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Size Versus Efficiency: A Case Study of US Commercial Carriers

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Abstract

As the demand for transportation with commercial aviation increases, each single day an airline will adjust their routes and services according to this demand. The main purpose of an airline is to increase the Shareholder Value Added (SVA) in their financial statements. Increasing the SVA value depends on high efficiency in daily flight operations. In this captioned paper, we researched five major airlines in US market American, Delta, United, Hawaiian, Jet Blue and Alaska airlines regarding to their efficiencies.

The data regarding 2012 - 2016 years for ten different airline variables were obtained from Diio Mi© software. After obtaining the data, the raw data was normalized. After, the efficiency of each airline for each selected year was calculated by Data Envelopment Analysis (DEA) in Lindo© optimization software. In the Conclusion, the efficiencies of all airlines were ranked according to calculated efficiency scores.

According to results, the efficiency of the airlines was relatively stable over the study time period and the airline with the most extensive fleet is in the lowest position in the efficiency ranking. We speculate based on the study results that one possible reason we obtained similar results for each year is that all the airlines in the study are major airlines and are competitors that benchmark each other in terms of efficiency and results with industrial optimization tools.

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Keywords: Airline Efficiency; US Airlines; Data Envelopment Analysis; Airline Productivity Factors

1. Introduction and Literature Review

Largani, Kaviam and Abdollahpor (2012) describe both the theory and potential applications of Shareholder Value Analysis (SVA), and discuss how shareholder value differs from traditional accounting measures of profitability. They contend that even projects that are profitable can, in fact, destroy shareholder value for enterprises. One difficulty however in comparing firms across sectors such as the airline industry is the challenge of distinguishing firms of

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different sizes and scales to determine their relative efficiency. Accordingly, in recent years Data Envelopment Analysis (DEA) has found increasing acceptance in many industries—including the airline sector—as a method of systematically measuring the input-output efficiencies of organizations either private or public.

A typical application of DEA normalizing comparative efficiency between competitors in a sector—such as airports or airlines—of different sizes whether within a single country or across borders utilizing historical input and output data. One research advantage of DEA is its versatility to measuring a wide range of input-output factors, and there is a substantial body of literature on the airline sector. For example, regarding recent research, Lu et al. (2012) looked at the effect of airline corporate governance on production and marketing for 30 airlines in the US using two-stage DEA. Controlling for average aircraft size, age and stage length they found that full-service carriers in the US were more efficient in marketing. But in contrast concerning corporate governance, the number of management committees and CEO-Chairman duality (i.e., both roles held by the same person) negatively impacted performance. More broadly related to corporate governance, some scholars have used DEA analysis to look at the performance of state-owned vs. non-state-owned carriers under liberalization. Utilizing DEA and a Malmquist productivity index study data between 2005 and 2009, Cao and Zhang (2015) concluded that non-state-owned airlines had both higher productivity and productivity improvement opportunities than state-owned Chinese airlines. They argue that the Chinese government reduce its support of state-run airlines in favor of fostering more non-state-owned ones. Shao and Sun (2016) used a network DEA to look at the comparative efficiency of 477 Chinese air routes in the wake of gradual, partial route liberalization. Their findings indicate that airports with many air routes also have high efficiencies, but that most Chinese air routes have a much lower efficiency for freight than for passengers.

A few recent DEA studies have looked at the technical efficiency of 'mainline' vs. 'low-cost carriers' (LCC). Barbot, Costa, and Sochirca (2008) used DEA and Total Factor Productivity (TFP) to look at a broad spectrum of carriers globally and concluded that LCC are in general more efficient than traditional carriers not because of size or input mix but rather because of the differences in their business models. Based on a bootstrapping DEA analysis of 42 airlines globally in 2006 that major traditional US and European carriers lagged in efficiency compared to LCC competitors, but interestingly were also less efficient than Asian peer airlines as a benchmark. Looking at both economic and environmental efficiencies, Chang et al. (2014) found similar results for Asian vs. European and US airlines but attributed it largely to fuel inefficiency and generally less diversified revenue sources. Yu, Chang, and Chen (2016) looked at 13 LCC airlines for the year 2010 and used DEA to look at capacity utilization and cost gaps with mainline airlines as factor inputs. In terms of study results, they found that more than half of the LCC airlines could benefit from improvements in capacity utilization. Duygun et al. (2016) using network DEA analysis to interestingly look at a broad range of European airline performance in the pre-Financial Crisis (2000-2007) and Financial Crisis (2008-2010) years. They found that European LCC adjusted more quickly than non-LCC airlines to the Financial Crisis. However, the authors also found that airlines in the 'EU-15' group in those years were much more efficient than their non-EU counterparts.

Several DEA airline comparison studies have been done at the individual country and regional levels as well. Gomes Junior et al. (2016) used both a classical and alternative DEA approach to look at airlines in Brazil. Tavassoli, Badizadeh, and Saen (2016) utilize a range adjusted approach to compare Iranian carriers. Marti, Puertas, and Calafat (2015) employ DEA to look at the comparative efficiency of 'hub and spoke' airlines in Spain with their point to point counterparts. Wenke and Barrios apply a Virtual Frontier Dynamic Range Adjusted Model (VDRAM) to look at 19 Latin American airlines over an extended period in the years 2010-2014. Their findings are exciting and contradict somewhat those in other regions, as the fleet mix in the form of smaller regional jets (Bombardier and Embraer for example) and public ownership, are found to result in higher efficiency. The authors postulate that this is due to the small, fragmented, regulated and publicly subsidized airline sector in Latin America.

