Alanya Akademik Bakış Dergisi
Yıl: 2021, C:5, S:2, ss.793-814

Alanya Academic Review Journal
Year: 2021, Vol:5, No:2, pp.793-814

Financial Efficiency Measurement in Airlines and Determining Factors of Efficiency

(Research Article)

Havayolu İşletmelerinde Finansal Etkinlik Ölçümü ve Etkinliği Belirleyen Faktörler

Doi: 10.29023/alanyaakademik.809865

Veysi ASKER
Assistant Research, Dicle University, Civil Aviation High School, Department of Aviation Management
veysi-asker@outlook.com
Orcid No: 0000-0002-8969-7822

Nurhan AYDIN
Prof. Dr. Anadolu University, Faculty of Economics and Administrative Sciences / Department of Business Administration
naydin@anadolu.edu.tr
Orcid No: 0000-0003-2240-2548

How to cite this article: *Asker, V. & Aydın, N. (2021). "Financial Efficiency Measurement in Airlines and Determining Factors of Efficiency". Alanya Academic Review Journal, 5(2), pp.793-814.*

ABSTRACT

The aim of the study is to compare airlines by carrying out measurement of efficiency of them obtaining different business models in terms of financial. The other aim is to reveal variables which have influence on score of efficiency. With this regard, airlines are separated into two groups, namely, traditional and low-cost airlines based on their business models. While the measurement of traditional and low-cost airlines efficiency was carried out with Data Envelopment Analysis, factors affecting efficiency scores of airlines were determined by Tobit regression model. According to the results of the study, airlines obtaining low-cost business model are more efficient than airlines obtaining traditional business model in terms of financial. Moreover, large-scale traditional airlines are more efficient than medium-scale traditional airlines. In terms of Tobit regression model, there are different results for two groups.

Keywords:

Efficiency, Data Envelopment Analysis, Tobit regression model, Traditional airlines, Low-cost airlines

Received: 13.10.2020
Accepted:19.05.2021

1. INTRODUCTION

Air transportation, which appeared in 1990s and firstly was used for military purposes, started to be used for civil purposes with converting military aircraft into passenger aircraft after the Second World War. However, the development of air transportation was affected negatively by strict regulations in its first periods. First of all, with the deregulation movement which occurred in the United States of America in 1978, it can be said that the number of regulations curbing the development of air transportation have started to decrease. In the following years, along with liberal regulations, firstly occurred in the United States of America and then Europe and Asia, respectively, air transportation improved significantly. Especially, along with improvements in technological area and increasing globalization, booming air transportation contributes significantly to the development of countries, regions and cities in terms of socially, economically and culturally by shortening the distances between countries.

Today, air transportation industry, which improves and flourishes significantly thanks to legal regulations, is accepted as one of global industries which a great number of companies operate. In air transportation industry, with new airlines, it is seen that competition is on the rise. In this respect, companies operating in air transportation industry must develop different strategies to sustain their activities, to increase their market shares and revenues, and to decrease their costs. Within this scope, while some airlines focus on decreasing their costs, some others try to differentiate themselves, and the rest focus on specific markets. With implementing these strategies, air transportation industry has developed different business models. Thanks to these business models, airlines improve their performances and hence obtain competitive advantage against their competitors.

In the industries such as air transportation industry where change and transformation occur quickly, operational and financial activities affect each other intensively, the topic of operational and financial performance has an important position. Especially, recent economic crises and fluctuations in the prices of fuel have increased the importance of financial performance with regards to airlines (Vasigh, 2015: 96).

The aim of this study is to make efficiency measurements of 54 airlines between the years 2010 and 2017 which obtain different business models and to determine factors affecting efficiency. There are some important points that distinguish this study from similar studies. The first of these is the financial comparison of the airline companies that have adopted a different business model. The second is the financial analysis of the efficiency of airline companies in the post-2009 global financial and economic crisis period.

In the following parts of this study, similar studies in the literature were mentioned and information related to Data Envelopment Analysis and Tobit regression model were given. In other sections, variables used in analysis and performed analysis were mentioned in detail. In the last part, conclusion and suggestions were given.

2. LITERATURE

When examining studies on efficiency measurement in air transportation industry, firstly, Schefczyk's (1993) study was seen. Schefczyk measured 15 airlines' operational efficiency between the years 1989 and 1992 by defending that operational performance measurement is easier than financial performance measurement. In the following years, Good et al. (1995) measured efficiency of the biggest 16 airlines which operate in the United States of America and Europe between the years 1976 and 1986 by Data Envelopment Analysis.

Scherega (2004), firstly, measured efficiency of 38 airlines and then estimated variables affecting efficiency scores of airlines with Tobit regression model. Chiou and Chen (2006) measured service and cost efficiency of 15 domestic air routes of a Taiwan-based airline with Data Envelopment Analysis. In the second part of the analysis, variables affecting service and cost efficiency of airline were estimated by Tobit regression model.

In some studies on Data Envelopment Analysis, efficiency measurements were made by classifying airlines' business models. Barbot et al. (2008) carried out the efficiency measurement of 10 low-cost and 39 traditional airlines operating on four different continents for 2005 with Data Envelopment Analysis and Total Factor Productivity index (TFP). Bhadra (2009) first performed the efficiency measurement for the 1985-2006 period of a total of 13 traditional and low cost airlines based in the United States by Data Envelopment Analysis and then used the Tobit regression model to determine the factors affecting efficiency. Lu et al. (2012) used the two-stage Data Envelopment Analysis technique to measure production and market efficiencies of 19 traditional and 11 low-cost airlines operating in the United States for 2010.

Lee ve Worthington (2014) performed efficiency measurement of 29 traditional and 13 low-cost airlines, using Data Envelopment Analysis to compare operational performance in 2006. Mallikarjun (2015) compared efficiency of large scale and small scale regional American airlines in 2012. In the study, operating expense and Available Seat Miles (ASM) were used as input variables. On the other hand, operating revenue and Revenue Passenger Miles (RPM) were used as output variables. Yu et al. (2016) performed efficiency measurement of 13 low-cost airlines, using Data Envelopment Analysis to measure capacity efficiency, market productivity and cost effectiveness in 2010. During the analysis process, number of employees and aircraft, total quantity of fuel and number of routes were used as input variables. As output variable, Available Seat Kilometers (ASK) was used. Saranga and Nagpal (2016) performed efficiency measurement of 9 traditional and 4 low-cost airlines operating in India for the years between 2005 and 2013, using Data Envelopment Analysis to investigate the link between operational and market efficiency. In the study which measured technical and cost efficiency, while the number of employees, personnel expense, operating expense and Available Passenger Kilometers (ASK) were used as input variables, total revenue and Revenue Passenger Kilometers (RPK) were used as output variables. In the second part of the study, Tobit regression model was established to determine degree of influence of total revenue, average flight distance, average aircraft utilization rate, operating expense and the state of being low-cost (dummy variable) on efficiency scores. Yu et al. (2019) performed efficiency measurement of 8 traditional and 5 low-cost airlines operating in China and India for the period 2008 and 2015, using dynamic Data Envelopment Analysis, to evaluate operational performance. In the study using operational efficiency indicators, while the number of aircraft and employees were used as input variables, Revenue Passenger Kilometers (RPK) and Revenue Tonne Kilometers (RTK) were used as output variables. In the second part of the study, Tobit regression model was established to determine degree of influence of the state of airline being state owned (dummy variable), low-cost (dummy variable), average flight distance and the number of routes flown intensively on efficiency scores.

