Movements of Domestic Airline Technical Efficiency Scores over Time: Implications for Future Industry Structure

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The volatile nature of the domestic airline industry has received much attention since deregulation in 1978. The large number of failures, mergers, bankruptcy filings, and operating loss reports has raised concerns that the future is bleak in terms of the number of carriers that will survive and prosper. Economic theory suggests that it is vital for firms to operate efficiently to compete. To avoid falling behind competitors, firms need to imitate any advances in efficiency-enhancing technology made by others in the industry. A panel data set of 11 domestic airlines, followed quarterly from 1970 to 1990, and three methods that are currently being pursued in the efficiency-measurement literature are used to explore the movements of technical efficiency over time in the industry. The analysis indicates that the efficiency scores of the carriers in the sample exhibit long-term relationships and move closer together over time.

The past two decades have proven highly disruptive to the American airline industry. The impetus behind the trend toward a more concentrated market structure was economic deregulation of the airline industry in 1978 by the Civil Aeronautics Board (CAB). Under regulation, firms had an incentive to select an inefficient combination of inputs, since the only means of competition was through service, which often meant "too many planes on too many routes" (*1*). It was widely believed that once the barriers to entry instituted by regulation were removed, such distortions would be eliminated and industry performance and efficiency would improve. Thus, whereas overcapitalization may have been the correct decision during regulation, on deregulation carriers found themselves with fleet configurations and labor commitments that were no longer optimal and had to be modified because of the intensified level of competition. The structure of fares, quality of service, and pace of modernization of airline capital have, therefore, changed dramatically.

Furthermore, substantial changes are likely to continue during the coming decade. One powerful force that will propel further change is the enormous growth of demand for airline services. Airlines have become a vital component of the world travel industry with passenger travel doubling since the U.S. airline industry was deregulated. A second stimulus to change is the increasingly competitive international market. For example, the prospect of integration of the European Community will remove current economic barriers in Europe; this deregulation will affect the airline industry and lead to the negotiation of new international agreements and the possibility of trans-Atlantic mergers.

In the light of these domestic and international challenges, the ability of U.S. carriers to operate efficiently is critical to their prospects for prosperity or survival. The goals of this research are to evaluate the performance of each domestic airline in the sample over time using alternative measures of relative technical efficiency and to use these measures to address the question of future industry composition. The identification of efficiency differentials among American carriers provides a means of ranking the airlines relative to one another through time. The ranking provides a way of ascertaining which carriers may be headed for trouble. In addition, at the managerial level, these measures indicate the success, or lack thereof, in performance enhancement. At the industry level, the hypotheses of cointegration and convergence of these efficiency scores over time can be tested to predict future industry movements.

Cointegration occurs when two variables do not move too far from one another although individually they move unpredictably through time. Convergence occurs when two variables move closer together over time. Theory suggests that the time series of efficiency scores for the airlines should move together (cointegration) or closer together (convergence) as technological advances become diffused throughout the industry. This argument is based on the assumption that the efficiency advances made by one carrier can be adopted by another; namely, improved technology is a public good available to any firm wishing to use it. Failure to exhibit cointegration or convergence would be indicative of a firm's inability to capitalize on this public good. Rigorous identification of the underlying reasons for differences in efficiency and the presence or absence of cointegration-convergence between carriers is the subject of future research.

DATA

The original Good-Sickles data set has been updated and consists of quarterly observations of 11 domestic carriers from 1970 to 1990 with a Department of Transportation (DOT) Group III classification. This category consists of certified carriers with the largest total annual operating revenues. Smaller carriers are categorized as Group I or Group II. The sample includes American (AA), Continental (CO), Delta (DL), Eastern (EA), Frontier (FL), Ozark (OZ), Piedmont (PI), Trans World Airlines (TW), United (UA), USAir (US), and Western (WA). The primary source of the data is the CAB Form 41 reports. The DOT's reporting requirements are extensive, and as of 1970 the data are rigorously audited to maintain a high degree of accuracy. Form 41 is therefore a rich and definitive source of data for industry analysis.

The input and output accounts of the Form 41 schedules were aggregated into four broad input indices and one output index (*2*).

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The input indices are capital (K, the number of aircraft), labor (L, an aggregate of pilots, flight attendants, mechanics, passenger and aircraft handlers, and other labor), energy (F, gallons of aircraft fuel), and a residual designating materials (M, which includes items such as advertising, supplies, outside services, passenger food, and maintenance materials). The aggregate output variable available for use is the quantity of revenue output (RTM, revenue ton-miles, which includes both passenger and cargo operations).