For US airlines, the specific subject of this paper, in addition to the previously described studies comparing them globally a few recent articles are looking at them individually. Barros, Liang, and Peypoch (2016) find that there is no evidence based on their research of US airline performance between 1998 and 2010 international alliance membership, size or merger and acquisitions improved the efficiency of the studied airlines. However, the authors note that except for Alaska, AirTran, and Southwest all the airlines became more efficient over time during those years. Mallikarjun applied a three-stage DEA approach to 2012 data from 27 US airlines to derive a four-factor efficiency model and concluded that, on average, those airlines classified as 'major' are more efficient than those classified as 'national.' He speculates that this is due to the benefit of economies of scale at times of market failure and that this is evident in subsequent mergers. A recent paper by Choi (2017) uses DEA to loos comprehensively at the efficiency and productivity evolution of 14 US airlines between 2006 and 2015. Choi finds that there is a clear division among US LCC airlines in terms of efficiency and productivity, with 'mega-LCC' airlines like JetBlue Airways and Southwest Airlines reaching limits to growth and becoming vulnerable to a new type of US 'ultra-LCC' such as Allegiant Air and Spirit Air Lines.

2. Subject Airlines Background

DEA utilizes linear programming to evaluate the efficiency of decision-making units ('DMU') relative to other units with similar goals and objectives (Anderson et al., 2016). To evaluate the efficiency of a single unit, a composite weighted entity was developed from individual unit historical data and then compared to the composite entity. In this way, the relative unit input utilization at either the composite entity utilization or at the individual unit level was compared to the composite output.

To evaluate the relative efficiency of airlines, a panel of six US airlines was chosen. These airlines include both major primarily domestic and international airlines. Three major airlines with international exposure were selected: American Airlines, Delta Airlines, and United Airlines. These airlines have extensive international route structures and they are considered the 'Big 3 in the United States aviation market (along with Southwest, which has a cross-border network). According to the statistics website Statista (n.d), these three airlines collectively have an average of 35% of the US domestic travel market for the seven-year period from 2010 to 2016. According to the same website source they had collectively 58% of the US domestic travel market in 2017. Their collective market share makes their inclusion essential in any efficiency evaluation of the US market.

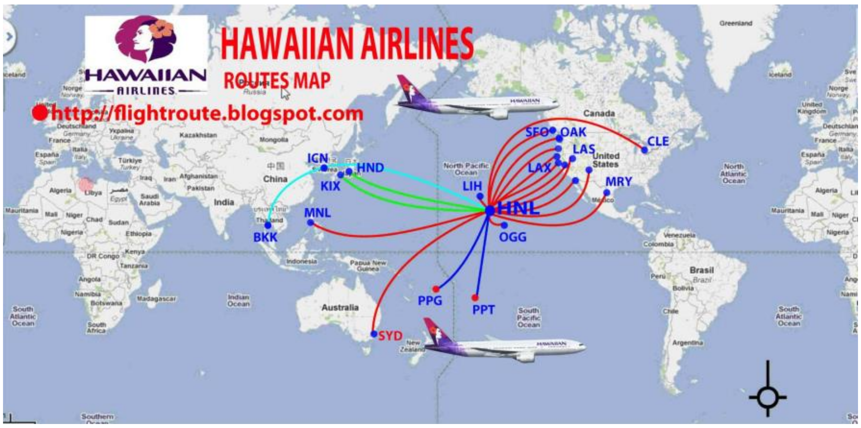
A second factor contributing to their inclusion in the study of these three US airlines was their participation in the major global alliance structure, and in fact, all three were founding members of the three global alliances existing today. American Airlines was a founding member of One World Alliance. The alliance was founded in 1999 by the founding airline according to their website About one world (n.d.). The One World Alliance has seen significant success since its inception, and One World was awarded seven of the leading international best airlines alliance titles in 2016. These awards included on-time performance service award for the fourth year, indicative of its operational efficiency and for that reason American Airlines is a good benchmark to evaluate other airlines in this study. Delta likewise was a founding member of Sky Team Alliance in 2000. Delta Airlines was awarded numerous titles in North America's leading airlines. And the performance of Delta performance exceeded One World Alliance counterpart, American Airlines. American Airlines came in second or third position in many recent years behind Delta in 2016 and 2017 according to the World Travel Awards website (n.d). Accordingly, Delta like its industry peer American, warranted inclusion in this study as one of the panel carriers. Lastly, United Airlines was a founding member Star Alliance in 1997, and today the airline is one of the most successful airlines in the US in terms of major legacy carriers. Although American, Delta Airlines and Southwest are arguably more successful in major Key Performance Indicators ('KPI') such as market share, United Airlines had preserved its place as the fourth major contributor to domestic market share in the US with an average of 8% market share from 2010 to 2016 according to Statista (n.d), and United Airlines held approximately 18% of US domestic market share in 2017. The success of United Airlines was fueled by its merger with Continental Airlines in 2010, as the new entity acquired leading presence in the main hubs according to Mouawad and Merced (2010). Accordingly, its inclusion in this DEA efficiency study was essential.