In most of the studies carried out in the air transportation industry, efficiency is measured from an operational point of view and the number of studies in which efficiency is measured from a financial point of view is very small. Pires and Fernandes (2012), in their study to examine the effects of the 2001 terrorist attack in the United States on the financial performance of airlines, measured the efficiency of 42 airlines in the period 2001-2002 by Data Envelopment Analysis. They used the malmquist total factor efficiency index to identify changes in the efficiency of airlines. In later years Wang et al. (2017), in their study to examine the financial performance of airlines, measured the efficiency of 49 airlines for the period 2008-2013 using the Data Envelopment Analysis technique. In this study, the total amount of debt, total operating expenses, fixed assets and total capital were evaluated as input variables, while market value and total income were evaluated as output variables. In order to determine the effect of total asset, the ratio of total debt to total asset, the ratio of long term liabilities to total asset, the rate of change in total revenues and airline's age variables on efficiency, truncated regression model was established. The study found that airlines performed worst in 2008 and 2009. While the ratio of total debt level to total assets and the age of the airline variables had a negative effect on efficiency, total assets, the ratio of long-term liabilities to total assets and the rate of change in total income variables had a positive effect on efficiency.

In recent years, studies examining the operational and financial efficiency of airline companies show that besides multi-criteria decision making methods (Pineda et al., 2018; Bakır et al., 2020; Kiracı and Bakır, 2020), slack-based (Chang et al., 2014), network (Lin and Hong, 2020) and fuzzy (Heydari et al., 2020) data envelopment analysis models are used.

It is thought that this study will contribute to the literature in that the number of studies in which the financial efficiency of the airlines is measured and the factors affecting the efficiency are examined is very small. This study also investigates the answer of which airlines applying different business models are more efficient.

3. DATA AND METHOD

3.1. Data Envelopment Analysis

Data Envelopment Analysis is a nonparametric efficiency measurement method developed to measure the relative efficiency measurements of units with homogeneous structure, expressed as decision-making units (Yolalan, 1993: 27). The Data Envelopment Analysis technique is an efficiency measurement technique that can measure the relative effectiveness of decision-making units with multiple input and output variables and is based on mathematical programming (Lang et al., 1995: 473). However, Data Envelopment Analysis is an analysis technique used to measure financial or operational efficiency in manufacturing activities, where many input and output variables cannot be directly performed by regression analysis (Akan and Çalmaşur, 2011: 17).

Data Envelopment Analysis is a method that allows relative efficiency measurement of decision making units by using various input and output variables (Pourjavad and Shirouyehzad, 2014: 144). Data Envelopment Analysis is also a measurement technique that measures the relative efficiency of decision-making units, assigns scores ranging between “0” and “1”, and has no parametric property (Ohsato and Takahashi, 2015: 513).

The Data Envelopment Analysis technique is a method of measuring the efficiency of decision-making units with similar properties through input and output variables, which are expressed as performance measurement indicators. In addition to this, it is a method that can measure the distance of other decision-making units to the efficiency limit by creating the efficiency limit according to the decision-making units that perform best (Zhou et al., 2018: 2).

The models in the Data Envelopment Analysis technique are classified based on different criteria. First, CCR models which are based on the assumption of constant returns to scale and input-output oriented DEA models. In later years, BCC models which are based on the assumption of variable returns to scale were used (Adler et al., 2002: 251).

3.1.1. CCR Models

Developed by Charnes, Cooper and Rhodes in 1978, the CCR model features the first basic DEA model. Based on the assumption of fixed returns by scale, this model is able to determine the source and amount of inefficiency by calculating the total efficiency scores of decision-making units (Charnes et al., 1978: 432).

The CCR model is able to measure the efficiency of decision-making units both individually and collectively based on the assumption of fixed returns by scale (Weng et al., 2009: 41). The mathematical expression of the CCR model is included below (Cook and Zhu, 2005: 5):

$$Q_k = \max\left(\theta + \varepsilon\sum_{i=1}^{m} S_i^- + \varepsilon\sum_{r=1}^{s} S_r^+\right) \tag{1}$$

Constraints,

$$\sum_{J=1}^{n} X_{ij}\,\beta_j + S_i^- - X_{ik} = 0 \qquad i = 1, \dots \dots m \tag{2}$$

$$\sum_{J=1}^{n} Y_{rj}\,\beta_j - S_i^- - \beta_j Y_k = 0 \quad r = 1, \dots . p \quad j = 1, \dots n \quad = 1, \dots . m \tag{3}$$

$$\beta_j \geq 0 \qquad\qquad S_i^- \geq 0 \qquad\qquad S_r^+ \geq 0$$

In the model,

θ: The expansion coefficient, which indicates at what rate to increase the output amount of decision-making units, for which the efficiency measurement has been performed relatively,

β_j : The density scores taken by the decision-making unit with variable "j" in output oriented models,

S_i^- : The idle scores of the decision-making unit with input variable "i",

S_i^+ :The idle scores of the decision-making unit with output variable "r",

3.1.2. BCC Model

The model, named BCC in the literature, was introduced in 1984 by Banker, Cooper and Charnes. The BCC model, based on the assumption of variable returns by scale, can determine the source and amount of inefficiency by measuring the technical efficiency of decision-making units. While the total efficiency of decision-making units can be measured with CCR models, the technical efficiency can be measured with BCC models (Cooper et al., 2007: 92).

The mathematical structure of the BCC model is shown below (Elsayed and Khalil, 2017: 2):

$$E_o = Max(\,\theta + \varepsilon \sum_{i=i}^{m} S_i^- + \varepsilon \sum_{r=1}^{p} S_r^+\,) \tag{4}$$

Constraints,

$$\sum_{j=1}^{n} X_{ij}\beta_j + S_i^- - X_{ik} = 0 \qquad i = 1,2, \dots m \tag{5}$$

$$\sum_{j=1}^{n} y_{rj}\beta_j - \theta Y_{rk} - S_r^+ = 0 \qquad r = 1,2,\dots p \tag{6}$$

$$\sum_{j=1}^{n} \beta_j = 1 \tag{7}$$

$$\beta_j \geq 0 \quad S_i^- \geq 0 \quad S_i^+ \geq 0 \quad j = 1,2,\dots n \quad i = 1,2\dots.m \qquad r = 1,2,\dots.p$$

3.2. Tobit Regression Model

The Tobit model first appeared in 1958 in a study by James Tobin. The Tobit model, found with the development of the Probit model, refers to models in which the dependent variable is located in a given range. James Tobin used the Tobit model in his study to estimate the relationship between household spending on durable consumer goods and household income (Gujarati and Porter, 2012: 574).