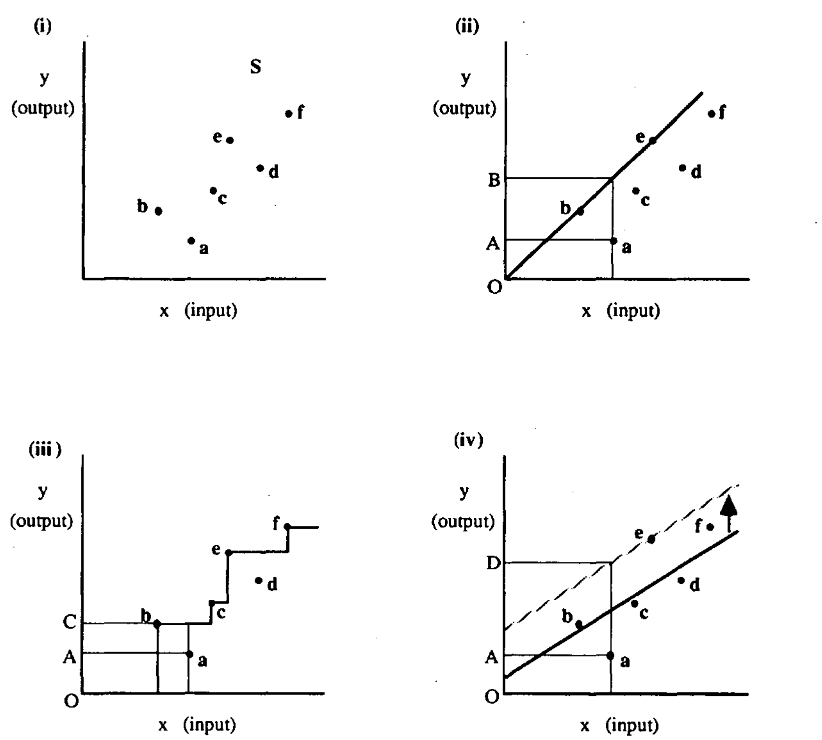
Two airline output and two capital stock characteristics are also calculated. The former characteristics are aircraft stage length (STAGE), which describes the average length of route segments (obtained by dividing aircraft miles by flights), and load factor (LOADF), which provides a measure of service quality and is often used as a proxy for service competition. A small average stage length means the carrier's aircraft spend only a short part of each flight at an efficient altitude. A low load factor, indicative of a large number of planes on a particular route, indicates high service quality. Deregulation has switched the focus from service quality (i.e., large number of flights) to price competition, causing load factor to increase as service has declined. The latter characteristics are the average size of the carrier's aircraft (KSIZE) and the percentage of a carrier's fleet that is jet (PJET). These two variables provide measures of the potential productivity of capital. For example, as the average size of a carrier's aircraft increases, more services can be provided without a proportionate increase in resources such as flight crews, passenger and aircraft handlers, and landing slots. On the other hand, the percentage of jets provides a measure of aircraft speed. Jets require proportionately less flight crew resources than turboprops because jets fly approximately three times as fast.

METHODS

Three methods currently pursued in the efficiency-measurement literature will be used to model technical inefficiency. The first two approaches, data envelopment analysis (DEA) and a variant of DEA called free disposable hull (FDH), differ from the third methodology, stochastic frontier analysis (SFA), in that the latter is based on statistical regression techniques.

Efficiency Measurement

Assume a panel data set where, for each time $t = 1, \ldots, T$, there are $n = 1, \ldots, N$ firms in the sample each consuming $j = 1, \ldots, J$ different inputs to produce $k = 1, \ldots, K$ different outputs. Assume that there exists a production set that can be constructed using all input and output observations from all time periods. The production technology, **S**, is thus defined as all possible combinations of inputs and outputs that are feasible, where feasibility means that the inputs can produce the outputs. For example, assuming only one time period and a one-input, one-output activity, a set **S** may be shown as in Figure 1 (i); Points a through f are input-output combinations observed of hypothetical firms.



Points a-f are hypothetical firms in a one-input, one-output industry.

FIGURE 1 Hypothetical example of different frontiers: (i) production technology, S; (ii) DEA frontier (constant returns to scale); (iii) FDH frontier; and (iv) SFA regression (constant returns to scale).

Efficiency measures are calculated as the distance from a production frontier. In general this distance is calculated in one of two ways in input-output space: either "horizontally," called input-based measurement since outputs are held constant, or "vertically," called output-based measurement since inputs are held constant. An output-based distance function holds inputs constant and expands outputs as much as possible without exceeding the boundaries or frontier of S. Similarly, an input-based function holds outputs constant and contracts inputs as much as possible without exceeding the boundaries of S. Under constant returns to scale, it does not matter which approach is chosen, since the values obtained from these two approaches are simply reciprocals. This study assumes constant returns to scale, which occur when outputs can be doubled by doubling inputs, since research on returns to scale in the airline industry has found that they satisfy this condition (*3*).

The next step is to define the boundary of S by using DEA, FDH, or SFA.

DEA

The first method, DEA, was introduced to economics by Charnes et al. (*4*) and has since found a multitude of applications including banks (*5–7*), the military (*8*), public schools (*9*), and hospitals (*10*). One reason for the proliferation of DEA applications is that it is a linear programming method that does not require price information. This is an empirical advantage since often the only data available are physical units of inputs and outputs. Other reasons for its widespread appeal are that it requires neither the assumption of cost minimization or profit maximization nor the specification of a production function. Furthermore, the computation of the relative efficiency for each firm under study, which may have multiple inputs and outputs, is easily executed on any computer with linear programming capabilities.

DEA, as its name suggests, creates an "envelope" of observed production points. It provides for flexible piecewise linear approximations to model the "best-practice" reference technology. Its flexibility lies in the ability to place constraints on the linear program to account for constant, decreasing, increasing, or variable returns to scale. Measures of technical efficiency levels are then developed for firms that operate inside this data envelope.