The fourth airline reviewed in the data set was due to its US domestic market share in 2017. Alaska Airlines was ranked fifth in terms of market share in 2017 by Statista website (n.d). Alaska has an interesting history since its inception in 1932 according to its website, Alaska airlines history by decade (n.d.). The airline has grown significantly and has steadily built its route structure throughout the years and today is fifth regarding US domestic air travel. Its route structure and excellent operational performance were factors in the choice as being one of the six selected carriers in this efficiency study.

The fifth airline in the airline data set is Jet Blue which is considered one of the more successful Low-Cost Carriers ('LCC') in the US travel market. The Airline has benefited from the deregulation act in 1978 in the 1990s (MacLennan, 2015). The company saw success with the economic boom in the 1990s with its relatively lower cost structure similar to the success of other LCC airlines in other countries. The company ranked as the fifth in terms of US market share in 2014 with profits over $400 million (source?). Jet Blue efficiency has contributed to its profitability levels. Its inclusion in the DEA study will lend comparison to the operational performance of more traditional carriers in the airline data set. A logical postulation is that Jet Blue might be expected to score highly in operational efficiency in this DEA study.

The sixth airline considered in the study is Hawaiian Airlines. Hawaiian Airlines is a unique case due to its network structure which is focused on flights located around six hours flight time from its Hawaiian home market (Figure 1). Its network structure targets both the US West Coast as well as Australian, Far East, and other Pacific island markets. This network structure requires a sufficient degree of efficiency in its day to day operations. Hawaiian, therefore, presents a compelling case to evaluate in this study vis a vis other airlines with greater potential economies of scale and network structures and a much different mix of short, medium and long-haul routes and fleets.

Figure 1 :Hawaiian Airlines Route Structure (Source: Flightroute.blogpost.com)



2. Mathematical Model Formulation

3.1 Variables and Collinearity Discussion

To utilize DEA to measure airline efficiency various and numerous inputs and outputs are required. In this study, five inputs and outputs were employed in the mathematical model for a period of five years (2012 to 2016). These inputs consider available resources utilization to the airlines, whereas the outputs cover the efficiency of those specific units to transform these inputs into outputs. To formulate the DEA model appropriately, each input and output is assigned specified weightings with all weightings adding to 1 per Anderson et al. (2016). These weightings are considered the contribution of each unit at the composite entity level. These weights were in turn added to both the input and output factors with an efficiency variable added to the input constraints, which is then used at a later stage to evaluate the efficiency of the specific unit in question. For this study, each weight was assigned the entity's first alphabetical letter. For example, American Airlines was designated 'A' and so forth, except for Alaskan Airlines, which to prevent variable duplication was assigned as 'S.'

The input and output mix contain both operational and financial variable. The use of both operational and financial variables ensure that efficiency is not only focused on either area. The profitability does not necessarily mean that the unit is operating efficiently and vice versa. The limitation to this is collinearity between variables. Some variables deemed necessary to the evaluation are highly correlated to other variables. A not on collinearity will be added after explaining each variables' category.

3.2 Input Variables

The input variables included in this study are defined as: Total operating expenses, fuel used, total salaries, available seat miles, and pilot numbers. These variables are considered to be required minimal inputs for any airlines to supply air travel. However, it must be acknowledged that pilot numbers may at least partially correlated to total salaries, and in fact correlation between pilots numbers and total salaries is found too high in all the airlines with a variance of 0.82 to 0.99 (with the lowest observed in Hawaiian and highest observed in Jet Blue). The other airlines also show high correlation but not as high as Jet Blue, so we speculate this may mean Jet Blue allocates a higher proportion of their salary portion to their pilots, whereas at other airlines increased salaries were less significant to pilots' salaries.

However, the correlation between total operating expenses and fuel cost factors is puzzling. American Airlines had a relatively high correlation between total operating expenses and fuel costs The correlation between both stood at 0.98, which might be somewhat expected intuitively. The second highest airline with a high degree of collinearity appeared to be Jet Blue, with a collinearity of 0.80. For Hawaiian, the collinearity stands at 0.54. This anomaly appears in the other three airlines with Delta and United Airlines showing a negative collinearity between total operating expenses and fuel cost used at the 30th percentile level. One possibility is that the widely varying correlation among the airlines in the study is due to the difference in fuel efficiency between the fleets, or perhaps due to fuel cost hedging strategy differences. But this is an area that warrants further research to understand the underlying causes. Although the collinearity between some inputs is high in some instances, these variables are included as they represent consistent relevant factors impacting comparative operational and financial efficiency in terms of total operating expenses among the study carriers.

3.3 Output Variables

The output variables for this study comprise: Total revenues passengers, property freight (i.e., revenue cargo); income before taxes; total yearly seats; and revenue flight hours. These variables are considered to be required determinants of the overall output level of any airline. Although some of the outputs, such as property freight, for example, are not applicable to all airlines, the variance is corrected by the weightings for the study airlines. Total revenue passenger figures are directly related to the economic performance of any airline. Income before the tax can be correlated as well to total revenue passengers; however, it also is impacted potentially by all other expenses as well. Intuitively, both figures are highly correlated, but the data indicates that the correlation between both variables is not as high as might be expected.