If a regression prediction does not obtain all of the observation scores or all the scores of the dependent variable can be observed but defined in a specific range or a limited manner, this requires the use of a different regression prediction model. Tobit models with restricted dependent variables are used in the analysis process of such data (Sengül et al., 2013: 87-88). Censoring is a condition in which the scores of dependent variables are only partially known. In this respect, another name of the Tobit model is also known as censored model (Greene, 2003: 224). The mathematical formula of the Tobit model is as follows (Üçdoğruk et al., 2001: 14):

$y_i = 0$ if $y_i^* \leq 0$,

$y_i = y_i^*$ if $y_i^* > 0$,

$y_i^* = x_i'\beta + u_i$ (i = 1,2,3….n)

x_i' = Independent variable which is observed for each state,

y_i = Latent dependent variable, which is limited to scores less than 0 or greater than 0 or equal to 0,

u_i= Error term,

β= Shows the coefficients to be estimated.

4. EMPIRICAL FINDINGS

In this study, financial efficiency measurement of 54 airline companies operating in many parts of the world and applying different business models was carried out through Data Envelopment Analysis. Then, Tobit regression model was established in order to determine the factors that influence the efficiency scores of airlines. Financial data on airlines were obtained from the Thomson Reuters Datastream Database.

The study included 37 traditional airlines and 17 low-cost airlines. Traditional airlines included in the study were included in the analysis in two separate groups, large and medium-sized, in order to give more reliable results of efficiency measurement. In the study, large-scaled traditional airlines include 19 airlines whose data can be accessed from among the World's top 25 airlines according to the Revenue Passenger Kilometers (RPK). Medium-sized traditional airlines include 18 airlines whose data can be accessed from among the largest 25-50 ranking in the World according to the Revenue Passenger Kilometers (RPK).

This process is very important because the selection of input and output variables to be used in the measurement of efficiency with Data Envelopment Analysis will directly affect the results of the analysis. In this study, similar studies in the literature were examined and the input and output variables used most in financial efficiency measurement were utilized. However, variables that best reflect the financial performance of the air transportation industry have also been used. The input and output variables used in the research are included in the table below.

Table 1. Input and Output Variables Used in DEA Analysis

Input Variables (Independent Variable)	**Abbreviations**
Total Capital / Total Asset	TC/ TA
Long Term Liabilities/ Total Asset	LTL/ TA
Fixed Asset/ Total Asset	FA/ TA
Current Asset/ Current Liabilities	CA/ CL
Output Variables (Independent Variable)	**Abbreviations**
Net Profit/ Net Sales Or Revenues	NP/ NS
Net Profit/ Total Asset	NP/ TA
Net Sales Or Revenues/ Total Capital	NS / TC
Net Sales Or Revenues/ Total Asset	NS / TA
Dependent Variables	**Abbreviations**
Total Efficiency	TE
Technical Efficiency	PTE

4.1. Data Envelopment Analysis Finding

After determining the input and output variables of the airlines, efficiency measurement for the period 2010-2017 was carried out through the Data Envelopment Analysis technique. The efficiency measurement of the airlines included in the study was carried out through the Deap 2.1 software program.

The efficiency measurement of airlines was carried through CCR and BCC models. While total efficiency scores of airlines are calculated with CCR model, technical efficiency scores are calculated with BCC model.

When examining studies on Data Envelopment Analysis in air transportation industry, there are two different views on which model should be used. According to the first view, output-oriented model should be used as airlines have limited control on input variables and airlines can increase their efficiency by modifying output variables (Bhadra, 2009; Assaf and Josiassen, 2011). According to the second view, input-oriented model should be used because airlines have more control on input variables than input variables (Sakthidharan and Sivaraman, 2018; Saranga and Nagpal, 2016). Due to input and output variables used in the study, output-oriented Data Envelopment Analysis will be used.

The efficiency scores of large-scale traditional airlines included in the analysis are shown in Table 2.

Table 2*. Efficiency Scores of Large-Scale Traditional Airlines

KOD	2010		2011		2012		2013		2014		2015		2016		2017	
	CCR	**BCC**	**CCR**	**BCC**	**CCR**	**BCC**	**CCR**	**BCC**	**CCR**	**BCC**	**CCR**	**BCC**	**CCR**	**BCC**	**CCR**	**BCC**
SU	0.584	0.597	0.842	**1.000**	0.911	0.915	0.541	0.551	0.768	**1.000**	0.761	**1.000**	**1.000**	**1.000**	0.668	0.674
AC	0.447	0.452	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	0.716	0.938	0.400	0.403	0.535	0.601	0.974	0.981
CA	**1.000**	**1.000**	0.844	**1.000**	**1.000**	**1.000**	0.601	**1.000**	0.738	**1.000**	0.724	0.728	0.840	**1.000**	0.908	**1.000**
AF/KL	0.495	0.594	0.838	0.927	0.628	0.619	0.743	**1.000**	**1.000**	**1.000**	0.949	**1.000**	0.527	0.527	0.457	0.506
AA	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	0.316	0.317	0.537	0.541	**1.000**	**1.000**	0.585	0.649	0.568	0.587
NH	0.314	0.378	0.571	0.679	0.393	0.404	0.207	0.225	0.282	0.283	0.337	0.354	0.406	0.477	0.539	0.582
AV	0.513	0.529	0.811	0.915	0.828	0.837	0.549	0.551	0.417	0.421	0.339	0.345	0.394	0.396	0.349	0.351
MU	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	0.935	**1.000**	0.752	**1.000**	0.868	0.877	**1.000**	**1.000**
CZ	0.754	0.738	0.892	**1.000**	0.812	**1.000**	0.595	0.597	0.508	0.547	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**
DL	0.689	0.699	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	0.586	0.588	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**
JL	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	0.704	0.732	**1.000**	**1.000**	**1.000**	**1.000**	0.879	**1.000**	**1.000**	**1.000**
KE	0.530	0.592	0.433	0.441	0.490	0.497	0.534	0.543	0.342	0.371	0.476	0.509	0.504	0.505	0.520	0.529
LA	0.850	0.861	0.759	0.803	0.353	0.363	0.312	0.312	0.393	0.428	0.383	0.388	0.297	0.298	0.322	0.335
LH	0.616	0.653	0.986	**1.000**	0.853	0.875	0.690	**1.000**	0.789	**1.000**	0.767	0.974	0.573	0.576	0.637	0.701

* in order to save space, the binary abbreviation codes given by IATA (International Air Transport Association) were used instead of the names of the airline companies.