The output-based efficiency score for an observation of inputs and outputs for a firm at a particular time is obtained from a linear programming operation carried out for every carrier in every time period. In the simple hypothetical one-period, one-input, one-output, six-firm example, this process creates a production technology frontier as shown in Figure 1 (ii). Firms b and e are efficient and have scores of 1; the other firms are inefficient and have scores less than 1. For example, Firm a's output-based score will be its vertical distance from the frontier given by the ratio OA/OB < 1.

FDH

FDH was recently developed by Deprins et al. (*11*). FDH has an additional advantage over DEA because it imposes one less restriction on the data: it does not require that convex combinations of every observed production plan be included in the production set. Therefore, whereas DEA creates a piecewise linear best-practice frontier, FDH creates a best-practice frontier resembling a staircase.

Figure 1 (iii) shows an FDH production frontier. Because linear combinations of observed productions are not allowed under FDH, Firm a's technology is now compared with only Firm b's technology rather than with a combination of Firm b and Firm e technology. As a result, Firm a's output-based score is given by the ratio OA/OC < 1. Note that under FDH (as compared with DEA) more firms are efficient (Firms b, c, e, and f are all now on the frontier and have scores of 1) and inefficient firms' scores are nearer to 1 because they are closer to the FDH frontier. In other words, firms do better using the FDH rather than the DEA framework.

Deprins et al. (*11*) claim that FDH is more valuable for managerial decision making than either DEA or SFA. This assertion is based on the fact that an FDH efficiency measure is relative to an observed point on the frontier. DEA and SFA allow the measure to be relative to a hypothetical point on the frontier, since both the DEA and SFA techniques allow for convex combinations of observed points to be included in the production set. Hence managers can look at an actual rather than a theoretically possible alternative to modify current practices and improve performance.

SFA

SFA, the classical statistical approach, specifies efficiency relative to a stochastic production function. Unlike the linear programming techniques that have no particular functional form to describe their boundary, SFA requires an a priori specification of the technology (*12–14*). Furthermore, this measure of efficiency is fundamentally different from the preceding linear programming techniques because, rather than comparing a firm with a best-practice or efficient frontier, it compares a firm with an average technology. Schmidt (*15*) labels this result "paradoxical" given the usual definition of a production function as maximizing output given a set of inputs. He points out, however, that this approach may be preferred because it allows standard types of statistical inference. In this respect, SFA provides a useful counterpart to the linear programming approaches.

The technology is specified as a Cobb-Douglas stochastic frontier production function (*14*). Using data from all time periods and for all firms, the natural logarithm of output is regressed on the natural logarithms of inputs, firm characteristics, and firm-specific dummies as well as a random error term. Firm-specific dummies (variables that have the value 1 for a particular firm and 0 for all other firms) are also interacted with time to capture variation over time. The coefficients of the dummies capture the firm-specific effects and are used to calculate the relative technical efficiency scores.

Figure 1 (iv) shows the production function under this approach. Since a regression, by definition, runs through the mean of the data and does not lie atop the observed points, it is not a frontier in the same sense as DEA and FDH; rather it can be thought of as a "statistical frontier" (*15*). Efficiency scores are calculated by determining the most efficient firm [Firm e in Figure 1 (iv)] and then measuring the other firms relative to it. This is achieved by shifting the estimated frontier up to the most efficient firm. In Figure 1 (iv) this shifted line is dotted and passes through Point e. Thus, Firm a's output-based score will be OA/OD < 1.

Cointegration

Once the various efficiency scores are obtained, the next step is to test whether they exhibit cointegration or convergence. Cointegration analysis examines the existence of long-term relationships between two variables each of which moves unpredictably through time. Such variables are called nonstationary. Cointegrated variables cannot move too far from one another. In contrast, a lack of cointegration suggests that the variables have no long-term link. To remain competitive, carriers would attempt to follow each other's efficiency advances, and as a result the efficiency scores should follow each other in the long run. Lack of cointegration of a firm's efficiency scores with those of its counterparts may indicate the firm's inability to capitalize on technology that the other carriers are using.

Before testing for cointegration it is necessary to test whether each carrier's time series of efficiency scores is nonstationary, since this analysis is not relevant if the series is stationary. Given nonstationarity, the cointegrating regression is estimated. Specifically, one carrier's efficiency score time series is regressed on a constant and another carrier's efficiency score time series. If the two time series are cointegrated, any linear combination of them will be stationary, and the residuals from the regression will also be stationary.

Engle and Granger (*16*) considered several tests to evaluate the null hypothesis of no cointegration and recommended two. One approach, popular because of its simplicity, is the Cointegrating Regression Durbin-Watson (CRDW), which tests whether the Durbin-Watson statistic of the cointegrating regression is significantly different from 0. It is a characteristic of a regression in which the residuals are nonstationary to have a DW statistic near 0. Thus, if a calculated DW exceeds the critical value, the null hypothesis of no cointegration is rejected in favor of cointegration.

The second test involves applying the augmented Dickey-Fuller method to the residuals obtained from a cointegrating regression. The simplest form of this test is based on the regression $\epsilon_t - \epsilon_{t-1} = a + b * \epsilon_{t-1}$, where ϵ_t is the error term in period t. If the coefficient of the lagged error term, b, is statistically significant, the error series is stationary, and a long-term relationship exists between the two variables in the cointegrating regression. Thus, the null hypothesis of no cointegration (H_0: $b = 0$) can be rejected in favor of cointegration.