3.4 Normalization

Due to differing units used to report the ten study variables and the different scale of airlines used in the analysis, the potential range of the published figures is broad and need to be normalized. Therefore a decision was made to ally a normal log on all figures. This provided a narrower span between figures with all the variables. Although one of the advantages of DEA is its usefulness to measure varying scale units for inputs and outputs, normalizing the data helps to reduce the number of digits without affecting the results (The logarithm transformation (n.d).; Bazargan, 2018). Therefore in this study, it should be noted normal log figures were used on all the variables.

3.5 Super-Efficient Airline

The DEA is a precious and versatile analytical tool. However, one of its drawbacks in relying completely on DEA is having an efficiency coefficient of 1 with the highest value unit for either the input and/or output. In order to avoid a false conclusion indicating that a single unit is more efficient than others when actually this is not the case, for this study a reference benchmark hypothetical 'super-efficient airline' was introduced similar to the methodology utilized by Bazargan and Vasigh (2003). These 'super-efficient airline' input variables are formulated using the minimum of all the normalized inputs, divided by two. Likewise, the outputs variables are also created utilizing the maximum of all normalized outputs, multiplied by 2 (Bazargan, 2018). To determine results the efficiency of airlines are compared and ranked in relation to this fictional 'super-efficient airline'.

4. Collection of Airline Data

The data of American, United, Delta, Hawaiian and Jet Blue Airlines were collected from DIIO- MI business intelligence service. After the collection of data, all of the inputs are crosschecked with airline annual financial reports. The results are shown on the table 4.1 below as;

Table 4.1 Airline Annual Data

	2016	2015	2014	2013	2012
AMERICAN AIRLINES					
Total Operating Expenses	35.117.351	28.548.964	24.802.772	24.271.912	24.783.905
Air Fuels Issued	3.579.833	3.043.742	2.473.776	2.522.138	2.435.076
Total Salaries	8.347.265	6.024.557	4.336.784	4.079.287	4.167.006
Available Seat Miles (000)	241.732.311	200.373.202	157.598.377	154.496.666	152.626.802
Pilots and Co - Pilots	12.702	12.563	8.587	7.890	7.737
Transport Revenues Passenger	27.872.122	24.016.489	20.319.240	19.571.269	18.723.374
Property Freight	637.801	649.529	654.233	613.570	621.463
Income Before Income Tax	4.443.710	3.636.913	1.628.768	1.875.035	2.491.148
Total Yearly Seats	177.312.403	142.573.350	107.443.539	106.498.746	106.804.338
Revenue Flight Hours (Airborne)	2.948.404	2.462.288	1.959.693	1.923.627	1.866.026
DELTA AIRLINES					
Total Operating Expenses	32.873.182	32.971.114	37.501.946	33.980.512	34.268.490
Air Fuels Issued	3.405.591	3.382.830	3.261.990	3.162.801	3.081.671
Total Salaries	8.225.246	7.662.184	6.712.560	5.806.586	5.261.027
Available Seat Miles (000)	225.276.441	220.436.969	212.235.000	204.209.504	200.879.776
Pilots and Co - Pilots	12.026	11.476	10.741	10.547	10.606
Transport Revenues Passenger	27.375.877	28.217.526	27.952.948	25.800.595	24.427.387
Property Freight	598.001	695.405	799.757	801.805	865.028
Income Before Income Tax	6.672.662	7.169.132	1.097.035	2.535.721	1.160.882

Total Yearly Seats	169.875.053	162.247.626	151.416.099	144.547.413	139.156.468
Revenue Flight Hours (Airborne)	2.616.210	2.533.064	2.388.844	2.285.783	2.245.894
UNITED AIRLINES					
Total Operating Expenses	32.215.184	32.696.839	36.524.653	37.028.055	37.111.349
Air Fuels Issued	3.253.470	3.204.519	3.180.759	3.204.239	3.238.514
Total Salaries	7.670.946	6.930.027	6.288.515	6.124.875	5.560.748
Available Seat Miles (000)	224.652.630	219.956.361	214.061.327	212.977.166	216.299.365
Pilots and Co - Pilots	11.282	11.128	10.563	10.255	9.899
Transport Revenues Passenger	25.239.309	26.160.401	26.615.312	25.853.019	25.666.233
Property Freight	719.611	754.249	767.944	739.758	884.536
Income Before Income Tax	3.821.885	4.220.941	1.110.173	637.223	656.763
Total Yearly Seats	119.737.731	113.097.094	107.523.827	107.634.451	111.681.534
Revenue Flight Hours (Airborne)	2.410.240	2.386.502	2.365.511	2.384.040	2.425.446
HAWAIIAN AIRLINES					
Total Operating Expenses	1.965.817	1.882.133	2.062.360	2.018.349	1.829.886
Air Fuels Issued	243.212	233.365	229.681	226.214	199.464
Total Salaries	439.741	351.966	324.638	299.667	262.099
Available Seat Miles (000)	18.350.779	17.701.414	17.077.794	16.854.202	14.695.599
Pilots and Co - Pilots	654	602	599	613	601
Transport Revenues Passenger	2.130.501	2.010.666	2.038.347	1.943.043	1.767.195
Property Freight	70.709	76.573	76.736	63.640	47.407
Income Before Income Tax	387.172	311.413	129.986	102.570	98.810
Total Yearly Seats	13.565.745	13.144.861	12.572.412	12.204.842	11.966.657
Revenue Flight Hours (Airborne)	149.104	144.747	140.262	140.073	126.170
JET BLUE AIRLINES					
Total Operating Expenses	5.324.318	5.217.767	5.308.982	5.027.297	4.622.313
Air Fuels Issued	759.779	699.857	638.742	604.115	563.284
Total Salaries	1.152.617	1.058.276	973.797	877.538	810.773
Available Seat Miles (000)	53.705.129	49.347.007	45.028.135	42.851.520	40.095.015
Pilots and Co - Pilots	3.021	2.830	2.566	2.311	2.183
Transport Revenues Passenger	6.012.836	5.893.119	5.343.136	4.971.433	4.549.403
Property Freight	4	14.149	17.548	15.664	11.694
Income Before Income Tax	1.215.707	1.096.783	617.920	278.732	208.366
Total Yearly Seats	45.850.742	42.339.091	39.027.644	37.161.130	35.134.050