QF	0.422	0.433	0.598	0.654	0.541	0.544	0.413	0.419	0.596	0.665	0.683	0.707	0.811	**1.000**	0.955	0.978
SK	0.607	0.631	0.970	**1.000**	**1.000**	**1.000**	0.836	**1.000**	0.726	0.791	0.613	0.621	0.648	0.693	0.599	0.621
OO	0.307	0.322	0.586	0.774	0.345	0.352	0.183	0.241	0.167	0.214	0.237	0.285	0.157	0.194	0.629	0.695
TK	0.267	0.292	0.679	0.756	0.578	0.596	0.590	0.592	0.623	0.617	**1.000**	**1.000**	0.204	0.204	0.263	0.267
UA	0.591	0.655	0.910	0.868	0.850	0.871	0.858	**1.000**	**1.000**	**1.000**	0.589	0.618	0.693	0.713	0.700	0.706

Table 2 shows that among large-scaled airlines, JL (Japan Airlines), DL (Delta Airlines), MU (China Eastern), CA (China Airlines), CZ (China Southern) and AA (American Airlines) performed better than other companies in the relevant period. NH (All Nippon Airways), AV (Avianca), KE (Korean Airlines), LA (Latam Airlines) and OO (Skywest) coded airlines were not efficient during the entire period.

As of 2010-2017, it was determined that the number of large-scaled traditional airlines included in the analysis reached the efficiency limit in different years was around 30%. Large-scaled airlines had their best financial performance in 2012 and their worst in 2010.

The efficiency scores of medium-scaled traditional airlines included in the analysis are shown in Table 3.

Table 3. Efficiency Scores of Medium-Scaled Traditional Airlines

KOD	**2010**		**2011**		**2012**		**2013**		**2014**		**2015**		**2016**		**2017**	
	CCR	**BCC**	**CCR**	**BCC**	**CCR**	**BCC**	**CCR**	**BCC**	**CCR**	**BCC**	**CCR**	**BCC**	**CCR**	**BCC**	**CCR**	**BCC**
AM	**1.000**	**1.000**	**1.000**	**1.000**	0.772	0.819	0.696	0.717	0.662	0.712	0.760	0.776	0.600	0.614	0.549	0.569
NZ	0.352	0.382	0.388	0.425	0.341	0.394	0.523	0.582	0.366	0.455	0.761	0.764	0.573	0.623	0.629	0.639
AS	0.344	0.465	0.603	0.715	0.467	0.503	0.935	0.981	0.782	0.833	**1.000**	**1.000**	0.766	0.801	0.892	0.902
OZ	0.463	0.472	0.824	0.935	0.637	0.653	0.445	0.461	0.447	0.496	0.563	0.575	0.811	**1.000**	**1.000**	**1.000**
CX	**1.000**	**1.000**	0.449	0.458	0.330	0.352	0.288	0.301	0.399	0.411	0.495	0.498	0.266	0.275	0.237	0.237
CI	0.204	0.303	0.403	**1.000**	0.372	0.386	0.421	0.428	0.408	0.417	0.525	0.534	0.461	0.503	0.430	0.481
CM	0.722	0.788	**1.000**	**1.000**	0.803	0.811	**1.000**	**1.000**	0.834	0.944	0.482	0.492	0.750	0.761	0.949	**1.000**
BR	0.489	0.589	0.367	0.384	0.269	0.371	0.365	0.467	0.368	0.466	0.495	0.545	0.451	0.522	0.455	0.502
AY	0.291	0.367	0.432	0.468	0.604	**1.000**	0.593	0.622	0.663	0.699	0.848	0.853	0.668	0.711	0.695	0.701

GA	0.490	0.621	0.732	0.765	0.675	**1.000**	0.584	0.606	0.740	0.781	0.922	0.954	0.974	**1.000**	**1.000**	**1.000**
HU	0.725	0.732	**1.000**	**1.000**	0.407	0.762	0.886	**1.000**	0.559	0.561	0.553	0.538	0.369	0.384	0.499	0.525
HA	0.622	0.641	0.472	0.533	0.460	0.498	0.466	0.556	0.431	0.506	0.682	0.724	0.803	0.813	**1.000**	**1.000**
QJ	0.221	0.241	0.427	0.437	0.730	0.728	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**
PR	0.568	0.575	0.827	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	0.739	**1.000**	0.841	0.841	0.969	0.974	0.513	0.552
SC	0.754	0.878	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	0.910	0.971	0.863	0.874	**1.000**	**1.000**	**1.000**	**1.000**
SQ	0.596	0.632	0.365	0.417	0.394	0.516	0.441	**1.000**	0.364	0.381	0.590	**1.000**	0.716	**1.000**	0.583	**1.000**
TG	0.616	0.651	0.399	0.412	0.488	0.495	0.410	0.413	0.429	0.464	0.322	0.331	0.347	0.355	0.452	0.477
VA	0.218	0.299	0.398	0.412	0.486	0.492	0.542	0.546	0.564	0.599	0.650	0.666	0.759	0.765	0.653	0.673

In Table 3, the efficiency measurement by Data Envelopment Analysis showed that among medium-scaled airlines, the SC (Shandong Airlines), QJ (Jet Airways), PR (Philippine Airlines) and CM (COPA Airlines) coded airlines performed better than the other airlines. NZ (Air Newzealand), BR (Ewa Airways), TG (Thai Airways) and VA (Virgin Australia) were not efficient during the entire period.

As of 2010-2017, it was determined that the number of medium-scaled traditional airlines included in the analysis reached the efficiency limit in different years was around 20%. Medium-scaled airlines had their best financial performance in 2017 and their worst in 2014.

The efficiency scores of the low-cost airlines included in the analysis are shown in Table 4.