Convergence

Whereas cointegration tests determine whether two nonstationary variables are tied together in a long-run equilibrium relationship, convergence tests determine whether there is a closing of the gap over time between inefficient and efficient carriers. Convergence theories are currently being pursued in the economic growth literature to determine whether productivity growth rates among countries have been converging over time. This theory can be extended to test how efficiency in the domestic airline industry has proceeded over the past two decades.

This hypothesis is tested two ways. The first measures the dispersion of the efficiency scores over time using the coefficient of variation. If convergence is present, the carriers' scores should cluster together more closely as time progresses. The second regresses the carriers' average growth rates in technical efficiency on a constant and the carriers' efficiency scores at the beginning of the sample period. An inverse correlation between the growth rate and the original efficiency score indicates convergence. In other words, the higher a firm's original 1970 level of efficiency, the slower that level should grow. The reason for this phenomenon again lies in the public good nature of technology, which means that there are spillover effects from leader carriers to follower carriers as the laggards learn from the innovators (*17*).

Efficiency Score Computation

The DEA and FDH linear programming computations were carried out using quarterly data from 1970 to 1990. The four inputs (K, L, M, and F) and one output (RTM) were used. Raw distance scores from each technique were then regressed on the characteristic variables (STAGE, LOADF, KSIZE, and PJET) as well as the dummies used in the SFA regression. Predicted values were obtained from each of these two regressions and normalized. Normalization is necessary to obtain values between 0 and 1 and is achieved by determining the largest predicted score from each time period and dividing it into the predicted scores for all airlines in that time period. This two-step procedure is necessary to control for differences in input and output characteristics that the stochastic frontier model includes as additional regressors (*18*). This modification allows for the comparison between the linear programming and stochastic frontiers results. The SFA regression was also carried out and the normalized scores determined.

Figure 2 shows the values of all three approaches for each airline over time. The notation on the time axis is year and quarter; for example, 70I refers to the first quarter of 1970. Not all graphs span the entire time period: Frontier ends 86II because it merged into People Express in 1985, which merged into Continental in 1987; Ozark ends 86III because it merged into TWA in September 1986; Piedmont and Western end 86IV because the former was absorbed by USAir in 1989 whereas the latter was acquired by Delta in December 1986. In some cases the data end before the actual mergers (several years for Piedmont) because after merger announcements are made, data reporting accuracy sometimes declines, and it was decided that a more conservative approach to data collection should be adopted.

RESULTS

General Observations

The SFA lines are much less volatile than the DEA and FDH plots because they are based solely on a linear regression. Furthermore, SFA consistently has only two break points for all carriers: one at 82II and one at 86IV. The first break point occurs when the industry leader, in terms of SFA efficiency measurement, switches from Frontier to Ozark. The second occurs when Ozark is absorbed by TWA leaving USAir the industry efficiency leader.

Whenever one carrier leapfrogs another to become industry leader under SFA, a break point will result because of the linear nature of the method and because the efficiency scores are now measured relative to a different airline. Frontier has the highest raw SFA efficiency score in each period until 82II and therefore has a normalized score of 1 in each of these periods. However, Frontier's raw score declines during this period, allowing other carriers' normalized efficiency scores to rise relative to it. Even-

