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Race to the bottom or swimming upstream: Performance analysis of US airlines

Dipasis Bhadra*

Office of Aviation Policy and Plans, US Federal Aviation Administration, Washington, D.C. 20591

Abstract

Data envelopment analysis is used to examine inter-temporal and peer group airline efficiency. Results for the US for 1985–2006 indicate that airline performance is converging over time. In particular, airlines inter-temporal inefficiency peaked earlier and then converged. Furthermore, using Tobit specifications it is seen that while demand intensity matters less in determining airlines inter-temporal inefficiency, their influence is stronger in determining peer group inefficiency. Block time, a representative of operational factors, tends to negatively impact airlines efficiency by imposing burdens on airline operations. Among the structural cost and revenue factors, fuel cost tends to affect inter-temporal inefficiency more robustly than it does to peer group efficiency. Labor pay tends to reduce inefficiency in case of inter-temporal while increasing peer group inefficiency. The events of September 11th had little or no impact on inter-temporal inefficiency but tended to reduce peer group inefficiency in a significant way. Finally, airlines efficiency tends to be robustly affected by block hours; reducing them increases efficiency.

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1. Introduction

Soon after the economic slowdown of the spring 2001 and terrorist attacks on September 11, 2001 (9/11), many experts predicted imminent merger and consolidations as commercial carriers in the US found themselves, once again, under tremendous market pressures. Unlike in economic slowdown of 1991/1992, this time the pressure was more intense and caused by domestic demand shocks from 9/11, wars in Afghanistan and Iraq, and Severe Acute Respiratory Syndrome (SARS), rapid low-cost carriers (LCC) expansion; Internet expansion in travel bookings; sustained low-fare environment; and unprecedented increase in jet fuel prices that took hold in late 2005. In December 2005, almost half of the US industry output, measured by available seat miles (ASM), was under bankruptcy protection.

Despite these severe market conditions, few of the predictions involving merger and consolidation have materialized. Except for the US Airways merger with America West in 2005, liquidation of ATA, and Aloha, shutdown of Skybus operations and Frontier’s declaration of bankruptcy – all in April 2008, and the merger between Northwest and Delta, the basic operational structure of the US commercial airline industry appears to look very much the same in early 2008 as it did prior to 9/11. The main commercial airlines (often termed as network or legacy carriers) that run predominantly hub-and-spoke networks remain in the business: American, United, Delta (now linked with Northwest), USAir (merged with America West), and Continental. Indeed, their market share shrank as LCCs, largely Southwest, jetBlue, Air Tran, Frontier, and Spirit, expanded. However, the call for mergers and consolidation continues, as evidenced by the recent announcement of Delta’s merging with Northwest.

The market share of the LCC has significantly expanded. What used to be a nascent sector in late 1990s has grown into a powerful part of the industry constituting more than a third of the output. Furthermore, they wield considerable pricing power often led by Southwest Airlines. Despite all these challenges, commercial airlines in the US have so survived perhaps one of the most relentless pressures from the market environment and external events. The challenges continue as the industry faces higher fuel prices and a slowing economy in the latter part of 2008. Lost in this discussion, however, is the adjustment that the US airlines, particularly the legacy carriers, have made in the last few years. Capacity was adjusted downward more than 20% as they have retrenched into their hubs, incorporated considerable schedule flexibility, cut back employment and benefits, reduced services and outsourced routes to regional carriers, overhauled their maintenance and repair stations, rationalized their fleet and expanded international operations where the revenue environment is relatively more favorable than the domestic markets. Due to this, combined with increased load factors and some slowly emerging pricing power demonstrated seen in increased fare and fees, the US airlines industry posted profit in 2007. Faced with increasing fuel

* Tel.: +1 202 267 9027.
E-mail address: dipasis.bhadra@faa.gov

1 A Google search reveals that there had been many speculations regarding airline consolidation and mergers, especially after 2001. The financial firms particularly hedge and equity funds from the Wall Street, who hold significant holdings in airlines stocks now, appear to be in favor of such consolidations while the US Congress and labor unions are generally against it.
prices and an economic downturn, however, it is widely believed that the industry will lose a large amount of money in 2008.