Table 4. Efficiency Scores of Low-Cost Airlines

KOD	**2010**		**2011**		**2012**		**2013**		**2014**		**2015**		**2016**		**2017**	
	CCR	**BCC**	**CCR**	**BCC**	**CCR**	**BCC**	**CCR**	**BCC**	**CCR**	**BCC**	**CCR**	**BCC**	**CCR**	**BCC**	**CCR**	**BCC**
G9	**1.000**	**1.000**	0.901	0.917	0.927	**1.000**	0.934	**1.000**	0.969	**1.000**	0.727	0.786	0.496	0.522	0.807	0.944
AK	**1.000**	**1.000**	0.577	0.715	**1.000**	**1.000**	0.472	0.503	0.173	0.173	0.554	0.563	**1.000**	**1.000**	**1.000**	**1.000**
G4	**1.000**	**1.000**	0.621	0.718	0.658	0.751	0.846	0.838	0.540	0.632	**1.000**	**1.000**	0.882	0.951	0.813	0.833
5J	**1.000**	**1.000**	0.695	0.716	0.635	0.781	0.422	0.422	0.626	0.981	**1.000**	**1.000**	**1.000**	**1.000**	0.858	0.921
U2	0.828	0.832	0.322	0.341	0.819	0.908	0.646	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	0.425	0.473
G3	0.801	0.921	0.416	0.433	0.839	0.851	0.375	0.381	0.637	0.698	**1.000**	**1.000**	**1.000**	**1.000**	0.801	**1.000**
6E	**1.000**	**1.000**	**1.000**	**1.000**	0.864	**1.000**	**1.000**	**1.000**	0.549	0.693	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**
B6	**1.000**	**1.000**	0.231	0.249	0.534	0.562	0.582	0.591	0.627	0.698	0.797	0.816	0.987	0.991	**1.000**	**1.000**
JT	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**

D8	0.774	0.954	0.638	0.641	0.652	0.679	0.562	0.589	0.739	0.771	0.500	0.578	0.605	0.725	0.407	0.472
FR	**1.000**	**1.000**	0.271	0.277	**1.000**	**1.000**	0.534	0.569	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**
WN	**1.000**	**1.000**	0.486	0.496	0.688	0.739	0.561	0.563	0.611	0.798	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**
NK	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	0.736	0.952	0.497	0.676	0.697	0.889
9C	0.827	**1.000**	**1.000**	**1.000**	0.662	0.732	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	0.487	0.533	0.683	0.706
VY	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**
WS	0.438	0.568	0.483	0.559	0.513	0.547	0.687	0.702	0.499	0.561	0.718	0.729	0.469	0.574	0.535	0.576
W6	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**

In Table 4, the efficiency measurement by Data Envelopment Analysis showed that the W6 (Wizz Air), VY (Vueling Airlines) and JT (Lion Air) coded airlines, all low-cost airlines, were efficient for both models during the entire period, while the D8 (Norwegian Air) and WS (Westjet Airlines) coded airlines were not efficient for both models during the entire period.

The G9-coded Air Arabia in 2012-2014, the U2-coded Easyjet only in 2013, the G3-coded Gol Linhas only in 2017, the 6E-coded Indigo only in 2012, and the 9C-coded Spring Airlines only in 2010 were efficient in terms of the BCC model. According to the CCR model, they were not efficient.

As of 2010-2017, it was determined that the number of low-cost airlines included in the analysis reached the efficiency limit in different years was around 47%. Low-cost airlines had their best financial performance in 2010 and their worst in 2011.

4.2. Tobit Regression Model Findings

In this part of the study, Tobit regression model was applied to determine the factors that influence the efficiency of airlines that have been measured financially by means of Data Envelopment Analysis. In this way, the factors that determine the efficiency of airlines applying different business model and which variables have a higher power of effect were tried to be determined. The models established during the implementation phase of the Tobit regression model were estimated through the STATA 14.2 package program.

While total and technical efficiency scores which were obtained by Data Envelopment Analysis were used as dependent variable, input and output variables used in Data Envelopment Analysis were used as independent variables.

Table 5 shows the Tobit regression models established to determine the factors that influence the financial efficiency scores of the airlines.

Table 5. Tobit Regression Models

Model 1 (Total Efficiency)	$TE_{it} = \beta_0 + \beta_1 NP/NS_{it} + \beta_2 NP/TA_{it} + \beta_3 NS/TC_{it} + \beta_4 NS/TA_{it} + \beta_5 TC/TA_{it} + \beta_6 LTL/TA_{it} + \beta_7 FA/TA_{it} + \beta_8 CA/CL_{it} + \varepsilon_{it}$

Model 2 (Technical Efficiency)	$PTE_{it} = \beta_0 + \beta_1 NP/NS_{it} + \beta_2 NP/TA_{it} + \beta_3 NS/TC_{it} + \beta_4 NS/TA_{it} + \beta_5 TC/TA_{it} + \beta_6 LTL/TA_{it} + \beta_7 FA/TA_{it} + \beta_8 CA/CL_{it} + \varepsilon_{it}$

Table 5 includes Tobit regression models. Accordingly, the factors affecting the total efficiency of airlines in the model 1 and the factors affecting their technical efficiency in the model 2 were examined.

Table 6. Large-Scale Traditional Airlines Tobit Regression Results (Total Efficiency)

Dependent Variable: TE				
Variables	**Coefficient**	**Std. Eror**	**z**	**p-value**
Constant	-1101.406	603.2398	-1.83	0.108
Net Profit/ Net Sales Or Revenues	42.61463	22.31122	1.91	**0.056*** **
Net Profit/ Total Asset	17.60131	24.97727	-0.70	0.481
Net Sales Or Revenues/ Total Capital	0.0003292	0.000129	2.56	**0.011** **
Net Sales Or Revenues/ Total Asset	3.850.297	2.038392	1.89	**0.059*** **
Total Capital / Total Asset	-10.1947	3.236625	-3.15	**0.002* **
Long Term Liabilities/ Total Asset	2.900.955	1.959032	-1.48	0.139
Fixed Asset/ Total Asset	-18.5851	5.741303	3.24	**0.001* **
Current Asset/ Current Liabilities	1.699.749	0.864982	1.97	**0.049** **
Number of Observations = 152				

Note: *, ** and *** values show that the test statistics are significant at 1%, 5% and 10% significance level, respectively.

According to Table 6, net profit/net sales, net sales/total capital, net sales/total asset and current asset/current liabilities ratios have positive and significant effect on total efficiency of large-scaled traditional airlines; total capital/total asset and fixed asset/total asset ratios have negative and significant effect.

Table 7. Large-Scale Traditional Airlines Tobit Regression Results (Technical Efficiency)

Dependent Variable: PTE				
Variables	**Coefficient**	**Std. Eror**	**z**	**p-value**

Constant	-62.74716	714.4388	-0.09	0.930
Net Profit/ Net Sales Or Revenues	59.21304	25.73391	2.3	**0.021****
Net Profit/ Total Asset	51.15.762	28.81586	-1.78	**0.076*****
Net Sales Or Revenues/ Total Capital	0.0000482	0.000148	0.33	0.744
Net Sales Or Revenues/ Total Asset	3.619759	2.609721	1.39	0.165
Total Capital / Total Asset	-20.66.674	4.550536	-4.54	**0.000***
Long Term Liabilities/ Total Asset	5.037.968	2.300518	-2.19	**0.029****
Fixed Asset/ Total Asset	-18.91751	7.211217	2.62	**0.009***
Current Asset/ Current Liabilities	0.3906795	1.049657	-0.37	0.710
Number of Observations = 152				

Note: *, ** and *** values show that the test statistics are significant at 1%, 5% and 10% significance level, respectively.