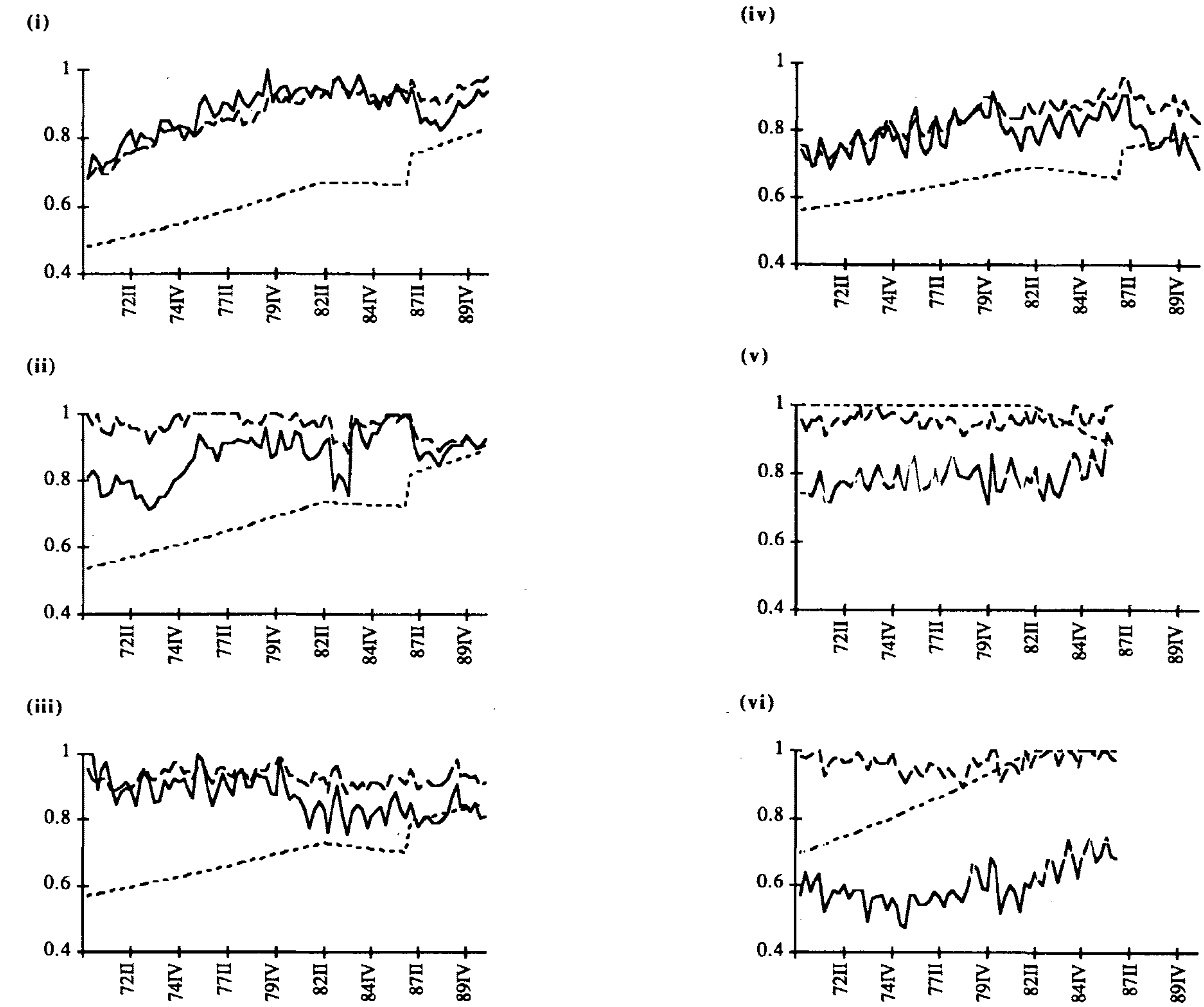


FIGURE 2 Time series of efficiency scores for each method and each airline: (i) American, (ii) Continental, (iii) Delta, (iv) Eastern, (v) Frontier, (vi) Ozark, (vii) Piedmont, (viii) Trans World, (ix) United, (x) USAir, and (xi) Western. (*continued on next page*)

tually Ozark catches up to and becomes more efficient than Frontier in Period 82II. After this Ozark's raw efficiency score grows much faster than its competitors, so their relative scores drop off. Frontier's and USAir's SFA lines drop off more quickly than the other carriers because their raw efficiency scores are declining over time.

In addition, the downturn in the SFA scores beginning in 1982 would probably not have occurred if capacity ton-miles instead of revenue ton-miles were used as the measure of output. The carriers were still moving approximately the same number of seats the same number of miles, so capacity was constant, but the percentage of seats filled declined, causing revenue ton-miles to fall. The carriers may have been operating as efficiently as before with respect to capacity ton-miles, but with respect to revenue ton-miles they were producing much less output with the same amount of input.

Finally, when Ozark merged with TWA, USAir became the leader in 86III because its raw scores were the highest among the remaining carriers. With USAir as the new leader, an upward-sloping line results as was the case under Frontier's leadership. Again, this occurs because USAir's raw scores are declining while the other carriers' raw scores are increasing over time, causing the other carriers' normalized scores to grow very quickly between 86III and 90IV.

A possible explanation for the declining raw efficiency scores of Frontier and USAir can be found in the convergence hypothesis, which states that laggards grow faster than leaders because it is easier to imitate than to innovate. As a result, firms like Frontier and USAir, which start out with the highest levels of SFA raw efficiency, grow more slowly or decline because the others in the sample are merely catching up to those with the more efficient technology.

Now consider the DEA and FDH plots, which follow each other much more closely than SFA because they are both based on linear programming. Correlation analysis reveals a relatively strong positive relationship between DEA and FDH (correlation coefficient = 0.369) compared with the relationship between DEA and SFA (correlation coefficient = -0.521) and between FDH and SFA (correlation coefficient = 0.134). Table 1 presents the correlation between each pair of methods for each airline and indicates the strong positive relationship between DEA and FDH. Associations between DEA and SFA and between FDH and SFA are much more

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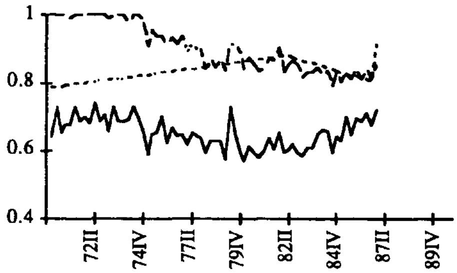

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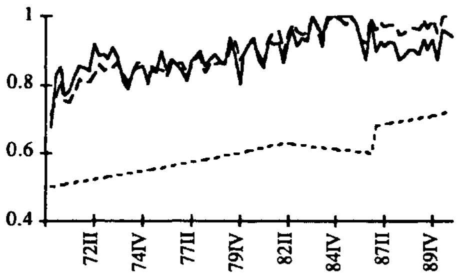