What used to be a clear distinction between legacy carriers and LCCs is fading away. The dual characteristics that once existed in unit cost, yield, fleet structure, and network configurations is narrowing in the US commercial airlines industry. Against the backdrop of high fuel prices and other costs of operations, the former cost advantages of LCCs is narrowing as legacy carriers continue their cost cutting and withdraw services from unprofitable routes. Although considerable structural problems still remain among the legacy carriers, namely, an older fleet structure and an aging labor population, their streamlined cost-conscious operations have led to increased efficiency of the industry. In a market environment where air transportation is essentially a standardized commodity, structural duality is difficult to maintain.

Under this backdrop, a number of empirical questions arise: Are the airlines efficiencies truly converging over time? How does the efficiency of commercial airlines industry compare to each other, legacy versus LCCs? What are the ways commercial airlines adjust under market pressures? What kinds of adjustment mechanism or factors shaping airlines during this period of time? What can be said about the structure of the industry as it moves forward? This paper addresses some of these questions.

2. Previous analysis

To analyze US airlines’ performance and financial efficiency in pre-deregulation (1970–1977), during-deregulation (1978) and post-deregulation periods (1979–1992), Sirerog and Norsworthy (2001) used total factor productivity (TFP) approach. In particular, they examined the distributions of airlines stock returns to investigate whether deregulation had influenced risk in any detectable fashion. Their empirical results showed strong negative effects of deregulation on airlines stock returns. Interestingly, however, the authors found strong negative and unexpected effects of deregulation on the variance of stock returns.

In an analysis of performance of 45 US airlines, Vasigh and Flemming (2005) used the TFP approach using data from 1996 to 2001. They found national airlines with $100 million to $1 billion in annual revenue in the US domestic market have higher TFP than major commercial carriers (carriers over $1 billion in annual revenue). Authors found the estimated productivity differential was rooted in the hub-and-spoke configurations that commercial air carriers operate in the US. TFPs are estimated by fitting parametric methods, e.g. Cobb-Douglas and translog production functions. In comparison, the DEA approach employs relatively fewer assumptions and calculates individual DMU’s position vis-à-vis the production frontier.

Fethi et al. (2000) studied the performance of 17 European airlines utilizing DEA technique over the period of 1991–1995. Results were then explored using a Tobit model in an effort to identify the effects of various explanatory variables on airlines inefficiency. Identifying inefficiencies and detecting their sources via Tobit model serves a variety of policy purposes, wherever else. Finally, a set of structural and managerial factors is identified and isolates their impact on observed variations in inefficiencies. Some of these factors have long been believed to play an important role in determining airline efficiencies.

3. DEA methodology to examine US airlines efficiency

The US airlines industry made significant adjustments between 1985 and 2006. Some are easily visible while others are not. For example, Fig. 1 illustrates that legacy airlines’ employment declined, on average, by 5% from 1985/2001 period to 2002/2006. The total job losses were even bigger: almost 10% less people were employed from the annual average 357,000 for 1985 to 2001 to 322,000 during 2002–2006. Changes in employment at American
Airlines, Alaska, and Continental were not been large enough to offset the losses incurred by other legacy carriers, namely, Delta, Northwest, United and USAir. The sharpest declines were observed at the USAir followed by the United.

During the same period, LCCs registered a 127% employment gain [Panel B], moving from an average of a little over 28,000 full time employees (FTEs) during 1985/2001 (dark bars), the LCC employment increased to more than 64,000 during 2002/2006 (gray bars). A large part of this has come about through Southwest’s absolute expansion and jetBlue’s relative expansion.

The expansion in aircraft fleet structure, on the other hand, has been largely steady. Other than USAir, all legacy carriers have expanded, on average, their aircraft fleet holding (Fig. 2). Interestingly, aircraft fleet expansion by the legacy carriers was accompanied by a decline in the number of FTEs while aircraft fleet expansion at the LCCs was accompanied with the increase in employment. This provides the first sign that one side of the sector, namely legacy carriers, was undergoing structurally different changes enhancing productivity than the LCCs. These changes are even more pronounced when changes in the wage and benefits are taken into account. For example, average pay per FTEs for LCCs has increased over 48% from 2000 level to 2006 while it registered only 16% increase for legacy carriers during the same time periods.

