tacit collusion. The estimated model, however, finds the effect of entry to be the same whether or not the entrant is a low-cost entrant into the market, **lgent_lc**. In addition, the market structure effects of slot constraints and dominated hub airports are highly significant and positive. This effect may reflect that price wars are targeted to routes where they inflict the most harm. In routes governed by an airport with only one major carrier who has a dominant share, that carrier may be targeting

smaller carriers at the hub; in other instances, the dominant carrier may be a target of directed price-cutting by other major carriers. Moreover, including the directed divergence measure, **ddv_R**, has no significance in the model. The cost-shift variable, defined as the jet fuel price index multiplied by route distance, isestimated to make a fare war less likely. Finally, the model controls for macroeconomic conditions using the system-wide load factor, seasonal dummies and the trend variable.

A number of robustness checks were carried out in this study. For example, the possibility of fixed[8] or random effects in the model cannot be dismissed and might be seen as a useful refinement. In **Table 3**, we report the same three models as in **Table 2**, but allowing for random effects. While there is some evidence of random effects, as shown by the significance of **rho**, most of the results are qualitatively unchanged, and only the effect of the fuel cost variable becomes insignificant. The point estimate of **rho** can be interpreted as the proportion of the total variation due to the random effects. We also find that our results remain unaffected by redefining the fare wars indicator with a 20% price change threshold in the lowest (rather than two lowest) quintiles of the distribution.

In exploring the estimated difference between the results on our assortativity index of multi-market contact and that obtained from Ross's measure, it is clear that the latter is monotonically decreasing in the number of carriers in the route because it sums the (always negative) correlations of each carrier pair. It would seem that a more plausible summary of the joint correlation across route networks would be the average correlation among the pairs present, **ammc_R.** **Table 4** reports how the averaging affects the reported results. We find that in both the probit and random effects probit models, **ammc_R** is negative and significant. This result affirms our earlier conclusion that multi-market contact reduces the risk of a fare war.

Moreover, in the right-hand columns, this variable has no significant effect when we include our assortativity index. In contrast, **mmc_n** is highly significant and again dominates this adjusted Ross measure.

**Section 5. Conclusions**

In this paper, we use the rank dominance method to obtain an initial set of fare war indicators in more than a thousand major route markets from 1996-1999 and find that the method appears to over-predict the frequency of fare wars. We then impose an additional restriction; that the fare decrease must exceed twenty percent of the value of the fare. This is the qualitative standard adopted by Morrison and Winston (1996), who found a 75 percent correlation between a fare war measure based on this standard and the number of references to fare wars found in *Aviation Week*, the *Wall Street Journal*, and the *New York Times*. Although we cannot claim that a 20% minimum fare cut constitutes an economically meaningful concept of fare wars, at least the employment of such a threshold greatly reduces the observed frequency and helps to focus empirical analysis on episodes involving price cuts that are quantitatively substantial. This approach provides an interesting synthesis of the rank dominance method with the qualitative standard used in other studies.

Indeed, our empirical results confirm a number of market structure effects. There are significant impacts on the probability of fare wars associated with having new carrier entry in the market, having a dominated carrier in the hub, slot constraints, as well as other business conditions. The estimated model finds surprisingly that the effect of entry to be the same whether or not the entrant is a low-cost entrant. An important innovation in the analysis attempted here is the quantification of multi-market contacts via a route-level index of the assortativity of route

systems for all carriers in each route analyzed. We argue this measure is appropriate and provides further confirmation that multi-market contacts generally reduce the risks of fare wars in the industry.