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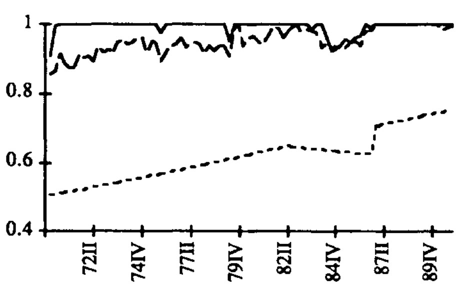

FIGURE 2 *(continued)*

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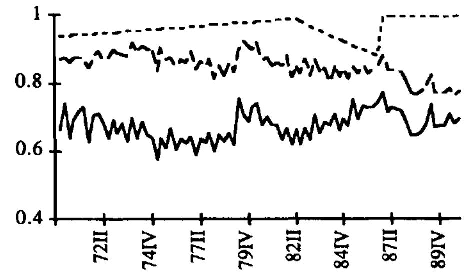

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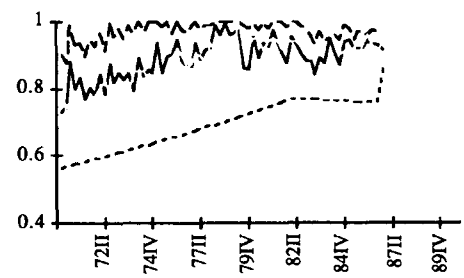


Legend:
Solid Line: DEA
Dashed Line: FDH
Dotted Line: SFA

The efficiency score is on the vertical axis and time is on the horizontal axis.

unpredictable from carrier to carrier. The linear programming, best-practice frontier techniques are apparently measuring technical efficiency in a different way from the statistical, average technology approach.

Some overall trends among the various lines are illuminating. The Big Three carriers—American, Delta, and United—are performing well. All three methods indicate that American's efficiency has been improving and that United's performance has remained strong throughout the past two decades. According to FDH and SFA, Delta's performance has remained steady or has improved, whereas DEA indicates only a slight downward trend. Another interesting result is apparent in the graph for Eastern, the only airline in the sample to fail. Both DEA and FDH indicate a deterioration in efficiency starting in the late 1970s. At that time Eastern began to experience labor unrest, which continued until Eastern's demise in early 1991.

Consider also the trends of the four firms that were merged or were facing merger into larger carriers in 1986. In general the scores for Frontier, Ozark, Piedmont, and Western were high or increasing, or both, just before this period. Ozark was recognized as the most profitable and best-managed carrier in the industry while it was operating, and this would have made it attractive to its competitors. Another influential factor in these mergers was the recession, during which carriers were not able to fill their planes because demand was no longer increasing as fast as it had in the past. Ozark and the other three carriers, however, had fleets of smaller aircraft and were not as adversely affected as the larger carriers. Thus, they would have been attractive to the larger carriers, who wanted to acquire the smaller carriers' capital equipment.

Cointegration

Since cointegration analysis can only be performed on nonstationary time series, tests for this characteristic are first performed on each carrier's time series of efficiency scores. The time series were found to be nonstationary for all carriers under all three methods with four exceptions: United and USAir DEA scores and Continental and Western FDH scores.

For the cointegration analysis of the SFA series, 110 cointegrating regressions are performed (each of the 11 carriers is regressed on one of the other 10 carriers). The simplest test for cointegration, the CRDW, indicates that cointegration does not exist between any two carriers. The second cointegration test also indicates no long-term relationships between most of the pairs of carriers with one exception: a pattern of cointegration exists between Ozark and the other carriers. This suggests that there was a leader-follower relationship between Ozark and the other carriers (consistent across all three efficiency-measuring technologies) that wished to emulate Ozark's position as the most profitable in the industry.

TABLE 1 Spearman Correlation Coefficients

	American:		Continental:		Delta:	
	FDH	SFA	FDH	SFA	FDH	SFA
DEA	0.773	0.570	0.400	0.497	0.674	-0.672
	(0.0001)	(0.0001)	(.0002)	(.0001)	(.0001)	(.0001)
FDH		0.898		-0.382		-0.138
		(0.0001)		(.0003)		(.2112)
	Eastern:		**Frontier:**		**Ozark:**	
	FDH	SFA	FDH	SFA	FDH	SFA
DEA	0.744	0.247	0.580	-0.305	0.739	0.601
	(0.0001)	(0.0235)	(.0001)	(.0128)	(.0001)	(.0001)
FDH		0.728		-0.200		0.231
		(0.0001)		(.1068)		(.0595)
	Piedmont:		**Trans World Airlines:**		**United Air:**	
	FDH	SFA	FDH	SFA	FDH	SFA
DEA	0.534	-0.663	0.859	0.639	0.289	0.024
	(0.0001)	(0.0001)	(.0001)	(.0001)	(.0076)	(.8254)
FDH		-0.600		0.862		0.818
		(0.0001)		(.0001)		(.0001)
	USAir:		**Western:**			
	FDH	SFA	FDH	SFA		
DEA	0.165	-0.064	0.664	0.566		
	(0.1341)	(0.5626)	(.0001)	(.0001)		
FDH		-0.335		0.175		
		(0.0018)		(.1527)		

(Probability > |R| under H_0: Rho = 0.)

These results are particular to the SFA method because of its linear nature. The SFA time series do not change direction often enough (only twice in our analysis) to determine whether the carriers are indeed following each other. Furthermore, the linear nature means that even the slightest difference in slope will reject the existence of comovement.

