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Safety, profitability and the load factor for airlines in the USA

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Abstract

This paper studies the causal relationship between safety, profitability and the load factor for US airlines taking airline deregulation into account. The results indicate that there is some evidence that profitability and the growth of load factor cause fatalities/accidents. Bivariate causality tests show that profitability does not cause fatalities/accidents.

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I. Introduction

The Airline Deregulation Act of 1978 virtually deregulated the airline operations in the United States. One of the main concerns with airline deregulation was that safety would be compromised. It was feared that with deregulation, the replacement of jet services by commuter services would lead to less safety. Almost all studies about airline safety, which have used data for jet services find that the safety record of jet services has improved after deregulation. In fact, safety had been increasing for a long time before airline deregulation. However, small communities lost jet service and they were being serviced by turboprops. More recently, these turboprops have often been replaced by small jets.

It was also thought that the load factor (the percentage of seats in a plane that is filled by paying passengers) would go up after deregulation as more airlines start to offer "no frills" tickets to a greater extent. Other things being equal, as the load factor goes up, it is sometimes feared that safety would be compromised. The effect of airline deregulation on profitability is uncertain. It was expected that airline deregulation would lead to more competition and thus drive down airfares. It was also expected that removal of restrictions on airfares would lower airfares. An increase in the load factor, other things being equal, was expected to increase profit.

This paper studies the causal relationship between the load factor, safety and profitability in the United States when airline deregulation is taken into account. No such study has been undertaken before.

II. Literature Review

Kanafani and Keeler (1990) is among the first studies to examine whether there was a change in safety level following deregulation. They use monthly data from January 1966 to December 1989. They run the following exponential (non-linear) regression:

$$DPM = \exp (a_1 + a_2 + a_3\, T.D) + u \qquad (1)$$

where DPM stands for fatalities per revenue passenger-mile in regularly scheduled service, T is a time trend (taking the value of 1 in January 1966, a value of 2 in February 1996 and so on) and D is the dummy variable having a value of 0 before January, 1979 and a value of 1 thereafter. a_3 shows the shift in the trend in the change of fatalities after deregulation. Because of the problem of heteroscedasticity, the equation is estimated by the method of nonlinear generalized weighted least squares. The results show that a_3 is not significant implying that there had been no change in the trend towards fatality. In other words, deregulation did not have any effect (positive or negative) on the airline industry's trend towards improved safety. After deregulation, many small communities were being served by the commuter airlines. Oster and Zorn (1989) find that commuter airlines had a higher fatality rate than that of trunk and local service airlines. However, they also find that the largest commuter airlines were substantially safer than the jet carriers which they had replaced. A good review of the airline safety debate is found in Rose (1992). Rose concludes by observing that airline safety had received much more attention relative to more significant risks. She also observes that American national obsession with airline safety may explain the high safety standards of the US air carriers.

The first study to look at the profitability and safety issue using time series data is by Adrangi, Chow and Raffiee (1997). They employ Granger causality tests between profitability and safety of airlines in the United States. There are a number of differences between the present study and the study by Adrangi, Chow and Raffiee. First, they do not take load factor into account in their causality tests. Thus, while their tests are confined to bivariate causality tests, we perform both bivariate and multivariate causality tests.

Second, to take airline deregulation into account, they split the data into two periods, pre-deregulation and post-deregulation periods and perform causality tests separately for these two periods. Since their data end in 1994 (safety data are up to 1992 only), they are able to use only 14 years of post deregulation data to test for Granger causality. This time period is too short to get any meaningful results. In our view, a more satisfactory way of dealing with the event of airline deregulation is to treat airline deregulation as a form of structural break. Our causality tests use data for the whole period. But, we treat airline deregulation as a structural break in our causality tests.

Third, our measures of profitability are different from the measures that they use. We also normalize the measures of profitability as they do. However, while we use operating profit per passenger and net operating profit per passenger, they use operating profit and net operating profit divided by total revenue.

III. Methodology, Data and the Results

We perform the block Granger (1969) block non-causality tests between profitability, safety and the load factor. The Granger block non-causality test can be described as follows. Consider the augmented vector autoregressive model:

$$z_t = a_0 + a_1 t + \sum_{i=1}^{p} \phi_i z_{t-i} + \Psi w_t + u_t \qquad (2)$$

where z_t is an m x 1 vector of jointly determined (endogenous) variables, t is a linear time trend, w_t is q x 1 vector of exogenous variables, and u_t is an m x 1 vector of unobserved disturbances. Let $z_t = (z'_{1t}, z'_{2t})'$, where z'_{1t} and z'_{2t} are m_1 x 1 and m_2 x 1 subsets of z_t, and $m = m_1 + m_2$. We can now have the block decomposition of (2) as follows:

$$z_{1t} = a_{10} + a_{11} t + \sum_{i=1}^{p} \phi_{i,11} z_{1,t-i} + \sum_{i=1}^{p} \phi_{i,12} z_{2,t-i} + \Psi_1 w_t + u_{1t} \qquad (3)$$

$$z_{2t} = a_{20} + a_{21} t + \sum_{i=1}^{p} \phi_{i,21} z_{1,t-i} + \sum_{i=1}^{p} \phi_{i,22} z_{2,t-i} + \Psi_2 w_t + u_{2t} \qquad (4)$$

The hypothesis that the subset z_{2t} do not 'Granger cause' z_{1t} is given by
H_G: $\phi_{12} = 0$ where $\phi_{12} = (\phi_{1,12}, \phi_{2,12} \ldots, \phi_{1p,12})$.