**Table 1. Effects of thresholds on the frequency of fare wars with Rank Dominance**

| Fare war indicator: | Number of routes | Number of fare wars | Percentage of fare wars |
|---|---|---|---|
| Pure R.D. measure, Lowest quintile,( pw1 ) | 13572 | 2833 | 0.209 |
| R.D. measure, Lowest quintile plus 10% threshold, (pw1t10) | 13572 | 1769 | 0.130 |
| R.D. measure, Lowest quintile plus 20% threshold, (pw1t20) | 13572 | 400 | 0.029 |
| | | | |
| Pure R.D. measure, Lowest two quintiles, (pw2 ) | 13572 | 3312 | 0.244 |
| R.D. measure, Lowest two quintiles plus 10% threshold, (pw2t10) | 13572 | 1616 | 0.119 |
| R.D. measure, Lowest two quintiles plus 20% threshold, (pw2t20) | 13572 | 336 | 0.025 |

**Table 2. Probit models of fare wars, based on adjusted Rank Dominance Criterion, plus 20% fare change threshold**

**Dependent Variable: pw2** **Observations: 13572** **Ones: 1616**

| | Model 1 | | Model 2 | | Model 3 | |
|---|---|---|---|---|---|---|
| Probit Estimates | | | | | | |
| Regressor | Coefficient | t-ratio | Coefficient | t-ratio | Coefficient | t-ratio |
| CONSTANT | 3.932 | 2.374 | 3.891 | 2.349 | 3.878 | 2.336 |
| MMC_n | -0.564 | -3.687 | | | -0.639 | -2.904 |
| MMC_R | | | 0.145 | 2.380 | -0.041 | -0.479 |
| DDV_R | -0.008 | -1.133 | -0.007 | -1.086 | -0.008 | -1.139 |
| FUEL_COST | -0.162 | -1.845 | -0.175 | -1.981 | -0.155 | -1.742 |
| HER2 | 0.161 | 1.071 | 0.184 | 1.185 | 0.179 | 1.152 |
| SLOTS | 0.159 | 2.643 | 0.114 | 1.934 | 0.165 | 2.686 |
| DOMHUB | 0.267 | 5.176 | 0.296 | 5.820 | 0.264 | 5.090 |
| LOAD_AVG | -7.790 | -3.211 | -7.697 | -3.179 | -7.759 | -3.196 |
| Q1 | 0.421 | 2.905 | 0.412 | 2.844 | 0.421 | 2.902 |
| Q2 | 0.415 | 2.149 | 0.406 | 2.109 | 0.414 | 2.142 |
| Q3 | 0.072 | 0.952 | 0.073 | 0.963 | 0.073 | 0.961 |
| LTREND | -0.261 | -7.616 | -0.261 | -7.646 | -0.260 | -7.596 |
| LGENT | 0.414 | 2.188 | 0.408 | 2.156 | 0.404 | 2.126 |
| LGENT_LC | -0.120 | -0.240 | -0.074 | -0.148 | -0.126 | -0.252 |
| LGLOADF | -0.495 | -1.958 | -0.559 | -2.193 | -0.475 | -1.856 |
| | | | | | | |
| LogL | -1488.526 | | -1492.821 | | -1488.412 | |
| LR Test | 172.054 | | 163.466 | | 172.283 | |

**Table 3. Random Effects Probit models of fare wars, based on Rank Dominance Criterion, plus 20% fare change threshold**