Revenue Flight Hours (Airborne)	832.390	778.709	723.808	694.420	647.844
ALASKA AIRLINES					
Total Operating Expenses	4.390.094	4.302.903	4.405.030	4.293.788	4.088.560
Air Fuels Issued	461.811	439.123	407.240	392.654	367.857
Total Salaries	933.235	874.409	800.123	734.590	679.861
Available Seat Miles (000)	38.720.547	35.917.395	32.434.497	30.416.563	28.185.008
Pilots and Co - Pilots	1.832	1.697	1.534	1.388	1.348
Transport Revenues Passenger	4.024.616	3.952.024	3.783.506	3.498.112	3.289.916
Property Freight	73.099	74.706	78.780	79.227	76.286
Income Before Income Tax	1.423.842	1.280.834	962.585	799.311	491.832
Total Yearly Seats	30.537.521	28.760.912	26.183.005	24.651.152	23.123.768
Revenue Flight Hours (Airborne)	515.493	489.141	454.170	439.963	414.511
SUPER EFFICIENT AIRLINE					
Total Operating Expenses	982.909	941.067	1.031.180	1.009.175	914.943
Air Fuels Issued	121.606	116.683	114.841	113.107	99.732
Total Salaries	219.871	175.983	162.319	149.834	131.050
Available Seat Miles (000)	9.175.390	8.850.707	8.538.897	8.427.101	7.347.800
Pilots and Co - Pilots	327	301	300	307	301
Transport Revenues Passenger	55.744.244	56.435.052	55.905.896	51.706.038	51.332.466
Property Freight	1.439.222	1.508.498	1.599.514	1.603.610	1.769.072
Income Before Income Tax	13.345.324	14.338.264	3.257.536	5.071.442	4.982.296
Total Yearly Seats	354.624.806	324.495.252	302.832.198	289.094.826	278.312.936
Revenue Flight Hours (Airborne)	5.896.808	5.066.128	4.777.688	4.768.080	4.850.892

The red coloured variables were used as input factors and purple coloured variables were used as output variables in linear programming calculations. The range of variables are very large to make calculations. Therefore we need to normalize the data with taking natural logarithm of all variables during the calculations.

5. Calculations

The management of company requires us to calculate the efficiency of each airline for each year. The required linear programming tool is Lindo software. In calculation with Lindo, we need to write a objective function regarding to efficiency of each airline.

In the calculations firstly, we need to define a composite airline which represents the sum of all airline variables. Then we will compare our calculated program results with the efficiency of the composite airline.

Let variables set as;

A = Efficiency of American Airlines,

U = Efficiency of United Airlines,

D = Efficiency of Delta Airlines,

H = Efficiency of Hawaiian Airlines,

J = Efficiency of Jet Blue Airlines,

S = Efficiency of Alaska Airlines,

Z = Efficiency of Super Efficient Airline,

C = Efficiency of Composite Airline.

The sample calculation for American Airlines and Delta for 2012 is given in the following section.

wa = weight applied to inputs and outputs for American Airlines

wu = weight applied to inputs and outputs for United Airlines

wd = weight applied to inputs and outputs for Delta Airlines

wh = weight applied to inputs and outputs for Hawaiian Airlines

wj = weight applied to inputs and outputs for Jet Blue Airlines

ws = weight applied to inputs and outputs for Alaska Airlines

wz = weight applied to inputs and outputs for Super Efficient Airline

Therefore we can write mathematical equations for each selected input and output variables as follows;

Output 1 for Composite Airline => wa Output A + wu Output U + wd Output D + wh Output H + wj Output J + ws Output S + wz Output Z. (1)

Input 1 for Composite Airline <= wa Input A + wu Input U + wd Input D + wh Input H + wj Input J + ws Input S + wz Input Z. (2)

5.1 American Airlines Calculation for 2012

The objective function of efficiency of American Airlines in 2012 is written below as;

Min C

Subject to

17.03 A + 17.35 D + 17.43 U + 14.42 H + 15.35 J + 15.22 S + 13.73 Z <= 17.03 C for total operating expenses,

14.71 A + 14.94 D + 14.99 U + 12.20 H + 13.24 J + 12.82 S + 11.51 Z <= 14.71 C for air fuels issued, 15.24 A + 15.48 D + 15.53 U + 12.48 H + 13.61 J + 13.43 S + 11.78 Z <= 15.24 C for total salaries,

