IBN HALDUN UNIVERSITY
SCHOOL OF GRADUATE STUDIES
DEPARTMENT OF AIR TRANSPORT MANAGEMENT

MASTER THESIS

EFFICIENCY ANALYSIS OF MAJOR AIRLINES: EXPLORING THE EFFECTS OF OPERATIONAL PERFORMANCE DETERMINANTS

KÜBRA ÇINAR YALÇIN

THESIS SUPERVISOR: ASSOC. PROF. ALİ OSMAN KUŞAKCI

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by

KÜBRA ÇINAR YALÇIN

A thesis submitted to the School of Graduate Studies in partial fulfillment of the requirements for the degree of Master of Science in Air Transport Management

THESIS SUPERVISOR: ASSOC. PROF. ALİ OSMAN KUŞAKCI

ISTANBUL, 2021

APPROVAL PAGE

This is to certify that we have read this thesis and that in our opinion it is fully adequate, in scope and quality, as a thesis for the degree of Master of Science in Air Transport Management.

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Prof. Dr. Ekrem Tatoğlu	________________	________________
Assoc. Prof. Dr. Muhammet Deveci	________________	________________

This is to confirm that this thesis complies with all the standards set by the School of Graduate Studies of Ibn Haldun University.

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ACADEMIC HONESTY ATTESTATION

I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

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ÖZ

HAVAYOLLARININ ETKİNLİK ANALİZİ: OPERASYONEL PERFORMANS ETKENLERİNİN ARAŞTIRILMASI

Yazar: Çınar Yalçın, Kübra
Hava Taşımacılığı Yönetimi Yüksek Lisans Programı
Tez Danışmanı: Doç. Dr. Ali Osman Kuşakcı
Ocak 2021, 84 sayfa

Sürekli değişen ve artan rekabet ortamında havayollarının operasyonel etkinlik ölçümü önemli araştırma konularından biri haline gelmiştir. Literatürde konuyla ilgili çokça araştırma olmasına rağmen havayollarının boyutları, düşük maliyetli iş modeli ve ittifak üyeliğinin havayollarının operasyonel faaliyetleri üzerine etkilerine yönelik yeterli sayıda araştırma bulunmamaktadır. Bu çalışma, dünyanın farklı bölgelerinden 38 tane havayolunun 2015 ve 2019 yılları arasındaki operasyonel performanslarını ve havayolu boyutlarının, havayolu modelinin ve ittifak üyeliğinin havayollarının performansları üzerinde etkisi olup olmadığını değerlendirmektedir. Bu doğrultuda ilk olarak ölçeğe göre sabit ve değişken getiri varsayımı altında 3 girdi ve 2 çıktıyla girdi odaklı Veri Zarflama Analizi (VZA) yapılmıştır. Aynı zamanda etkin olan havayolları arasındaki performans farklarını daha iyi ortaya koyabilmek için girdi odaklı, ölçeğe göre sabit getirili süper-etkinlik analizi yürütülmüştür. Performansa etki eden faktörlerin etkisi Mann-Whitney U-test ile ölçülmüştür. Çalışmadan çıkan sonuçlar, havayollarının büyük çoğunluğunun ölçek etkinsizliği sebebiyle etkinlik sınırını yakalayamadıklarını göstermiştir. Bununla birlikte arz edilen koltuk kilometreye (AKK) göre değerlendirildiğinde şirketlerin boyutlarının etkinlik üzerinde istatistiksel olarak önemli bir etkisi olmadığı görülmüştür. Diğer yandan, düşük maliyetli havayollarının, tam hizmet sağlayan havayollarına göre daha etkin olduğu saptanmıştır. Son olarak, ittifak üyesi havayollarının ittifak üyesi olmayan havayollarına nazaran daha düşük performans gösterdiği belirlenmiştir.