According to Table 7, net profit/net sales, net profit/total asset and long term liabilities/total asset ratios have positive and significant effect on technical efficiency of large-scaled traditional airlines; total capital/total asset and fixed asset/total asset ratios have negative and significant effect.

Table 8. Medium-Scaled Traditional Airlines Tobit Regression Results (Total Efficiency)

Dependent Variable: TE				
Variables	**Coefficient**	**Std. Eror**	**z**	**p-value**
Constant	435.3806	598.053	0.73	0.467
Net Profit/ Net Sales Or Revenues	29.99.861	18.23184	1.65	**0.084*****
Net Profit/ Total Asset	1.817.831	23.35163	0.08	0.938
Net Sales Or Revenues/ Total Capital	0.0941276	0.04608	2.04	**0.041****
Net Sales Or Revenues/ Total Asset	3.721916	1.764929	2.11	**0.035****
Total Capital / Total Asset	-1.432.276	3.42981	0.42	0.676
Long Term Liabilities/ Total Asset	3.683.281	2.854.654	-1.29	0.197

Fixed Asset/ Total Asset	3.80521	6.551.261	-0.58	0.561
Current Asset/ Current Liabilities	-5.273.947	1.819.662	-2.9	**0.004***
Number of Observations = 144				

Note: *, ** and *** values show that the test statistics are significant at 1%, 5% and 10% significance level, respectively.

According to Table 8, net profit/net sales, net sales/total capital and net sales/total asset ratios have positive and significant effect on total efficiency of medium-scaled traditional airlines; current asset/current liabilities ratio has negative and significant effect.

Table 9. Medium-Scaled Traditional Airlines Tobit Regression Results (Technical Efficiency)

Dependent Variable: PTE				
Variables	**Coefficient**	**Std. Eror**	**z**	**p-value**
Constant	784.3295	692.6901	3.13	0.258
Net Profit/ Net Sales Or Revenues	26.50562	22.45751	1.18	0.238
Net Profit/ Total Asset	8.454898	29.2724	-0.29	0.773
Net Sales Or Revenues/ Total Capital	0.067058	0.052473	1.28	0.201
Net Sales Or Revenues/ Total Asset	1.719802	2.086472	0.82	0.410
Total Capital / Total Asset	-7.279739	3.839395	-1.9	**0.058*****
Long Term Liabilities/ Total Asset	19.58584	3.409046	-5.75	**0.000***
Fixed Asset/ Total Asset	9.546106	7.334218	1.30	0.193
Current Asset/ Current Liabilities	-4.150924	2.092334	-1.98	**0.047****
Number of Observations = 144				

Note: *, ** and *** values show that the test statistics are significant at 1%, 5% and 10% significance level, respectively.

According to Table 9, total capital/total asset and current asset/current liabilities ratios have negative and significant effect on technical efficiency of medium-scaled traditional airlines; long term liabilities/total asset ratio has positive and significant effect.

Table 10. Low Cost Airlines Tobit Regression Results (Total Efficiency)

Dependent Variable: TE

Variables	**Coefficient**	**Std. Eror**	**z**	**p-value**
Constant	1475.052	404.5322	3.65	**0.000***
Net Profit/ Net Sales Or Revenues	37.51668	9.041321	4.15	**0.000***
Net Profit/ Total Asset	13.89739	11.500	1.21	0.227
Net Sales Or Revenues/ Total Capital	-0.468112	0.3190152	-1.47	0.142
Net Sales Or Revenues/ Total Asset	2.412907	1.364884	1.77	**0.077*****
Total Capital / Total Asset	-12.11053	3.950281	-3.07	**0.002***
Long Term Liabilities/ Total Asset	3.76603	2.716497	-1.39	0.166
Fixed Asset/ Total Asset	7.271833	3.76349	-1.93	**0.053*****
Current Asset/ Current Liabilities	-2.936782	705.15225	-4.16	**0.000***
Number of Observations = 136				

Note: *, ** and *** values show that the test statistics are significant at 1%, 5% and 10% significance level, respectively.

According to Table 10, net profit/net sales, net sales/total asset and fixed asset/total asset ratios have positive and significant effect on total efficiency of low cost airlines; total capital/total asset and current asset/current liabilities ratio has negative and significant effect.

Table 11. Low Cost Airlines Tobit Regression Results (Technical Efficiency)

Dependent Variable: PTE				
Variables	**Coefficient**	**Std. Eror**	**z**	**p-value**
Constant	2.030819	4.189428	4.15	**0.000***
Net Profit/ Net Sales Or Revenues	42.1238	10.1578	-0.04	0.966
Net Profit/ Total Asset	0.5274682	1.252.945	-1.25	0.212
Net Sales Or Revenues/ Total Capital	-0.4472962	0.358485	1.08	0.280
Net Sales Or Revenues/ Total Asset	1.54271	1.428368	-3.49	**0.000***

Total Capital / Total Asset	-14.99	4.294207	-1.53	0.125
Long Term Liabilities/ Total Asset	4.391228	2.864436	-2.36	**0.018****
Fixed Asset/ Total Asset	9.115059	3.864073	-3.85	**0.000***
Current Asset/ Current Liabilities	-3.122265	0.811982	4.85	**0.000***
Number of Observations = 136				

Note: *, ** and *** values show that the test statistics are significant at 1%, 5% and 10% significance level, respectively.

According to Table 11, net sales/total asset, long term liabilities/total asset and fixed asset/total asset ratios have positive and significant effect on technical efficiency of low cost airlines; current asset/current liabilities ratio has negative and significant effect.

5. CONCLUSION

In this study, where the financial performance of the airlines applying different business models for the period 2010-2017 was compared, efficiency measurement of the airlines was first performed by Data Envelopment Analysis. In the later stage, the variables that had an effect on the efficient scores were estimated by the Tobit regression model.

As a result of the efficiency measurement made by Data Envelopment Analysis for the period of 2010-2017, the number of efficient companies in large-scaled traditional airlines was 30%, 20% in medium-scaled traditional airlines and 47% in low-cost airlines. In this respect, it can be said that low-cost airlines outperformed traditional airlines in terms of financial efficiency.

Large-scaled traditional airlines performed better financially than medium-scaled traditional airlines. In this respect, it can be said that as the scale size increases in traditional airlines, the efficiency will increase.

W6 (Wizz Air), VY (Vueling Airlines) and JT (Lion Air) coded low-cost airlines were efficient for both models during the entire period. On the other hand, all traditional airlines were not efficient for the same period. As of 2010-2017, out of large-scaled traditional airlines, NH (All Nippon Airways), AV (Avianca), KE (Korean Airlines), LA (Latam Airlines) and OO (Skywest) coded airlines; out of medium-scaled traditional airlines, NZ (Air Newzealand), BR (Ewa Airways), TG (Thai Airways) and VA (Virgin Australia) coded airlines and out of low-cost airlines, D8 (Norwegian Air) and WS (Westjet Airlines) coded airlines were not efficient throughout the entire period.