DEA and FDH, however, present the opposite conclusion. There are 72 pairs of carriers if United and USAir are excluded from the cointegration analysis of the DEA series. The two cointegration tests find 70 and 65 long-term relationships, respectively. If a 10 percent significance level is adopted instead of a 5 percent level, the second test yields 69 cointegrated pairs out of 72. Similarly, for FDH, omitting Continental and Western, the two tests yield 56 and 57 cointegrated pairs out of the possible 72. This is an overall acceptance rate of 86 percent.

Convergence

The convergence results also support the theory that technological advances become dispersed throughout the industry. Table 2 gives the coefficient of variation for each year and each method. For each of the three methods the amount of dispersion in 1990 is less than in 1970, which indicates convergence in technical efficiency. However, the coefficients for both DEA and FDH reach their lowest value in 1987 before rising through the remaining periods. This result may be attributable to the loss in 1986 of four carriers in the sample. The absorption of these competitors may have reduced the pressure among the survivors to continue their efforts to keep up with each other.

The second test of convergence involves the regression of growth rates on a constant and the initial efficiency levels. This also supports convergence. Figure 3 shows the carriers' average growth rates versus their initial levels. A negative relationship can be detected for all three methodologies. When a regression line is estimated for each method, the slope is negative and significantly different from 0 in all cases.

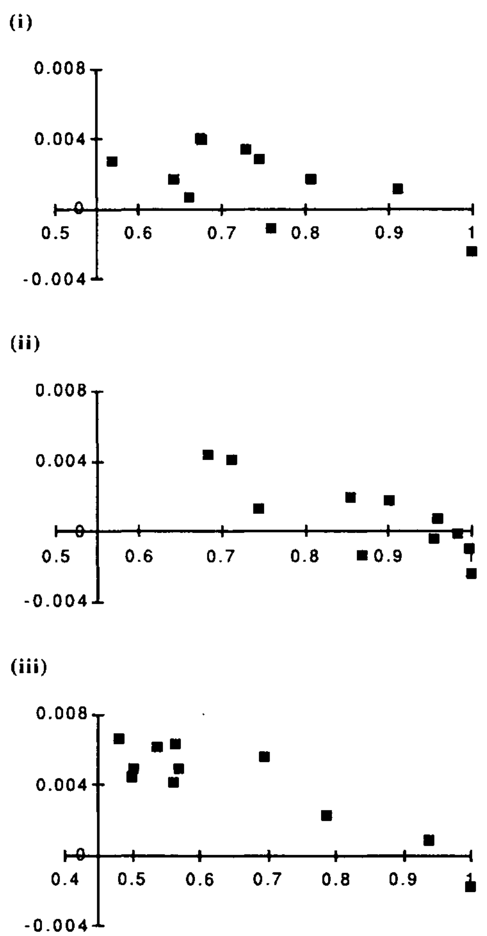
CONCLUSIONS

Economic theory suggests that, as an industry becomes more competitive, it becomes more important for a firm within that industry

TABLE 2 Coefficients of Variation

Year:	DEA:	FDH:	SFA:
1970	15.32	12.06	26.73
1971	14.64	10.83	25.78
1972	14.28	9.02	24.86
1973	15.53	8.34	23.96
1974	15.19	7.26	23.09
1975	18.09	7.57	22.25
1976	17.23	6.71	21.44
1977	17.23	6.47	20.67
1978	17.62	6.31	19.94
1979	15.57	5.03	19.26
1980	16.78	5.27	18.62
1981	16.87	5.59	18.04
1982	16.95	6.10	17.50
1983	15.87	5.97	17.04
1984	14.50	6.45	16.64
1985	13.20	6.19	16.31
1986	12.23	6.01	15.55
1987	9.89	5.39	12.30
1988	12.20	7.30	11.75
1989	11.21	7.36	11.23
1990	12.65	8.37	10.77

to perform efficiently relative to other firms if it is going to survive. This theory suggests two time patterns. First, the efficiency scores of the firms within the industry should not move too far from one another. If efficiency-enhancing technological advances made by one firm are not adopted by another firm, the two firms' efficiency scores will move apart. As a result, the firm that fails to follow innovations will eventually be driven out of the industry because its inputs are not being efficiently converted into outputs. Thus there is an incentive to keep up with movements of efficiency exhibited by other firms. This phenomenon is called cointegration. Second, the efficiency scores of the firms within the industry should also exhibit convergence over time. In other words, the scores should move closer together as firms realize that success in an increasingly competitive environment requires that they close efficiency gaps and become more alike in technical efficiency. To determine whether domestic airline carriers exhibit these two characteristics, three methods of measuring technical efficiency were performed. In general the hypotheses of cointegration and convergence were supported, indicating that the carriers are adopting efficiency advances made within the industry.



The average growth rate of efficiency is on the vertical axis and the initial 1970 efficiency score is on the horizontal axis.

FIGURE 3 Relationship between average growth rate of technical efficiency and initial levels: (i) DEA, (ii) FDH, and (iii) SFA.