Many other changes are less visible and often less noticed. For example, re-optimized schedule changes (Jiang and Barnhart, 2006), use of over-water and Q routes (Bhadra and Hogan, 2008), restructuring contracts including outsourcing routes to regional service carriers (RJs) (Hogan et al., 2007), and de-peak or de-hubbing (Franke, 2003) have been noted as means for restructuring services and cost. In addition, rationalized gasoline use by reducing extra weight (e.g. removing minimal accessories including reading materials and pillows, cleaning toilet in between segment stops, etc.) has also been noted in the press and elsewhere.

Faced with industry, market and regulatory rigidities creating obstacles for industry consolidation, US airlines have had very little choice but to enhance productivities at every level of resource use. Many of these restructuring steps have been tremendously effective in enhancing efficiency. In production economics literature
(see Varian (1999) for a basic discussion), efficiencies have been examined in two ways: technical and allocative. A firm is said to be allocatively efficient when the price it receives in the market place is equal to marginal costs associated with producing the extra unit of service. Technical efficiencies, on the other hand, evaluate a firm’s ability to produce maximum level/s of output (either single or multiple output) given the levels of input(s). The output-oriented approach to technical efficiency, first developed by Charnes et al. (1978) (CCR) and later modified by Banker et al. (1984) (BCC), captures the underlying production technology and productivity implications under constant returns to scale (CCR) and variable returns to scale (BCC). Alternatively, a firm can minimize the use of resources in order to produce a given level of output (i.e. input-oriented approach). Compared to the output-oriented method, input-oriented technical efficiency too captures both constant and variable returns to scale. While technical efficiencies relate primarily to the physical relationship underlying the production of goods and services, allocative efficiency refers to a firm’s allocation decisions faced with market prices for inputs and outputs. Thus, physical inputs and outputs are considered key to understanding technical efficiencies, while input prices and output prices are key to understanding allocative efficiency. Here the focus is on technical efficiency.

In panel A of Fig. 3, a basic output-oriented CCR model is presented for one-output and one-input case as an example. The input–output relationship of a firm or so called decision-making unit (DMU) in DEA is given. Thus, DMU1 is observed to produce at a point A by using a given amount of input (horizontal axis) to produce a certain amount of output (corresponding point in vertical axis). Other DMU’s input–output relationships are given by points B, C, D, and E.

Given these observations on the input used and output produced, one can derive the underlying production technology for the industry without any knowledge of the true production function, a substantial benefit leading to DEA evolution. In order to uncover the production function, let us draw a series of straight lines tangent to the observed relationships of DMUs. Straight lines touching the observed relationships at B and E represent the input–output relationships of DMU1 and DMU2, respectively. Notice that they are also observed upper bounds of the production technology representing the DMUs’ input–output relationships. This is because a line tangent to B when shifted downward parallel to point A reduces output, but does not reduce correspondingly, the level of input. Thus, DMU1 must be technically inefficient in comparison to DMU2. The same is true for point E. By drawing such lines and finding where the maximum output level is produced (frontier) and producible (observed), the technical efficiency frontier of the DMUs is drawn. A ratio of producible level of output over produced level of output provides a measure or index of technical inefficiency. For measuring relative efficiencies of a homogeneous set of DMUs for multi-input/multi-output frontier, the efficiency index can be constructed by taking the ratio of weighted sum of outputs over weighted sum of inputs. By construction, the lower bound of the index is restricted to be 1, representing technical efficiency while index value greater than unity indicates technical inefficiency. This measure of technical inefficiency is used for the empirical analysis.