Table 12 shows variables that have a significant effect on efficiency scores which are obtained by Tobit regression model.

Table 12. Traditional and Low Cost Airlines Tobit Regression Results

	TOTAL EFFICIENCY	TECHNICAL EFFICIENCY

Traditional Airlines (Large-Scaled)	**NP/NS*** (+)** **NS/TC**(+)** **NS/TA***(+)** **TC/TA* (-)** **FA/TA*(-)** **CA/CL**(+)**	**NP/NS** (+)** **NS/TA***(+)** **TV/TA* (-)** **LTL/TA**(+)** **FA/TA*(-)**
Traditional Airlines (Medium-Scaled)	**NP/NS*** (+)** **NS/TC**(+)** **NS/TA**(+)** **CA/CL*(-)**	**TC/TA*** (-)** **LTL/TA*(+)** **CA/CL**(-)**
Low Cost Airlines	**NP/NS* (+)** **NS/TA***(+)** **TC/TA* (-)** **FA/TA***(+)** **CA/CL*(-)**	**NS/TA*(+)** **LTL/TA**(+)** **FA/TA*(+)** **CA/CL*(-)**

Note: *, ** and *** values show that the test statistics are significant at 1%, 5% and 10% significance level, respectively.

According to table 12, current asset/current liabilities ratio has positive effect on the total efficiency of large-scaled traditional airlines, it has negative effect on the total and technical efficiencies of medium-scaled traditional and low-cost airlines. This shows that while the increase in liquidity has a positive effect on the efficiency of large-scaled traditional airlines, it has a negative effect on the efficiency of medium-sized traditional airlines and low-cost airlines.

Net profit/net sales ratio has a positive impact on the overall efficiency of traditional and low cost airlines. This suggests that the increase in net profit/ net sales ratio has positively affected the efficiency of traditional and low-cost airlines.

While fixed assets / total assets ratio had a negative impact on the total and technical efficiencies of large-scaled traditional airlines, it had positive effect on the total and technical efficiencies of low-cost airlines. This indicates that the increase in fixed assets negatively affects the efficiency of large-scaled traditional airlines, while positively affects the efficiency of low-cost airlines.

It was determined that total capital/total asset ratio had negative effect on the total and technical efficiencies of large-scaled traditional airlines; on the technical efficiency of middle-sized traditional airlines and on the total efficiency of low cost airlines. This suggests that the increase in equity has adversely affected the efficiency of traditional and low-cost airlines.

The net sales / total asset ratio was found to have a positive effect on the total efficiency of traditional airlines and the total and technical efficiency of low cost airlines. This suggests that the increase in net sales has adversely affected the efficiency of traditional and low-cost airlines.

The net sales / total capital ratio has a positive impact on the overall efficiency of large-scaled traditional airlines and on the technical efficiency of medium-scaled traditional airlines. This indicates that the increase in net sales/equity ratio has positively affected the efficiency of traditional airlines.

The long-term liabilities/ total asset ratio has a positive effect on the technical efficiency of traditional airlines and low-cost airlines. This suggests that the use of long term liabilities has positively affected the efficiency of traditional and low-cost airlines.

The net profit/ total asset ratio has been found to have a positive and meaningful impact on the technical efficiency of large-scaled traditional airlines. This indicates that the increase in profitability has positively affected the efficiency of large-scaled traditional airlines. There was no significant relationship between the profitability ratio and the efficiency of medium-sized traditional and low-cost airlines.

The results of both financial efficiency analysis and regression analysis of the airlines applying the traditional and low-cost business models showed different results for both groups. In this respect, this study provides the opportunity to develop new strategies to increase operational and financial efficiency by providing the managers of airlines to examine, evaluate and analyze the data resulting from efficiency and regression analysis.

REFERENCES

ADLER, N., FRIEDMAN, L. and SINUANY-STERN, Z. (2002). "Review of Ranking Methods in the Data Envelopment Analysis Context", European Journal of Operational Research, 140: 249-265.

AKAN, Y. and ÇALMAŞUR, G. (2011). "Etkinliğin Hesaplanmasında Veri Zarflama Analizi ve Stokastik Sınır Yaklaşımı Yöntemlerinin Karşılaştırılması", Atatürk Üniveristesi İktisadi İdari Bilimler Dergisi, 25: 13-32.

BAKIR, M., AKAN, Ş., KIRACI, K., KARABASEVIC, D., STANUJKIC, D. and POPOVIC, G. (2020). "Multıple- Crıteria Approach Of The Operational Perfomance Evaluation İn The Airline Industry: Evidence From Emerging Market", Romanian Journal of Economic Forecasting, *23*(2): 149-172.

BARBOT, C., COSTA, A. and SOCHIRCA, E. (2008). "Airlines Performance in the New Market Context: A Comparative Productivity", Journal of Air Transport Management, 14 (5): 270-274.

BHADRA, D. (2009). "Race to The Bottom or Swimming Upstream: Performance Analysis of US Airlines", Journal of Air Transport Management, 15(5): 227-235.

CHANG, Y.-T., PARK, H.-s., JEONG, J.-B. and LEE, J.-w. (2014). "Evaluating Economic And Environmental Efficiency Of Global", Transportation Research Part D, 27(1): 46-50.

CHARNES, A., COOPER, W. W. and RHODES, E. L. (1978). "Measuring The Efficiency of Decision Making Units", European Journal of Operational Research, 2(6): 429-444.

CHIOU, Y. C. and CHEN, Y. H. (2006). "Route-Based Performance Evaluation of Taiwanese Domestic Airlines Using Data Envelopment Analysis. Transportation Research Part E: Logistics and Transportation Review, 42(2): 116-127.

COOK, W. D. and ZHU, J. (2005). Modeling Performance Measurment Application and Implementation Issues in DEA, Springer, New York.

COOPER, W., SEIFORD, L. and TONE, K. (2007). Data Envelopment Analysis a Comprehensive Text with Models, Applications References and Dea- Solver Software, Springer, Newyork.

ELSAYED, A. and KHALIL, N. S. (2017). "Evaluate and Analysis Efficiency of Safaga Port Using DEA-CCR, BCC and SBM Models–Comparison with DP World Sokhna", IOP Conference Series: Materials Science and Engineering, 245(4): 1-11.

GOOD, D. H., RÖLLER, L.-H. and SICKLES, R. C. (1995). "Airline Efficiency Differences Between Europe and the US: Implications For The Pace of EC İntegration And Domestic Regulation", European Journal of Operational Research, 80(3): 508-518.

GREENE, W. H. (2003). Econometrıc Analysıs, Prentice Hall, New Jersey.