**Dependent Variable: pw2t20** **Observations: 13572** **Ones: 336**

| Random Effects Probit Estimates | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Model 1 | | | Model 2 | | | Model 3 | | |
| Regressor | | Coefficient | t-ratio | | Coefficient | t-ratio | | Coefficient | t-ratio | |
| CONSTANT | | 3.971 | 1.978 | | 3.989 | 1.988 | | 3.928 | 1.937 | |
| MMC_n | | -0.743 | -2.837 | | | | | -0.806 | -2.558 | |
| MMC_R | | | | | 0.201 | 1.983 | | -0.036 | -0.291 | |
| DDV_R | | -0.010 | -1.089 | | -0.010 | -1.060 | | -0.010 | -1.093 | |
| FUEL_COST | | -0.080 | -0.575 | | -0.099 | -0.715 | | -0.074 | -0.530 | |
| HER2 | | 0.172 | 0.723 | | 0.194 | 0.789 | | 0.185 | 0.746 | |
| SLOTS | | 0.220 | 2.010 | | 0.155 | 1.471 | | 0.225 | 2.009 | |
| DOMHUB | | 0.324 | 3.680 | | 0.363 | 4.233 | | 0.322 | 3.600 | |
| LOAD_AVG | | -8.785 | -2.992 | | -8.782 | -3.011 | | -8.757 | -2.970 | |
| Q1 | | 0.514 | 2.459 | | 0.508 | 2.437 | | 0.513 | 2.447 | |
| Q2 | | 0.478 | 1.845 | | 0.474 | 1.837 | | 0.477 | 1.838 | |
| Q3 | | 0.109 | 1.009 | | 0.108 | 1.009 | | 0.109 | 1.014 | |
| LTREND | | -0.312 | -8.450 | | -0.312 | -8.459 | | -0.312 | -8.446 | |
| LGENT | | 0.546 | 2.027 | | 0.542 | 1.992 | | 0.538 | 1.927 | |
| LGENT_LC | | -0.193 | -0.281 | | -0.153 | -0.223 | | -0.195 | -0.284 | |
| LGLOADF | | -0.251 | -0.680 | | -0.312 | -0.836 | | -0.238 | -0.628 | |
| RHO | | 0.339 | 7.409 | | 0.339 | 7.315 | | 0.339 | 7.210 | |
| | | | | | | | | | | |
| LogL | | -1407.751 | | | -1410.719 | | | -1407.716 | | |

**Table 4. Estimates with Revised (average) Ross MMC Variable**

| Probit and Random Effects Probit Estimates | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | | | | | |
| Regressor | | Coefficient | t-ratio | | Coefficient | t-ratio | | Coefficient | t-ratio | | Coefficient | t-ratio | |
| CONSTANT | | 3.672 | 2.225 | | 3.672 | 1.849 | | 4.033 | 2.432 | | 4.092 | 2.038 | |
| MMC_n | | | | | | | | -0.931 | -2.980 | | -1.134 | -2.607 | |
| AMMC_R | | -0.239 | -2.663 | | -0.334 | -2.144 | | 0.249 | 1.359 | | 0.268 | 1.035 | |
| DDV_R | | -0.007 | -1.098 | | -0.010 | -1.069 | | -0.008 | -1.152 | | -0.010 | -1.102 | |
| FUEL_COST | | -0.171 | -1.943 | | -0.094 | -0.682 | | -0.144 | -1.618 | | -0.062 | -0.441 | |
| HER2 | | 0.177 | 1.148 | | 0.181 | 0.736 | | 0.207 | 1.337 | | 0.214 | 0.862 | |
| SLOTS | | 0.126 | 2.137 | | 0.175 | 1.646 | | 0.176 | 2.866 | | 0.238 | 2.143 | |
| DOMHUB | | 0.287 | 5.617 | | 0.350 | 4.075 | | 0.259 | 5.003 | | 0.316 | 3.530 | |
| LOAD_AVG | | -7.726 | -3.189 | | -8.796 | -2.994 | | -7.706 | -3.174 | | -8.690 | -2.948 | |
| Q1 | | 0.414 | 2.861 | | 0.510 | 2.433 | | 0.421 | 2.898 | | 0.513 | 2.443 | |
| Q2 | | 0.409 | 2.121 | | 0.476 | 1.835 | | 0.412 | 2.132 | | 0.474 | 1.826 | |
| Q3 | | 0.073 | 0.958 | | 0.108 | 1.005 | | 0.074 | 0.977 | | 0.111 | 1.027 | |
| LTREND | | -0.261 | -7.631 | | -0.312 | -8.439 | | -0.260 | -7.581 | | -0.311 | -8.439 | |
| LGENT | | 0.402 | 2.131 | | 0.539 | 2.001 | | 0.397 | 2.093 | | 0.528 | 1.918 | |
| LGENT_LC | | -0.075 | -0.150 | | -0.153 | -0.223 | | -0.150 | -0.298 | | -0.211 | -0.307 | |
| LGLOADF | | -0.546 | -2.151 | | -0.302 | -0.814 | | -0.437 | -1.705 | | -0.203 | -0.539 | |
| RHO | | | | | 0.339 | 7.339 | | | | | 0.340 | 7.197 | |
| | | | | | | | | | | | | | |
| LogL | | -1492.101 | | | -1410.086 | | | -1487.614 | | | -1407.324 | | |
| LR Test | | 164.904 | | | | | | 173.879 | | | | | |