Anahtar Kelimeler: Düşük Maliyetli Havayolları, Havayolu Etkinliği, Havayolu İttifakları, Veri Zarflama Analizi

ABSTRACT

EFFICIENCY ANALYSIS OF MAJOR AIRLINES: EXPLORING THE EFFECTS OF OPERATIONAL PERFORMANCE DETERMINANTS

Student Name: Çınar Yalçın, Kübra

MSc in Air Transport Management

Thesis Supervisor: Assoc. Prof. Ali Osman Kuşakcı

January 2021, 84 Pages

In a changing and increasingly competitive era, operational performance evaluation of airlines has become one of the most important research topics. Although there are many studies about the efficiency analysis of airlines in the literature, existing research on the effects of size, business model and alliance membership are relatively scarce. This study evaluates the performance of 38 airlines from different regions of the world between 2015 and 2019 assessing the effects of size, business model and alliance membership on the operational performance of the airlines. In this regard, first, constant returns to scale (CRS) and variable returns to scale (VRS) input-oriented data envelopment analysis (DEA) models with 3 inputs and 2 outputs were implemented. To discriminate between efficient airlines, input-oriented CRS model super-efficiency DEA was also used. The determinants of operational efficiencies were assessed applying Mann-Whitney rank-sum tests. The results of the analyses show that majority of airlines suffer from scale inefficiency. Additionally, it was found that the size of airlines measured in available seat kilometer (ASK) has no statistically significant effect on the performance. On the other hand, low-cost airlines were found to be more efficient than full-service carriers. Lastly, the airlines without alliance membership have performed better than the airlines with alliance membership.

Keywords: Airline Alliances, Airline Efficiency, Data Envelopment Analysis, Low-Cost Carriers

ACKNOWLEDGEMENT

I feel I have learnt a lot while writing this thesis. Foremost, I would like to thank to my advisor Assoc. Prof. Ali Osman Kuşakcı for his motivation and guidance. Every sentence from him shed light on this study.

I wish to acknowledge the support and great love of my dear mother and father. Their belief kept me going on this study.

There are no proper words to convey my gratitude for my husband Özgür Yalçın who blessed my life with his unwavering love, support, and patience. Without his help and encouragement, this study would have remained as a dream.

Kübra Çınar Yalçın

ISTANBUL, 2021

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CHAPTER I

INTRODUCTION

As the airline industry grows year by year, governments acquaint themselves with the economical contribution of air transportation. Countries seriously benefit from the performance of airline industry and they try to take actions to increase their air transport activities. Economic growth, privatization of airline industry and open skies policies adapted by Asia-Pacific regions have expanded air traffic and these all have brought growth to the industry (Yu, Chen, & Chiang, 2017). Over the past decades, with the growth of industry, airlines have been faced with several transformations. The restructuring of the global airline industry initially started with deregulation of the United States (US) airline industry in 1978 and has been followed by the liberalization of European airline industry in 1986 which gave right to airlines to serve on any routes and price (Min & Joo, 2016). Fu, Oum, & Zhang, (2010) indicated that liberalization has led the airlines to improve their operational efficiency mainly in two ways. First, it gives flexibility to airlines for their network and price optimization and hence, they improve their efficiency. Second, as a consequence of liberalization, increased competition has forced airlines to operate more efficiently.

Airlines always have been in the need of gearing up in this increasingly competitive area to cope with the fast changes in the industry (Yu et al., 2017). In the past, less efficient airlines went bankrupt and the gap created by the bankruptcy of them was filled as the new entrants emerged as a new type of business model; low-cost carriers (LCC). The "landscape of the battlefield" has been transformed by the emergence of low-cost carriers who offer lower prices than their incumbent counterparts (Kuljanin, Kalić,Caggiani, & Ottomanelli, 2019). Gorin and Belobaba, (2004) suggested that low-cost entry leads to decrease in fares and revenues for incumbent airlines.

In order to survive in these new market conditions, airlines operating in the old order feel the need of adapting different strategies such as global alliances. As forming alliance groups has become popular between many airlines, various research have been conducted about the benefits of it. Brueckner, (2001); Gaggero and Bartolini (2012); Iatrou and Alamdari (2005); Oum and Park (1997)) suggested that alliances enable access to foreign markets; increase traffic, network and brand awareness; offer benefits to customers; provide cost saving and enable cooperation between members.