These results are suggestive with respect to the direction of future industry structure. First, conventional wisdom holds that the firms remaining in the industry were able to do so because they adjusted to the increasing competitive pressure, whereas those that failed were not able to adapt. This observation is supported by the empirical evidence presented here. For example, Eastern's efficiency scores declined sharply before its demise in 1991. In addition, smaller carriers that exhibited strong or improving efficiency in 1986 were absorbed by the larger carriers, which found their performance and fleet configurations attractive. Finally, each of the remaining carriers has a general time pattern that is steady or increasing over time, and each of these carriers is still in the industry.

Furthermore, it is generally accepted that deregulation has led to more efficient use of resources in the industry. The evidence of cointegration and convergence provides empirical evidence to support this belief. As the firms have followed one another and become more alike, the industry's efficiency level has improved. The average efficiency under DEA was 0.789 in 1970, compared with 0.862 in 1990. For FDH the values are 0.882 and 0.917, respectively, and for SFA the values are 0.653 and 0.829, respectively. It can be argued that this is a positive effect of deregulation that most likely will continue into the future.

A final point concerns the applicability of this analysis to other industries. In particular, other transportation sectors such as trucking could be similarly studied.

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REFERENCES

1. Wykoff, F. C. Comment on Measurement and Efficiency Issues in Commercial Banking. In *Output Measurement in the Service Sectors* (Z. Griliches, ed.). University of Chicago Press, Chicago, Ill., 1992, pp. 279–287.
2. Sickles, R. C., D. Good, and R. L. Johnson. Allocative Distortions and the Regulatory Transition of the U.S. Airline Industry. *Journal of Econometrics*, Vol. 33, 1986, pp. 143–163.
3. White, L. J. Economies of Scale and the Question of Natural Monopoly in the Airline Industry. *Journal of Air Law and Commerce*, Vol. 44, 1979, pp. 545–573.
4. Charnes, A., W. W. Cooper, and E. Rhodes. Measuring Efficiency of Decision Making Units. *European Journal of Operational Research*, Vol. 2, 1978, pp. 429–444.
5. Berg, S. A., F. R. Forsund, and E. S. Jansen. Technical Efficiency of Norwegian Banks: The Non-Parametric Approach to Efficiency Measurement. *The Journal of Productivity Analysis*, Vol. 2, 1991, pp. 127–142.
6. Charnes, A., W. W. Cooper, Z. M. Huang, and D. B. Sun. Polyhedral Cone-Ratio DEA Models with an Illustrative Application to Large

Commercial Banks. *Journal of Econometrics*, Vol. 46, No. 1/2, Oct.–Nov. 1990, pp. 73–91.

7. Sherman, H. D., and F. Gold. Branch Bank Operating Efficiency: Evaluation with DEA. *Journal of Banking and Finance*, Vol. 9, 1985, pp. 297–315.
8. Charnes, A., C. T. Clark, W. W. Cooper, and B. Golany. A Developmental Study of DEA in Measuring the Efficiency of Maintenance Units in the U.S. Air Forces. *Annals of Operations Research*, Vol. 2, 1985, pp. 95–112.
9. Charnes, A., W. W. Cooper, and E. Rhodes. Evaluating Program and Managerial Efficiency: An Application of Data Envelopment Analysis to Program Follow Through. *Management Science*, Vol. 27, No. 6, June 1981, pp. 668–697.
10. Sherman, H. D. Hospital Efficiency Measurement and Evaluation: Empirical Test of a New Technique. *Medical Care*, Vol. 22, No. 10, 1984, pp. 922–938.
11. Deprins, D., L. Simar, and H. Tulkens. Measuring Labor-Efficiency in Post Offices. In *The Performance of Public Enterprises: Concepts and Measurement* (M Marchand, P. Pesieau, and H. Tulkens, eds.). Elsevier Science Publishers B.V. (North-Holland), Amsterdam, Netherlands, 1984, pp. 243–267.
12. Aigner, D. J., C. A. K. Lovell, and P. Schmidt. Formulation and Estimation of Stochastic Frontier Production Function Models. *Journal of Econometrics* , Vol. 6, No. 1, July 1977, pp. 21–37.
13. Schmidt, P., and R. C. Sickles. Production Frontiers and Panel Data. *Journal of Business and Economic Statistics* , Vol. 2, No. 4, Oct. 1984, pp. 367–374.
14. Cornwell, C., P. Schmidt, and R. C. Sickles. Production Frontiers with Cross-Sectional and Time-Series Variation in Efficiency Levels. *Journal of Econometrics* , Vol. 46, No. 1/2, Oct.–Nov. 1990, pp. 185–200.
15. Schmidt, P. Frontier Production Functions. *Econometric Reviews*, Vol. 4, No. 2, 1985–1986, pp. 289–328.
16. Engle, R. F., and C. W. J. Granger. Cointegration and Error Correction: Representation, Estimation and Testing. *Econometrica*, Vol. 55, No. 2, March 1987, pp. 251–276.
17. Baumol, W. J. Productivity Growth, Convergence and Welfare: What the Long-Run Data Show. *American Economic Review*, Vol. 76, No. 5, Dec. 1986, pp. 1072–1085.
18. Good, D. H., L. H. Roller, and R. C. Sickles. Airline Efficiency Differences Between Europe and the U.S.: Implications for the Pace of EC Integration and Domestic Regulation. *European Journal of Operations Research* (forthcoming).