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**Appendix 1: Data Sources**

The data used in this study are a compilation of two principal sources. The *Origin and Destination Survey* is a ten percent random sample of all domestic airline tickets available on a quarterly basis. The survey contains information on fares and coupon segments on an individual basis, but information on the date of the flight is confined to the quarter of use. The *T100 Domestic Segment* data is a monthly census non-stop service by US carriers in the domestic market. This data is aggregated to the route and carrier level.

The records were screened in an attempt to avoid certain types of problem. First, to avoid some anomalous or inconclusive reporting, we eliminated tickets reporting fares less than $20 and more than $1500, ones where no discernible destination was reported, more than three coupons each direction, and those reporting an international origin or destination. Routes were then selected starting with all origins and destinations within the largest 100 airports. For inclusion in the sample, data on the route (origin-destination pair) had to meet criteria for all quarters 1996-1999. These criteria included (a) the minimum number of flights must exceed daily service for the quarter; (b) route must have at least 100 O&D observations per quarter ; (c) routes are treated uni-directionally, e.g., Chicago O'Hare to Los Angeles (LAX) and LAX to Chicago O'Hare are separate routes.

| | Table A1: Variables used in analysis | | | | |
|---|---|---|---|---|---|
| **Variable** | | **Mean** | **Std Dev** | **Minimum** | **Maximum** |
| year | calendar year | 1998 | 0.817 | 1997 | 1999 |
| quarter | calendar quarter | 2.500 | 1.118 | 1 | 4 |
| ltrend | Trend variable= (year-1997)*4 +quarter; in natural logs | | | | |
| pw1 | price war indicator =1 from RD test on bottom quintile | 0.209 | 0.406 | 0 | 1 |
| pw2 | price war indicator =1 from RD test on bottom 2 quintiles | 0.244 | 0.430 | 0 | 1 |
| pw1t10 | price war indicator =1 if pw1 =1 and change in price is at least 10% | 0.130 | 0.337 | 0 | 1 |
| pw2t10 | price war indicator =1 if pw2 =1 and change in price is at least 10% | 0.119 | 0.324 | 0 | 1 |
| pw1t20 | price war indicator =1 if pw1 =1 and change in price is at least 20% | 0.029 | 0.169 | 0 | 1 |
| pw2t20 | price war indicator =1 if pw2 =1 and change in price is at least 20% | 0.025 | 0.155 | 0 | 1 |
| totdval | dollar value of sampled round trip tickets in the route | 147849 | 115469.120 | 15508 | 1026429 |
| herf | Herfindahl Index, scaled | 4735.8 | 1744 | 1227 | 10000 |
| numfirms | Number of effective competitors , the reciprocal of the Herfindahl | 2.410 | 0.911 | 1 | 8.149 |
| sdl | Indicator variable =1 if Delta present in the market | 0.259 | 0.438 | 0 | 1 |