The basic analytical framework with the assumption of constant return to scale can be formalized for activities by establishing the observed input–output relationships. Under input maximization (whose objective is to maximize output while keeping the same level of inputs or using less), the model can be described as:

\[
\begin{align*}
\text{Max} \; \theta & \quad \text{subject to} \\
\sum_{i=1}^{n} x_i \lambda_i & \leq X_0 \\
\theta y_0 - \sum_{j=1}^{q} Y_j \lambda_j & \leq 0 \\
\lambda_j & \geq 0, \quad \text{all } j.
\end{align*}
\]

where \(x_i\) is the input for DMU, \(y_j\) is the corresponding output, \(\lambda_i\) are the weights of DMU, and \(\theta\) is the shrinking or slack factor by which output can be increased. In other words, Eq. (1) states that DMU is said to be efficient if no other input combinations (from the observed data) can produce more output than \(Y_0\). If there are other input combinations that can produce more output than \(Y_0\), then DMU is termed as efficient in relation to other observed DMUs. Thus, the solution to the above linear programming (LP) problem finds the increment in levels of output given the observed level of inputs. A more generalized case of multiple output and input can be formalized by formulating an LP problem as:

\[
\begin{align*}
\max \phi & + \epsilon \left( \sum_{i=1}^{m} S_i^+ + \sum_{r=1}^{s} S_r^- \right) \\
\text{subject to} & \\
\sum_{j=1}^{m} x_{ij} \phi_j + s_i & = x_{io}, \quad i = 1, 2, \ldots, m; \\
\sum_{j=1}^{m} y_{ij} \phi_j - s_r & = \phi y_{io}, \quad r = 1, 2, \ldots, s; \\
\lambda_j & \geq 0, \quad j = 1, 2, \ldots, n.
\end{align*}
\]

where \(x_{ij}\) is required to produce \(y_{ij}\) and is the input, \(r\) is the output and \(j\) is the DMU unit. Furthermore, it is necessary that both input and output quantities meet strong positive and quasi-positive conditions as \(x_{ij} > 0\) and \(y_{ij} \geq 0\). The \(s_i^-\) and \(s_r^+\) are variables to
account for any slackness in input use while \( e > 0 \) is a non-Archimedean element defined to be smaller than any positive real number. The solution to the LP problem stated in Eq. (2) thus finds the increase in levels of output given the same observed levels of input uses (for other DMUs). This output-orientation provides insights into DMU’s technical efficiency. When \( \sum \limits_{j=1}^{n} \lambda_j = 1 \), there are variable returns to scale (VRS) (Zhu, 2004). The focus here is on output-oriented VRS technical efficiency.

4. Discussion of results

4.1. DEA results

For the discussion in this paper, I consider one output and six inputs. Available seat miles (ASM) is used as output of the airlines. Inventory adjustment of seats provides airlines active control to wither a difficult environment. Airlines adjust ASM quite frequently as had been the case soon after 9/11 and continue to do so at present. Unlike other aspects of the business (e.g. revenue passenger miles (RPM) or load factor (LF)), airlines have a greater decision-making authority over ASM and thus it serves as a good choice for output. Inputs are gallons of jet fuel, number of full time employees (FTEs); ratio of flight stage miles to trip stage miles; utilization of aircraft (in hours); number of seats per aircraft; and number of aircraft. Annual data for 1985–2006 is used. Data come from Airline Monitor’s processing of Form 41 and T100 database that is publicly available at the US Department of Transportation’s Bureau of Transportation Statistics.

Vasigh and Flemming (2005) used RPM in addition to ASM as outputs, although airlines typically have very little control over the demand side of the market as usually represented by RPM. The RPM, i.e. those paying for a seat mile, results from a mixture of demand and price. Airlines produce and supply ASMs given an anticipated price and a host of other factors. Important in all are the FTEs and jet fuel. Together, they accounted for almost 60% of the airlines’ operating expenses in 2008. Often, these inputs are considered to be variable costs of production and important factors in determining airlines performance. The ratio of flight stage to trip lengths is considered to be representing airlines’ underlying preference for network configuration. For example, a passenger traveling from city A to city C non-stop has the same flight stage and trip length. However, if this itinerary requires a stop-over at city B, the flight stage miles increases without necessarily reducing the trip length between A and C. With a considerable reliance on hub-and-spoke network (Bhadra and Texter, 2004), especially by the legacy carriers, it is expected that trip length and flight stage would diverge. The opposite would be true if the representative airline preferred spoke-to-spoke network, as appears to be the case for some of the LCCs. Since so much of the airlines business appears to ride on network configuration, consideration of this input as a measure of network configuration in the production of output, ASM, seems appropriate.