18.84 A + 19.12 D + 19.19 U + 16.5 H + 17.51 J + 17.15 S + 15.81 Z <= 18.84 C for available seat miles,

8.95 A + 9.27 D + 9.2 U + 6.4 H + 7.69 J + 7.21 S + 5.71 Z <= 8.95 C for pilots and co-pilots,

16.75 A + 17.01 D + 17.06 U + 14.38 H + 15.33 J + 15.01 S + 17.75 Z => 16.75 for transport revenues passenger,

13.34 A + 13.67 D + 13.69 U + 10.77 H + 9.37 J + 11.24 S + 14.39 Z => 13.34 for property freight,

14.73 A + 13.96 D + 13.4 U + 11.5 H + 12.25 J + 13.11 S + 15.42 Z => 14.73 for income before tax,

18.49 A + 18.75 D + 18.53 U + 16.3 H + 17.37 J + 16.96 S + 19.44 Z => 18.49 for total yearly seats,

14.44 A + 14.62 D + 14.70 U + 11.75 H + 13.38 J + 12.93 S + 15.39 Z => 14.44 for revenue flight hours,

A + D + U + H + J +S + Z = 1

A,D,U,H,J,S,Z,C =>0

According to calculation results, the objective function is equal to 0,839.

5.2 Delta Airlines Calculation for 2012

The objective function of efficiency of Delta Airlines in 2012 is written below as;

Min C
Subject to
17.03 A + 17.35 D + 17.43 U + 14.42 H + 15.35 J + 15.22 S + 13.73 Z <= 17.35 C for total operating expenses,

14.71 A + 14.94 D + 14.99 U + 12.20 H + 13.24 J + 12.82 S + 11.51 Z <= 14.94 C for air fuels issued,

15.24 A + 15.48 D + 15.53 U + 12.48 H + 13.61 J + 13.43 S + 11.78 Z <= 15.48 C for total salaries,

18.84 A + 19.12 D + 19.19 U + 16.5 H + 17.51 J + 17.15 S + 15.81 Z <= 19.12 C for available seat miles,

8.95 A + 9.27 D + 9.2 U + 6.4 H + 7.69 J + 7.21 S + 5.71 Z <= 9.27 C for pilots and co-pilots,

16.75 A + 17.01 D + 17.06 U + 14.38 H + 15.33 J + 15.01 S + 17.75 Z => 17.01 for transport revenues passenger,

13.34 A + 13.67 D + 13.69 U + 10.77 H + 9.37 J + 11.24 S + 14.39 Z => 13.67 for property freight,

14.73 A + 13.96 D + 13.4 U + 11.5 H + 12.25 J + 13.11 S + 15.42 Z => 13.96 for income before tax,

18.49 A + 18.75 D + 18.53 U + 16.3 H + 17.37 J + 16.96 S + 19.44 Z => 18.75 for total yearly seats,

14.44 A + 14.62 D + 14.70 U + 11.75 H + 13.38 J + 12.93 S + 15.39 Z => 14.62 for revenue flight hours,

A + D + U + H + J +S + Z = 1

A,D,U,H,J,S,Z,C =>0

According to calculation results, the objective function is equal to 0,826.

During the calculations, we calculated all of the objective functions for 30 different optimization models with same methodology. The results of the calculations were given in the results section.

6. Results

To recap, the inputs and outputs for each airline for each year were given a weight to contribute to the composite airline. An extra airline that was called the ‘super-efficient airline’ was added to the set of the airlines in question. The inclusion of this airline enables a reflective evaluation of the efficiency of the other airlines instead of having many airlines with efficiency index of 1 because one or more input or output is relatively lower (inputs) or higher (outputs) compared to other airlines. Employing this technique, none of the airlines scored a 1 efficiency index. Instead, all airlines were less efficient than the ‘super-efficient airline’ which was the only airline scoring a 1. The ranking of the airlines as evident in the Lindo calculations are depicted in Table 6.1.

Table 6.1 Airline Efficiency Score Results

	2016	**2015**	**2014**	**2013**	**2012**
AMERICAN AIRLINES	0,830	0,836	0,845	0,845	0,839
DELTA AIRLINES	0,8339	0,832	0,8325	0,833	0,826
UNITED AIRLINES	0,833	0,832	0,832	0,831	0,823
HAWAIIAN AIRLINES	0,958	0,958	0,958	0,958	0,958
JET BLUE AIRLINES	0,900	0,903	0,905	0,907	0,902
ALASKA AIRLINES	0,917	0,919	0,923	0,925	0,921

So, we can order the efficiency scores for six different airlines regarding each selected year variables as follows;

H > S > J > A > D > U for 2012,

H > S > J > A > D > U for 2013,

H > S > J > A > D > U for 2014,

H > S > J > A > D = U for 2015,

H > S > J > D > U >A for 2016.