1.1. Aim of the Study

In the changing and increasingly competitive environment, airlines always need to operate efficiently to survive. They are trying to have a seat in such a fragile industry and remain competitive against their competitors by using their limited resources. The strategies formed by airlines against the increasing competition may affect their performance. Since the evaluation of operational performance is an important indicator to the management of the transportation industries; by evaluating the performance, airlines can develop solutions that lead to more efficient operations (Yu et al., 2017).

In the literature, there are many studies about the operational performance of airlines. Although previous studies investigated the airline performance in a variety of aspects, the potential impacts of size, business model and alliance membership have not been sufficiently focused on. Therefore, the aim of this study is to analyze the operational efficiency of 38 airlines from different regions of the world between 2015 and 2019 and to assess the effects of various determinants on their performance such as size, business model and alliance membership.

1.2. Objectives of the Study

Comparative studies of airline performance have gained more attention during the last two decades. Many researchers dealing with airline performances used several types of methodologies, and DEA is one of the most used methods regarding the assessment of efficiency. In this context, DEA is used in this work as the method to analyze operational efficiencies of the airlines under evaluation. Further, determinants behind the efficiency of these airlines are assessed by performing post-hoc analysis. The data is gathered from the annual reports of airlines and the analysis is conducted with 3 inputs and 2 outputs.

This study builds on the previous studies and contributes to the airline efficiency literature by evaluating the operational efficiency of airlines in various aspects. The results presented in the study enlighten several issues such as how effective airlines are being managed, and to what extent size, business model, and alliance membership have impact on the operational performance. This study may also inspire further research on the determinants of airline operational performance.

The rest of the study is structured as follows: Chapter 2 gives an overview of the worldwide airline industry, provides information about the background of low-cost carriers and airline alliances. Chapter 3 reviews the literature relevant to the performance analysis of airlines. Chapter 4 contains the data and methodology implemented. Chapter 5 reveals the empirical findings of the study. Chapter 6 summarizes the results and concludes.

CHAPTER II

WORLWIDE AIRLINE INDUSTRY

2.1. Overview of Worldwide Airline Industry

Over the last few decades, most of the industries have faced several economic difficulties on a global scale but the airline industry is not one of these. Furthermore, the sector has continued to grow year by year. Passenger traffic is one of the main drivers of this growth. International Civil Aviation Organization (ICAO, 2019) reported that in 2019, 4.5 billion passengers travelled by air on scheduled flights which is a 3.6 % increase compared to 2018. Table 2.1 shows that world passenger traffic reached 8,685.667 million revenue passenger kilometers (RPKs) with 4.9% increase in 2019.

Table 2.1. Passenger and Passenger-Kilometer Growth Between 2010-2019

Year	Passenger		Passenger-kilometer	
	(million)	Annual Increase (%)	(million)	Annual Increase (%)
2010	2,708	8.7	4,930.250	8.0
2011	2,873	6.1	5,254.557	6.6
2012	3,007	4.6	5,535.641	5.3
2013	3,141	4.5	5,839.696	5.5
2014	3,320	5.7	6,188.735	6.0
2015	3,560	7.2	6,652.791	7.5
2016	3,798	6.7	7,144.498	7.4
2017	4,066	7.1	7,716.542	8.0
2018	4,331	6.5	8,278.782	7.3
2019	4,486	3.6	8,685.667	4.9

Source: ICAO Air Transport Reporting Form A and A-S plus ICAO Estimates

The global economy and airline facilities have a two-way positive relationship. When the economy grows, air traffic demand increases and when demand increases, airlines generate revenue and it contributes to gross domestic product (GDP) of the world and the country that the airlines belong to. Hu, Xiao, Deng, Xiao, and Wang, (2015) found that 1% increase in air passenger traffic led to an increase of 0.943% in GDP. The demand of an airline is measured by RPK and Figure 2.1 shows the relationship between RPK and GDP (IATA, 2019b). Here, it can be assumed that airlines are the main generators of air traffic and they contribute to world economy directly.