Over the years, evidence has emerged that two operational factors leading to LCC efficiency are their quick turn-around of aircraft and rational fleet structure. Quick turn-around is, ultimately, reflected by utilization of aircraft. Rationalized fleet structure is represented by a measure of seats per aircraft; more homogeneous the number of seats per aircraft, the more rational fleet structure airlines are presumed to have (e.g. B737 for Southwest; or A320 for jetBlue). Larger aircraft may produce higher ASMs but at the cost of higher turn-around time. Furthermore, a heterogeneous fleet structure (i.e. variable number of seats per aircraft) may also impose burdens on productive efficiency that cannot be clearly understood without comparing performance of one airline (i.e. those using homogeneous fleet structure) to another (i.e. those using heterogeneous fleet structure). Utilizing aircraft efficiently is a variable input while seats per aircraft and number of aircraft are essentially fixed capital investments. In determining both the levels and efficiency behind given levels of ASM, these variables also play crucial roles.

A relatively long period – 1985 to 2006 – is considered for two reasons: first, airlines adjustments are often cyclical, intricately related to economic ups-and-downs. Technical adjustments that are not long enough are often unable to capture these cycles. Second, airlines operations are capital-intensive and require a long gestation period. This often requires substitution among resources that cannot be captured in a short time horizon. Consideration of longer time periods thus provides a greater window into understanding the nature of the substitutions that lead ultimately to technical efficiency.

There are two components to technical efficiencies. First, an airline can be evaluated on the basis of its own technical performances over time – inter-temporal self-efficiency. That is, given the data for 22 years, one can use DEA methodology to evaluate representative airline’s own technical efficiency over time. For the 13 airlines and 22 years, runs were made to answer the question of how each airline has performed over time. As noted by Gillen and Lall (1997b) this is one of the significant benefits of the DEA measure in that it can be used for both inter-temporal as well as cross-sectional comparisons (Fig. 4).

The vertical axis measures the score of technical inefficiencies and the horizontal axis reporting annual years. As discussed earlier, the index has a lower bound of unity and represents efficient operation (i.e. producible equals to ASM produced), while index values greater than unity represents inefficiency. Results presented in the above figure indicates that while some airlines (Air Tran, Frontier, and Spirit) were doing relatively poorly in the beginning of their operations, their technical efficiencies improved and began to converge towards the index value of unity (i.e. technically efficient) as time progressed. Given limited operational history, for Spirit and Air Tran (erstwhile Valu Jet) in particular, doing well-required time and learning. Southwest’s inter-temporal performance deteriorated between 1995–2000 and again in 2003. In the beginning of the period and shortly after 2003, Southwest’s inter-temporal performance approached unity. It is also evident that almost all legacy carriers have done relatively poorly when compared against its inter-temporal performance earlier. However, all the legacy carriers appear to have gradually improved their technical efficiencies. In the final 3 years, for example, all the carriers’ performances converged to unity. Thus, in aggregate, airlines seem to learn from their past operational performances and improved technical efficiencies when compared to their own historical performance.

However, doing well compared to one’s own performance does not mean that one cannot still do poorly compared with, or that one is efficient more generally. In an industry that is as competitive as the airline industry, suppliers also need to perform well within their peer group and over time. Thus, an annual technical efficiency index is constructed for each of the 13 airlines – a peer group efficiency index. How well each airline performed within its own industry group in a particular year and over time is the focus of the next result. Results are seen in Fig. 5.

All the LCCs registered efficient operations in the peer group efficiency measure throughout. This result does not come as a surprise and further confirms the existing belief that LCCs are technically efficient providers of air travel. The peer group

\[2\] Air Tran, Frontier and Spirit did not begin their operations until 1994. jetBlue began its operation in 2000. Given these, the actual number of LP runs for this and subsequent exercises were 244.
inefficiency appeared to have been concentrated around in the middle of the 1990s, particularly during 1994–2000 and is pronounced for airlines such as Continental, Northwest, Alaska and USAir. A further interesting point is to note that prior to 1994 only Delta and Continental registered inefficient in their peer group comparison. Interestingly, American Airlines and United – two of the major legacy carriers – are found to be technically efficient.