However, before we perform such tests, we have to ensure that the variables involved are stationary. If the variables are non-stationary in their levels, but stationary in their first differences, then cointegration tests can be performed. If the variables are cointegrated, causality tests can still be performed but an error correction form needs to be used.

We use Phillips-Perron (1988) test because the test is well suited for analyzing time series whose differences may follow mixed ARMA (p,q) processes of unknown order in that it the test statistic incorporates a nonparametric allowance for serial correlation and heteroscedasticity in testing the regression. Consider the following equation:

$$y_t = \tilde{c}_0 + \tilde{c}_1 y_{t-1} + \tilde{c}_2 (t - T/2) + \nu_t \qquad (5)$$

where T is the number of observations and ν_t is the error term. The null hypothesis of a unit root is: $\tilde{c}_1 = 1$. We can drop the trend term to test the stationarity of a variable without the trend.

All data are from the Air Transport Association website (http://www.airlines.org/home/default.aspx). The annual data are for the period from 1947 to 1998. Data for the later years are not available. The variables are defined as follows. Two measures of air safety are used. These are fatal accidents per million aircraft miles (FAPMAM) and passenger fatalities per million aircraft miles (PFPMAM). Two measures of profitability are used. These are real operating profit per passenger (ROPPP) and real net operating profit per passenger (RNOPP). Finally, load factor (LF) is the system-wide load factor.

The results of the Phillips-Perron unit root tests are given in table 1. The results show that while FAPMAM, PFPMAM, ROPPP and RNOPPP are all stationary, LF is not. We use critical values at the 5 percent level of significance. Since LF is not stationary, we can use the growth rate of LF (which we call GLF) in our causality analysis provided that GLF is stationary. The table shows that GLF is stationary. Thus, in the causality tests, we use GLF along with other variables. Our causality analysis takes airline deregulation into account as a structural break. Following Kanafani and Keeler (1990), 1979 is taken to be the year of the structural break. In this study, the structural break is taken into account by treating it as an exogenous variable.

Since we have two measures of profitability and two measures of safety, and the growth of load factor is also included in the causality tests, a large number of causality tests need to be conducted. In all causality tests, we take into account the structural break for airline deregulation. The results of multivariate and bivariate causality tests are given in table 2.

The results show that there is some evidence that profitability and the growth of load factor Granger caused fatalities/accidents. The evidence is stronger when real net operating profit per passenger (RNOPPP) is used. Bivariate causality tests between measures of profitability and the measures of safety show that there is no evidence that profitability Granger causes fatalities/accidents. This leads us to conclude that the growth of load factor and not profitability contributes to the Granger causality. We also conduct Granger causality tests between the growth rate of load factor and profitability. There is strong evidence that the causality flows from profitability to the growth of load factor. This is true for both measures of profitability. There is no evidence of reverse causality that the growth of load factor Granger causes profitability.

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Table 1. Phillips-Perron (PP) Unit Root Tests (Truncation lag = 3[*])

Variable	PP Test Statistic[**]	Critical Value
FAPMAN	T_μ = -3.5383	-2.9190
FAPMAM	T_τ = -4.6078	-3.4987
PFPMAM	T_μ = -5.0047	-2.9190
PFPMAM	T_τ = -7.4327	-3.4987
ROPPP	T_μ = -3.2766	-2.9190
ROPPP	T_τ = -4.0352	-3.4987
RNOPPP	T_μ = -3.6222	-2.9190
RNOPPP	T_τ = -4.4117	-3.4987
LF	T_μ = -1.4291	-2.9190
LF	T_τ = -1.6990	-3.4987
GLF	T_μ = -6.9432	-2.9202
GLF	T_τ = -6.9729	-3.5005

[*]The truncation lag of 3 was determined using the Schwert Criterion. The truncation lag = integer [$4(T/100)^{1/4}$] where T stands for the number of observations.

[**] T_μ and T_τ and are test statistics (1) with drift and no trend and (2) with drift and trend respectively.

Table 2. Multivariate and Bivariate Granger Block Causality Tests

Cause	Effect	Test Stat.(*)	Probability(**)
ROPPP, GLOAD	FAPMM	12.25(3)	.057(6)
ROPPP, GLOAD	PFMAM	11.77(3)	.067(6)
RNOPPP, GLOAD	FAPMM	13.70(3)	.033(6)
RNOPPP, GLOAD	PFMAM	12.71(3)	.048(6)
ROPPP	FAPMM	3.97(3)	.265(3)
ROPPP	PFMAM	5.67(3)	.129(3)
RNOPPP	FAPMM	1.66(3)	.647(3)
RNOPPP	PFMAM	2.01(3)	.570(3)
ROPPP	GLOAD	19.10(3)	.000(3)
GLOAD	ROPPP	5.66(3)	.129(3)
RNOPPP	GLOAD	20.57(3)	.000(3)
GLOAD	RNOPPP	3.86(3)	.277(3)

Note: The test statistic indicates the chi-square value. The probability refers to the probability of accepting the null hypothesis of no causality

*indicates the number of lags which was determined by using the Akaike Information Criterion (AIC)

**indicates the degrees of freedom of the chi-square distribution