According to the overall estimation, we can conclude that

H > S > J > A >D > U

The inclusion of this airline did not affect the ranking of efficiency of the airlines. The differences between the structure of the airlines was the reason behind not seeing a difference between results with ‘super-efficient airline’ and without. The three major US airlines have different structure than the three other airlines which are more LCC model carriers. The three major airlines focus on scheduled international and domestic flights maintaining a lower yield than the point-to-point counterpart LCCs. The intuition that LCCs are inherently more efficient than other model airlines is confirmed using the DEA analysis. Hawaiian airline was the most efficient airline in the four years (table 4.3). Alaska Airlines and Jet Blue was the second and third most efficient airlines. The three legacy carriers proved to be less efficient than the LCCs with American Airlines in the forth position, Delta Airlines in the fifth position, and United in the last position.

The positions of the three legacy carriers come as a surprise because Delta Airlines was expected to be more efficient than American Airlines given its sterling record in the last few years. However, the superiority of American and Delta Airlines compared to United Airlines was expected. Moreover, the merger between American Airlines and US Airways had prospect of enhanced efficiencies given the performance of US Airways (Moss, 2013). The concern was the troubled American Airlines with its potential to file for bankruptcy. The expected biggest airline in terms of US domestic traffic would potentially means more efficient airline. The DEA analysis did not reflect the post-merger performance as the efficiency rank of the airline maintained its position through the years. Surprisingly, the airline was less efficient in 2016. This can only be explained by the time needed to integrate the two airlines together and reducing the inefficient redundancies in their operations.

7. Conclusion

This research report presents a DEA study of the efficiency of six major airlines in the United States with American, Delta, United, Hawaiian and Jet Blue in the sample set. The data study containing operational and financial operations for a five-year period between2012 to 2016 was collected from the DIIO research database. Secondly, the data was coded utilizing a normalization process. Finally, relative efficiency scores were generated from the DEA study and are used for ranking the six study panel airlines regarding relative efficiency. According to the results, all the airlines are efficient in relative terms to the ‘super-efficient airline’ open proxy. The ‘Super-efficient airline was constructed methodologically by multiplying the maximum output by two and then dividing corresponding the minimum input by two. The study results obtained a minimum score of efficiency in the calculated values of a 0.82. Although 18% lower efficiency in comparison to the composite airline (including the super-efficient airline) is considered acceptable, the airline industry has a very slight profit margin that the 18% lower efficiency can be a potential cause for revisiting the overall operational efficiency of the airlines. Accordingly, it can be inferred that the efficiency scores are too low to define any airline in the study as particularly inefficient and can conclude that all the airlines are efficient at an acceptable efficiency score of 82%. However, these airlines are advised to pursue extensive research to evaluate if these efficiency scores can be further enhanced given their existing structure.

The efficiency of Delta and United Airlines correspond so tightly that only a 0.005 % difference exists in efficiency rankings at most. The efficiency rankings are also similar for American Airlines in the year 2016 and in that year the airline had the minimum efficiency ranking. However, it should be noted that the difference in the efficiency of American Airlines changed only change 0.06% at most during the study period. Accordingly, we can conclude that the efficiency of the airlines was relatively stable over the study period for these airlines. The corollary to this is that based on the study results an airline must accept some efficiency loss with regards to operational constraints. This is evident in that the airline with the most extensive fleet is in the lowest position in the efficiency ranking, as explained earlier.

We speculate based on the study’s results that one possible reason we obtained similar results for each year is that all the airlines in the study are significant airlines and are competitors that benchmark each other concerning efficiency and results. However, there are efficiency differences between the larger three airlines in the study and smaller three airlines. Delta, American, and United are often described as industry peers, the ‘Big 3’ of the US airline industry. All three share common characteristics like multiple hubs, extensive domestic and international connecting traffic, and are ‘anchor’ US major alliance partners who have emerged from Chapter 11 bankruptcy reorganization and mergers. They also all have labor union agreements in an industry marked by benchmarking in wage negotiations among the Big 3 and over time this may result in a convergence in cost structures, but this is an area that warrants further research to determine if empirical research can validate this hypothesis.

One additional speculation conclusion is that as the airline grows in scale, revenue optimization efficiencies become more difficult. In contrast to the Big 3, the other airlines in the study (Hawaiian, Jet Blue, and Alaska) can be described as having different, ‘niche’ business model characteristics and this may be a contributing factor to their having higher efficiencies as compared to the fictitious ‘super-efficient’ comparison airline. But Hawaiian, Jet Blue and Alaska airlines are of sufficient size to employ similar optimization tools for all their operational and financial decisions. Like United, American, and Delta their network schedule, operations, revenue management and pricing optimization use sophisticated decision support tools albeit for a more straightforward network and fleet structure.

Finally, we would expect over time to see some similarities regarding cost inputs like fuel, labor, and pilots over time as these carriers’ benchmark against the Big 3 and in some cases (where their networks overlap) each other. This is however merely a postulation as well and further research using an expanded airline data set including possibly smaller and potentially less optimized airlines to determine if this is definitively the case empirically.

All the conclusions as mentioned above can support areas for potential research using the same mathematical model. Possible research can produce two separate models for each airline structure. This will create a fairer evaluation and would not reflect differences based on size, composition, fleet count, operational model, or agreements with third parties. The efficiency ranking will be based on business structure and strategies. Another way to tackle that is to produce two or more fictitious airlines representing each model and mode based on the average performance of single category airlines. Furthermore, the efficiency comparison can be against LCCs in different area locations, like comparing LCCs in Europe versus the US versus the Far East. Similarly, the comparison can include flag carriers in the separate area. Still, it is believed that using DEA to evaluate efficiency is a potent tool to help companies enhance their SVAs.