Generally speaking, the performance of US airlines have steadily converged over time. In 2006 and the year before, only USAir and Alaska demonstrated technical inefficiencies compared to all their peers. In 2004, Continental demonstrated technical inefficiency in addition to Alaska. While Alaska continues to operate, USAir has now merged with America West. The latter’s performance had been fairly robust (with an efficiency index value of unity) over the entire

![Intertemporal (In) Efficiency](image)

**Fig. 4.** Inter-temporal self-efficiency.

![Peer Group Efficiency Comparison over Time](image)

**Fig. 5.** Peer group efficiency over time.
period. On the other hand, Continental demonstrated inefficiencies in 2003/2004 in comparison to its peer group, and subsequently, entered into bankruptcy in 2005. Interestingly, however, Delta did not show similar performance but it too entered into bankruptcy in the same year.

4.2. Tobit models

To provide some explanation for the variation in inter-temporal and peer group performance measures a set of variables that may have played roles in determining overall technical inefficiencies are examined. External and internal conditions under which airlines operate often influence overall productive efficiencies of airlines. For example, structural factors influencing demand such as load factor (LF), revenue passenger miles (RPMs), and yield provide external market pressure to perform productively well. As intensity of demand rises – with increasing LF and RPM accompanied with falling yield – it is expected that the pressure on airlines performing well may also rise. Greater demand intensity, however, is not necessary for technical efficiency. An airline can technically perform well irrespective of demand intensity but oftentimes airlines may have some latitude over demand intensity variables, particularly LF, provided they can influence its technical performance.

Factors such as number of departures (departures), number of passengers (passengers), aircraft days (AirCraft_Days), and block hours (block_hours) similarly provide operational environment within which airlines provide services. Increasing the number of passengers, when combined with larger number of departures, would require increased number of days that aircraft will have to service (i.e. longer hours of utilization). Increased block hours, on the other hand, would increase airlines efficiencies controlling for demand conditions and route characteristics.

Structural cost and revenue performance indicators are represented by operating ratio (of revenue and expenses; Oper_Ratio), fuel cost per gallons (in cents; Fuel_Cost_Gallon), and pay per FTEs (Pay_Empl). These factors too may influence airlines’ technical efficiencies in ways that are not captured in determining the magnitude of the technical efficiencies. Operating under a high cost environment, generally speaking, may induce higher technical efficiencies out of the resource use. On contrary, a supportive operating ratio may lead to higher efficiencies via X-inefficiencies and other managerial slacks. Finally, airlines made significant adjustments in their network following the events of 9/11. To capture this, a dummy variable is deployed that takes a value of unity on, and after, 2001 and zero before. Constructing these variables (i.e. structural demand intensity, operational factors, and structural cost and revenue performance factors) allows consideration of the proportion of the variation in observed efficiency that can be explained by the structural variables (i.e. model fit), and their affecting the proportion of efficiency.

To accomplish explaining this true or net efficiency index, the efficiency index generated from the DEA LP runs are used as dependent variables in regressions to identify the variables which may affect efficiency. The DEA efficiency measure has a lower bound of unity. By taking natural logs of the efficiency measure, I establish a lower bound for technical efficiency as zero and non-zero upper bound representing technical efficiency. In situations like these, it is customary (Gillen and Lall, 1997a,b; Diana, 2006) to use censored regression or Tobit model. Under this method, the dependent variable is censored at zero (called left censor) and right censored to values that are unbounded. The standard Tobit model can be represented as follows for observation \( i \):

\[
Y_i^* = \beta X_i + \epsilon_i \\
y_i = 0 \quad \text{if} \quad y_i^* \leq 0 \\
y_i = y_i^* \quad \text{if} \quad y_i^* > 0
\]