| saa | Indicator variable =1 if American present in the market | 0.262 | 0.440 | 0 | 1 |
| sas | Indicator variable =1 if Alaska Air present in the market | 0.034 | 0.181 | 0 | 1 |
| sco | Indicator variable =1 if Continental present in the market | 0.149 | 0.356 | 0 | 1 |
| shp | Indicator variable =1 if America West present in the market | 0.084 | 0.278 | 0 | 1 |
| snw | Indicator variable =1 if Northwest present in the market | 0.122 | 0.327 | 0 | 1 |
| stw | Indicator variable =1 if TWA present in the market | 0.069 | 0.253 | 0 | 1 |
| sua | Indicator variable =1 if United Airlines present in the market | 0.298 | 0.457 | 0 | 1 |
| sus | Indicator variable =1 if US Air present in the market | 0.187 | 0.390 | 0 | 1 |
| swn | Indicator variable =1 if Soutwest present in the market | 0.068 | 0.252 | 0 | 1 |
| mmc_n | Assortativity index, based on counts of markets served | 0.859 | 0.196 | 0.430 | 1 |
| mmc_$ | Assortativity index, based on value of markets served | 0.830 | 0.240 | 0.285 | 1 |
| ent_dl | Indicator variable =1 if Delta entered into the market | 0.001 | 0.037 | 0 | 1 |
| ent_aa | Indicator variable =1 if American entered into the market | 0.004 | 0.064 | 0 | 1 |
| ent_as | Indicator variable =1 if Alaska Air entered into the market | 0.000 | 0.012 | 0 | 1 |
| ent_co | Indicator variable =1 if Continental entered into the market | 0.001 | 0.027 | 0 | 1 |
| ent_hp | Indicator variable =1 if America West entered into the market | 0.001 | 0.024 | 0 | 1 |
| ent_nw | Indicator variable =1 if Northwest entered into the market | 0.000 | 0.019 | 0 | 1 |
| ent_tw | Indicator variable =1 if TWA entered into the market | 0.001 | 0.030 | 0 | 1 |
| ent_ua | Indicator variable =1 if United Airlines entered into the market | 0.002 | 0.046 | 0 | 1 |
| ent_us | Indicator variable =1 if US Air entered into the market | 0.002 | 0.043 | 0 | 1 |
| ent_wn | Indicator variable =1 if Soutwest entered into the market | 0.001 | 0.035 | 0 | 1 |
| ext_dl | Indicator variable =1 if Delta exited the market | 0.003 | 0.051 | 0 | 1 |
| ext_aa | Indicator variable =1 if American exited the market | 0.002 | 0.043 | 0 | 1 |
| ext_as | Indicator variable =1 if Alaska Air exited the market | 0.000 | 0.015 | 0 | 1 |
| ext_co | Indicator variable =1 if Continental exited the market | 0.001 | 0.035 | 0 | 1 |
| ext_hp | Indicator variable =1 if America West exited the market | 0.001 | 0.038 | 0 | 1 |
| ext_nw | Indicator variable =1 if Northwest exited the market | 0.001 | 0.028 | 0 | 1 |
| ext_tw | Indicator variable =1 if TWA exited the market | 0.001 | 0.035 | 0 | 1 |
| ext_ua | Indicator variable =1 if United Airlines exited the market | 0.001 | 0.034 | 0 | 1 |
| ext_us | Indicator variable =1 if US Air exited the market | 0.002 | 0.043 | 0 | 1 |