References

About one world (n.d.) Retrieved from https://www.oneworld.com/general/about-oneworld

Alaska airlines history by decade (n.d.) Retrieved from https://www.alaskaair.com/content/about-us/history/history-by-decade

Anderson, D. R., Sweeney, D. J., Williams, T. A., Camm, J. D., Cochran, J. J., Fry, M. J. &. Ohlmann, J. W. (2016). *And introduction to management science* (14. ed., ed.). Boston, Massachusetts: Cengage Learning.

Barbot, C., Costa, A. & Sochirca, E. (2008). Airlines performance in the new market context: A comparative productivity and efficiency analysis. *Journal of Air Transport Management, 14,* 270-274

Barros, C., Liang, Q.B. & Peypoch, N. (2013). The technical efficiency of US airlines. *Transportation Research Part A, 50,* 130-148.

Video on normalising data for DEA project. Bazargan, M. (Director). (2018) [Video/DVD] Daytona Beach, FL: Embry-Riddle Aeronautical University.

Bazargan, M., & Vasigh, B. (2003). Size versus efficiency: A case study of US commercial airports. *Journal of Air Transport Management, 9*(3), 187-193. doi:10.1016/S0969-6997(02)00084-4

Cao, Q., Lu, J. & Zhang, J. (2015). Productivity efficiency analysis of the airlines in China after deregulation. *Journal of Air Transport Management, 42,* 135-140

Chang, Y-T, Park H-S, Jeong J-B. & Lee, J-W, Q.B. (2014). Evaluating economic and environmental efficiency of global airlines: A SBM-DEA approach. *Transportation Research Part D, 27,* 46-50.

Choi, K. (2017). Multi-period efficiency and productivity changes in US domestic airlines. *Journal of Air Transport Management, 59,* 18-25

Duygun, M., Prior, D., Shaban, M. & Tortosa-Ausina, E. (2016). Disentangling the European airlnes efficiency puzzle: A network data envelopment analysis approach. *Omega 60,* 2-14.

Gomes Junior, S.F.., dos Santos Rubem, A.P., Soares de Mello, J.C.C.B., & Meza, L.M. (2016). Evaluation of Brazilian airlines nonradial efficiencies and targets using an alternative DEA approach. *International Transactions in Operational Research, 23,* 669-689

Largani, M. S., Kaviani, M., & Abdollahpour, A. (2012). A review of the application of the concept of Shareholder Value Added (SVA) in financial decisions. Procedia-Social and Behavioral Sciences, 40, 490-497

Leading airlines in the united states from 2010 to 2016, based on domestic market share (n.d) Retrieved from https://www.statista.com/statistics/445683/united-states-domestic-market-share-of-leading-airlines/

Lee, B. & Worthington, A.C. (2014). Technical efficiency of mainstream airlines and low-cost carriers: New evidence using bootstrap data envelopment analysis truncated. *Journal of Air Transport Management, 38,* 15-20

The logarithm transformation. Retrieved from https://people.duke.edu/~rnau/411log.html

Lu, W-M., Wang W-K., Hung, S-W, & Lu E-T (2012). The effects of corporate governance on airline performance: Production and marketing efficiency perspectives. *Transportation Research Part E, 48,* 529- 544.

MacLennan, A. (2015, April 27). How JetBlue airways became america's 5th largest airline. *The Morley F*ool Retrieved from https://www.fool.com/investing/general/2015/04/27/jetblue-airways-part-1-history.aspx

Mallikarjun, S. (2015) Efficiency of US airlines: A strategic operating model. *Journal of Air Transport Management, 43,* 46-56

Marti, L, Puertas, R. & Calafat, C. (2015) Efficiency of airlines: Hub and spoke versus point-to-point.. *Journal of Economic Studies, 42,* 157-166

Moss, D. L. (2013, November 21). Delivering the benefits? efficiencies and airline mergers. American Antitrust Institute. Retrieved from https://www.antitrustinstitute.org/sites/default/files/AAI_USAir-AA_Efficiencies.pdf

Mouawad, J., & Merced, M. (2010, May 2,). United and continental said to agree to merge. *The New York Times* Retrieved from http://www.nytimes.com/2010/05/03/business/03merger.html

Shao, Y. & Sun, C. (2016) Performance evaluation of China's air routes based on network data. *Journal of Air Transport Management, 55,* 67-75

Tavassoli, M., Badizadeh, T. & Saen, R.F. (2016) Perfomance assessment of airlines using range-adjusted measure, strong complementary slackness condition, and discriminant analysis. *Journal of Air Transport Management, 54,* 42- 46

Wanke, P. & Barros, C.P. (2016) Efficiency in Latin American airlines: A two-stage approach combining Virtual Frontier Dynamic DEA and Simplex Regression. *Journal of Air Transport Management, 54,* 93-103

Yu, M-M, Chang, Y-C, & Chen, L-H. (2016) Measurement of airlines' capacity utilization and cost gap: Evidence from low-cost carriers. *Journal of Air Transport Management, 53,* 186-193