The dependent variable, \( y_i \), has a logarithmic value of 0 and a non-zero value for representing efficiency. While signs of estimated parameters (\( \beta \)) provide usual explanations, unlike ordinary least squares, the estimated coefficients of the Tobit model do not provide the marginal effects. The marginal effect of variable \( x_j \) is derived as:

\[
\frac{\partial E[y_i]}{\partial x_j} = \beta_j \phi_i
\]

The conditional marginal effect for variable \( j \) is derived as:

\[
\frac{\partial E[y_i | y_i > 0]}{\partial x_j} = \beta_j \left[ 1 - B' \phi_i \sigma \phi_i - \left( \frac{\phi_i}{\phi_i} \right)^2 \right]
\]

The SAS LIFEREG procedure is used to estimate the log of variations in performance index as the dependent variable and structural demand intensity, operational factors, and structural cost and revenue performance indicators as regressors. The results of the estimation for inter-temporal efficiency index are reported in Tables 1 and 2.

As noted, the efficiency index is represented by natural logs with a lower bound of zero. When this is regressed over the sets of exogenous variables discussed above, a positive coefficient would imply increasing inefficiency and vice versa. Following this, it is evident that inter-temporal inefficiency of airlines is not statistically dependent upon the structural demand intensity factors, such as LF, RPMs, and yield. In other words, external market conditions have no impact on how efficiently airlines bring their services over time.

On the other hand, operational factors have mixed results; while departures and passengers do not appear to have statistically detectable impact on inefficiencies, increasing block hours tend to increase airline inefficiencies while increasing number of aircraft days tend to reduce it. These two latter variables are statistically significant. Increased block time, while holding demand variables constant, increases airlines inefficiencies due to its imposition of time cost (i.e. padded or actual time) to serve the same demand. This finding hastens the need for improved technology and other reforms in the National Airspace System (NAS) that may help to reduce the block time between two travel points. Strong negative relationship between block time and efficiency also highlights the fact that carriers may find significant cost savings from actions that may indirectly reduce block time. Faced with typical trade-offs between hub connectivity (enhancing revenue) and productivity (cost enhancing), legacy carriers often try to maximize connectivity by accepting cost penalties for schedule constraints. Barring new technology and procedural improvement throughout the NAS (i.e. global solution), a certain reduction in connectivity at local airports (i.e. local solution) via de-peakng, for example, may result in substantial cost savings (e.g. release of aircraft, schedule integrity and punctuality) through reduction in congestion and thus average block time, as had been the case with American Airlines at Chicago’s O’Hare and Dallas-Fort Worth (Franke, 2003). Utilizing aircraft longer hours, on the other hand, reduces inefficiency. Faster turnaround and longer utilization hours for aircraft help airlines operate more efficiently and the result confirms this.

The structural revenue-cost condition (as captured by oper_-ratio) does not have any statistically detectable impact on airlines inter-temporal inefficiency. However, cost drivers such as pay per FTEs and fuel cost tend to reduce inefficiencies. These are significant results that one would expect for evaluating efficiencies over time. Increasingly, airlines operate under a high cost environment, especially after tripling of fuel cost in less than 3 years. Faced with this, airlines found ways to combine resources to deliver the same or higher levels of output. Consequently, their efficiencies improved
over time. Interestingly, 9/11 does not have any statistical impact on inefficiencies.

Results from the Tobit analysis explaining peer group inefficiencies are different than those reported for inter-temporal inefficiencies. Peer group inefficiencies report results for airline performance in comparison to those in their peer group for each year. Unlike the earlier results, structural demand intensity factors, namely LF and RPMs, affect airlines peer group inefficiencies in statistically significant ways. While increasing LF tends to increase inefficiency, increasing RPMs tend to reduce it. Increased LF leaves very little flexibility for airlines to achieve their productive efficiencies: the more seats filled on an aircraft (i.e. very little excess capacity), the less efficient its operations are, controlling for all other factors. Lack of flexibility that accompanies higher LF perhaps leads to increased inefficiency. Increased RPMs, on the other hand, tend to reduce inefficiency in a statistically significant way when evaluating peer group efficiency. The higher the overall demand for airline service, the greater the need to improve technical efficiency within the industry.