GUJARATI, D. N. and PORTER, D. C. (2012). Temel Ekonometri. (Ü. Şenesen. ve G. Şenesen, Çev.), Literatür Yayıncılık, İstanbul.

HEYDARI, C., OMRANI, H. and TAGHIZADEH, R. (2020). "A fully fuzzy network DEA-Range Adjusted Measure model for evaluating airlines efficiency: A case of Iran", Journal of Air Transport Management, 89(3): 1-18.

KIRACI, K. and BAKIR, M. (2020). "Evaluation Of Airlines Performance Using An Integrated Crtıc And Codas Methodology: The Case of Star Alliance Member Airlines", Studies in Business and Economics, 15(1): 83-99.

LANG, P., YOLALAN, R. and KETTANI, O. (1995). "Controlled Envelopment By Face Extension", Journal of the Operational Research Society, 46(4): 473-491.

LEE, B. and WORTHINGTON, A. (2014). "Technical Efficiency of Mainstream Airlines and Low-Cost Carriers: New Evidence Using Bootstrap Data Envelopment Analysis Truncated Regression", Journal of Air Transport Management, 38(2): 15-20.

LIN, Y.-H. and HONG, C.-F. (2020). "Efficiency and effectiveness of airline companies in Taiwan and Mainland China", Asia Pacific Management Review, *25*(1): 13-22.

LU, W.-M., WANG, W.-K., HUNG, S.-W. and LU, E.-T. (2012). The Effects of Corporate Governance on Airline Performance: Production and Marketing Efficiency Perspectives. Transportation Research Part E, 48(2): 529-544.

OHSATO, S. and TAKAHASHI, M. (2015). "Management Efficiency in Japanese Regional Banks: A Network DEA", Procedia - Social and Behavioral Sciences, 172(1): 511-518.

PINEDA, P. G., LIOU, J. J., HSU, C.-C. and CHUANG, Y.-C. (2018). An integrated MCDM model for improving airline operational andfinancial performance. Journal Of Air Transport Management, 68 (2): 103-117.

PIRES, H. M. and FERNANDES, E. (2012). Malmquist Financial Efficiency Analysis For Airlines", Transportation Research Part E, 48(5): 1049-1055.

POURJAVAD, E., and SHIROUYEHZAD, H. (2014). "A Data Envelopment Analysis Approach For Measuring The Efficiency in Continuous Manufacturing Lines: A Case Study", International Journal of Services and Operations Management, 18(2): 142-158.

SCHEFCZYK, M. (1993). "Operational Performance of Airlines: An Extension of Traditional Measurment Paradigms", Strategic Management Journal, 14(4): 301-317.

SCHERAGA, C. A. (2004). "Operational Efficiency Versus Financial Mobility in The Global Airline İndustry: A Data Envelopment and Tobit Analysis" Transportation Research Part A, 38(5): 383-404.

ŞENGÜL, Ü., ESLAMIAN, S. and EREN, M. (2013). "Türkiye'de İstatistiki Bölge Birimleri Sınıflamasına Göre Düzey 2 Bölgelerinin Ekonomik Etkinliklerinin VZA Yöntemi ile Belirlenmesi ve Tobit Model Uygulaması", Çanakkale Onsekiz Mart Üniversitesi Yönetim Bilimleri Dergisi, 11(21): 75-99.

ÜÇDOĞRUK, Ş., AKIN, F. and EMEÇ, H. (2001). "Türkiye Hanehalkı Eğlence Kültür Harcamalarında Tobit Modelin Kullanımı", Gazi İktisadi ve İdari Bilimler Fakültesi Dergisi, 3(3):13-26.

VASIGH, B. (2015). Foundations Of Airline Finance: Methodology And Practice, Routledge Taylor & Francis Group, New York.

WANG, W.-K., LIN, F., TING, I. W., KWEH, Q. L., LU, W.-M. and CHIU, T.-Y. (2017)." Does Asset-Light Strategy Contribute to The Dynamic Efficiency of Global Airlines?", Journal of Air Transport Management, 62(4): 99-108.

WENG, S. J., WU, T., BLACKHURST, J. and MACKULAK, G. (2009). "An Extended DEA Model For Hospital Performance Evaluation and İmprovement", Health Service Outcomes Research Method, 9(9): 39-53.

YOLALAN, R. (1993). İşletmelerarası Göreli Etkinlik Ölçümü, Milli Prodüktivite Merkezi Yayınları, Ankara.

ZHOU, H., Yi, Y., CHEN, Y. and ZHU, J. (2018). "Data Envelopment Analysis Application in Sustainability: The Origins, Development and Future Directions", European Journal of Operational Research, 264(1): 1-16.

APPENDIX - Airlines and IATA Codes

TRADITIONAL AIRLINES (LARGE SCALED)		**TRADITIONAL AIRLINES (MEDIUM SCALED)**		**LOW COST AIRLINES**	
KOD	**AIRLINES**	**KOD**	**AIRLINES**	**KOD**	**AIRLINES**
SU	AEROFLOT	AM	AEROMEXICO	G9	AIR ARABIA
AC	AIR CANADA	NZ	AIR NEW ZEALAND	AK	AIRASIA
CA	AIR CHINA	AS	ALASKA AIR	G4	ALLEGIANT AIR
AF/KL	AIR FRANCE - KLM	OZ	ASIANA AIRLINES	5J	CEBU PASIFIC AIR
AA	AMERICAN AIRLINES	CX	CATHAY PACIFIC	U2	EASYJET
NH	ALL NIPPON AIRWAYS	CI	CHINA AIRLINES	G3	GOL LINHAS
AV	AVIANCA	CM	COPA HOLDINGS	6E	INDIGO
MU	CHINA EASTERN	BR	EVA AIRWAYS	B6	JETBLUE AIRWAYS
CZ	CHINA SOUTHERN	AY	FINNAIR	JT	LION AIR
DL	DELTA AIR LINES	GA	GARUDA INDONESIA	D8	NORWEGIAN AIR
JL	JAPAN AIRLINES	HU	HAINAN AIRLINES	FR	RYANAIR
KE	KOREAN AIRLINES	HA	HAWAIIAN AIRLINES	WN	SOUTHWEST AIRLINES
LH	LATAM AIRLINES	QJ	JET AIRWAYS	NK	SPIRIT AIRLINES

LA	LUFTHANSA	PR	PHILIPPINE AIRLINES	9C	SPRING AIRLINES
QF	QANTAS AIRWAYS	SC	SHANDONG AIRLINES	VY	VUELING AIRLINES
SK	SAS	SQ	SINGAPORE AIRLINES	WS	WESTJET AIRLINES
OO	SKYWEST	TG	THAI AIRWAYS	W6	WIZZ AIR
TK	TURKISH AIRLINES	VA	VIRGIN AUSTRALIA		
UA	UNITED CONTINENTAL				