| | **Table A1: Variables used in analysis, continued** | | | | |
|---|---|---|---|---|---|
| **Variable** | | **Mean** | **Std Dev** | **Minimum** | **Maximum** |
| ext_wn | Indicator variable =1 if Soutwest exited the market | 0.000 | 0.000 | 0 | 0 |
| ext_oth | Indicator variable =1 if Major other than Soutwest exited the market | 0.013 | 0.111 | 0 | 1 |
| ent_oth | Indicator variable =1 if Major other than Soutwest entered the market | 0.012 | 0.108 | 0 | 1 |
| loadf | Load factor; ratio of number of passengers to number of seats | 0.702 | 0.103 | 0.274 | 0.9734 |
| lgloadf | Load factor, lagged one quarter | 0.702 | 0.103 | 0.274 | 0.9734 |
| distance | great circle distance between origin and destination | 1032.600 | 611.182 | 100 | 4502 |
| slots | Indicator variable =1 if origin or destination airport was slot constrained | 0.235 | 0.424 | 0 | 1 |
| domhub | Indicator variable =1 if origin or destination airport was dominated hub | 0.411 | 0.492 | 0 | 1 |
| load_eop | System-wide load factor, based on last month of quarter | 0.700 | 0.024 | 0.667 | 0.735 |
| load_avg | System-wide load factor, based on average over quarter | 0.704 | 0.036 | 0.653 | 0.761 |
| dev_gdp | Deviation of nominal GDP from trend | 2.038 | 29.458 | -42.08 | 60.1 |
| dev_rgdp | Deviation of real GDP from trend | -0.655 | 24.953 | -39.879 | 50.074 |
| jet_fuel | Index of jet fuel prices; New York spot market | 51.219 | 9.987 | 35.843 | 68.145 |
| Fuel_cost | jet fuel price index times route distance; scaled by 100000 | 0.529 | 0.335 | 0.0358 | 3.068 |
| dl_aa | Interaction term for joint presence of Delta and American | 0.082 | 0.275 | 0 | 1 |
| dl_as | Interaction term for joint presence of Delta and Alaska | 0.008 | 0.092 | 0 | 1 |
| dl_wn | Interaction term for joint presence of Delta and Southwest | 0.012 | 0.107 | 0 | 1 |
| aa_tw | Interaction term for joint presence of American and TWA | 0.014 | 0.117 | 0 | 1 |
| aa_ua | Interaction term for joint presence of American and United Airlines | 0.110 | 0.313 | 0 | 1 |
| aa_hp | Interaction term for joint presence of American and America West | 0.008 | 0.086 | 0 | 1 |
| hp_wn | Interaction term for joint presence of America West and Southwest | 0.022 | 0.145 | 0 | 1 |
| ua_as | Interaction term for joint presence of United Airlines and Alaska | 0.010 | 0.102 | 0 | 1 |
| ua_wn | Interaction term for joint presence of United Airlines and Southwest | 0.013 | 0.112 | 0 | 1 |
| wn_as | Interaction term for joint presence of Southwest and Alaska | 0.009 | 0.093 | 0 | 1 |
| rtddv | Route-level directed divergence measure | 1.065 | 2.907 | -6.335 | 95.998 |
| orgddv | directed divergence measure for the airport of origin | 0.226 | 1.589 | -4.857 | 72.043 |
| desddv | directed divergence measure for the airport of destination | 0.465 | 1.567 | -2.836 | 67.191 |
| ddv_R | Sum of all three directed divergence measures | 1.778 | 3.871 | -13.133 | 96.133 |
| mmc_R | Sum of all pairwise carriers' route structure correlation coefficients; from Ross(1997) | -0.373 | 0.443 | -1.7103 | 0 |
| lgent | Indicator variable =1 if any carrier entered into the market; lagged one quarter | 0.0134836 | 0.1153378 | 0 | 1 |
| lgent_lc | Indicator variable =1 if any "low cost" carrier entered into the market; lagged one quarter | 0.0020631 | 0.0453758 | 0 | 1 |

**Endnotes**

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[1] There is, of course, some subjectivity in determining which quintiles are of interest, but Ross (1997) found her results to be fairly robust to this choice.

2. Direct comparisons are difficult, because Busse (2002) conducts her analysis at the carrier level rather than the route level. She finds 31 episodes of price wars among 14 major carriers over an 8 year period.

3. For an economic application in health economics, a recent study of social interaction among physicians by Fournier, Prasad and Burke (2002) employs a similar assortativity index,

4. This multi-market contact measure is just one minus the assortativity index defined in Newman (2002). We use one minus the assortativity index, since multi-market contact and assortativity are inversely related in this application. In the literature on social interaction, two groups are perfectly assortative if there is contact between members within a group, but no contact between members in different groups. In the current application, this corresponds to a disjoint route structure for a pair of airlines.

5. Routes involving slot-constrained airports at the origin and/or destination were identified. These airports include Kennedy and LaGuardia in New York, Chicago O'Hare, and Washington National.

6. These are identified in Morrison (1997).

7. Moreover, using the criterion alone to identify fare wars produces anomalies in probit models designed to explain its determinants.

8. The fixed effects model can only be specified for grouped observations to avoid the incidental parameter problem. We specified fixed effect using carrier dummies. In that model, nothing was qualitatively changed.