As with inter-temporal efficiencies, block hours are the only operational factor that appears to increase airlines inefficiency. Similar to the earlier explanation, increased block hours, when controlled for other operational factors, imposes unnecessary burdens on the production process and thus increases airlines inefficiency. Interestingly, while the intensity of aircraft use leads to a reduction in inter-temporal inefficiency, aircraft days are not statistically significant in explaining peer group efficiency.

Among the cost and revenue drivers, while fuel cost tends to increase inter-temporal efficiency, it is statistically insignificant in case of peer group efficiency. In other words, while fuel cost matters over time to attain greater efficiency, faced with the same unit cost, it tends to matter very little while comparing efficiency amongst the airlines. Furthermore, while pay per FTEs tends to increase inter-temporal efficiency, it tends to reduce peer group efficiency. That is, higher pay may improve an airline’s own efficiency over time (i.e. improving labor morale and generally improving working conditions), however, it tends to increase inefficiency when comparing within the peer group. In other words, while pay and benefit may matter to establish an operationally efficient airline over time, it is no match against peer group competition. Finally, while events of 9/11 have had little or no impact on inter-temporal efficiency, it tends to reduce inefficiency while comparing peer group inefficiency.

5. Conclusions

The paper offered a DEA approach to evaluate self-efficiency of airlines over time and across their peer group over time using 22 years of data. Airlines’ inter-temporal inefficiency peaked earlier over the period and converged during later years. Southwest performed somewhat less efficiently during two periods when compared against its own overall performance. Furthermore, the peer group results indicate that airlines inefficiency peaked during mid-1990s and were concentrated amongst a handful of airlines. All LCCs have been found to perform efficiently while compared within their own peers. Use of Tobit model to explain variations in airlines inefficiencies show that while demand intensity matters less in determining airlines’ inter-temporal efficiency, it matters more in determining peer group inefficiency. In particular, load factors tend to increase inefficiency while revenue passenger miles tend to reduce it. Among the operational factors, only block hours affect inefficiency; the longer the block hours, the less efficient airlines operations are. Among the structural cost and revenue factors, fuel cost tends to affect inter-temporal inefficiency more robustly than it does to peer group efficiency. Pay for labor, on the other hand, tends to reduce inefficiency in case of inter-temporal while increasing peer group inefficiency. Finally, the events of 9/11 have had little or no impact on inter-temporal inefficiency but tend to reduce peer group inefficiency in a significant way.

These results have potential policy implications. First, airline productivity appears to be converging over time. From the radical changes that took place over the last few years a single and relatively more efficient industry appears to be emerging. In an industry in which firms have similar performances, the possibility of them merging remains fairly high. The present merger scenario, led by Delta-Northwest, may be a prelude to this and perhaps what is to come. Second, it may not be useful to distinguish airlines, under these circumstances, by their operational characteristics (e.g. network versus LCCs). Third, airlines efficiency tends to be robustly affected by block hours; reducing them increases efficiency. In the short run, airlines can undertake schedule adjustments reducing block time and thus improving technical efficiency. In the long run, however, sustained reduction in block time would require fundamental changes in the route structures and underlying procedures leading to NAS-wide investments (e.g. NextGen technologies). Fourth, employees pay and benefit matter more in determining the long-term performance of the individual airline but less so when facing peer group competition. Therefore, labor policy will have to be harmonized if a unified industry structure is envisioned in the future. Finally, managerial control over LF and RPM should lessen. These controls have very little impact on the technical efficiency of airlines. Technical efficiency, in turn, determines long-term profitability.
Acknowledgement

An earlier version of this paper was presented at the annual meetings of the Transportation Research Board annual meeting in Washington DC in 2008. I would like to thank the participants and for their suggestions. I would also like to thank Jacqueline Kee, Kevin Gormley and Sheila McHale of The MITRE Corporation’s Center for Advanced Aviation System Development and Michael Wells of the Federal Aviation Administration’s Air Traffic Operations Service for their comments and suggestions. Comments and suggestions from two anonymous referees and the Editor of this Journal are also greatly appreciated.

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