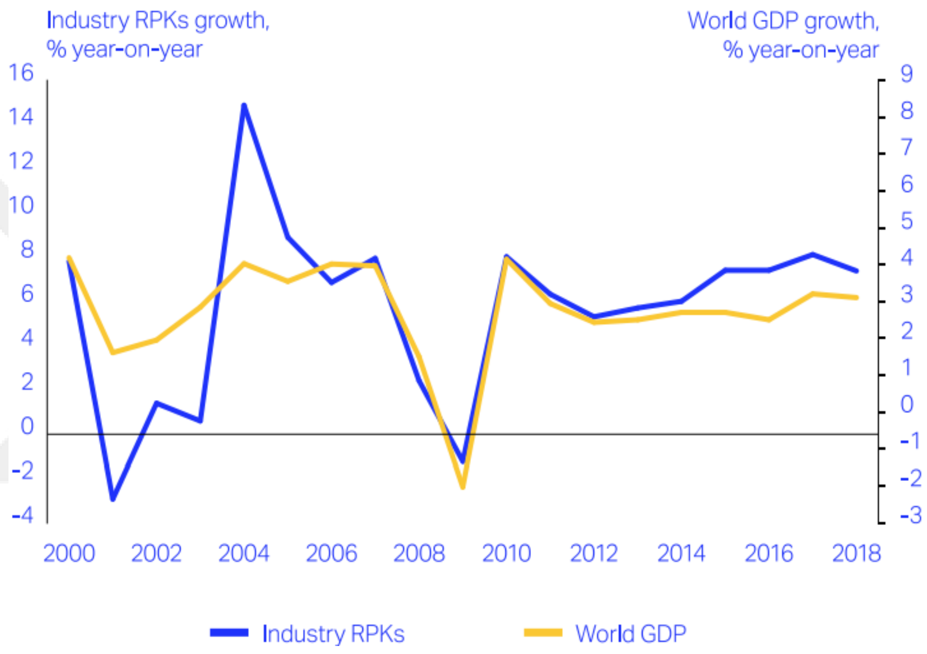

Figure 2.1. RPK vs. World GDP Growth

Source: IATA, IMF

Air transport boosts the economic development worldwide. Governments also benefit from the satisfactory performance of the airline industry. As the airlines serve more, they generate revenue and it contributes to the economic development. The tax revenue generated by airlines and their customers are forecasted to reach to $US 136 billion in 2020. Another wider economic impact of the increased airline activity is on the jobs in the sector itself, in the supply-chain and the jobs generated as ripples. As capacity and traffic grow, airlines continue to hire more employees. Total number of employees of airlines worldwide is estimated to reach 2.95 million in 2020 (IATA, 2019a). Brueckner (2003) found that 10% increase in air traffic led to 1% increase in service-related jobs. The jobs created by airlines are not only productive for airline employers but also for the economies in which they are employed. Transport costs have decreased more than 50% when compared to twenty years ago. The number of commercial fleets is also expected to increase to 31,375 aircrafts. Industry wide RPK increased by 4.2% in 2019. A stable growth in RPK is forecasted for 2020 (IATA, 2019a). The detailed information about worldwide airline industry can be seen in the Table 2.2.

Table 2.2. Worldwide Airline Industry 2018-2020F

Worldwide airline industry	2018	2019E	2020F
Tax revenues, $billion	125	129	136
% change over year	4.5%	3.5%	5.2%
Transport cost, $US/RTK (2018$)	77.8	76.0	74.0
Compared to 1998	-54%	-55%	-56%
Employment, million	2.89	2.90	2.95
% change over year	3.1%	0.3%	1.6%
Aircraft fleet	29,507	29,805	31,375
% change over year	4.4%	1.0%	5.3%
RPKs, billion	8,330	8,680	9,038
% change over year	7.4%	4.2%	4.1%

Source: IATA 2019 End-Year Report

It is clear from the Figure 2.2 that there is a slow-down in the growth rate of RPK for each region in 2019. The reasons behind this growth slow-down are the worldwide economic situation, less trade activity, political and geographical problems across regions. Total RPK increased 4.2% worldwide in 2019. RPK increase of African airlines is 4.9%, of European and Latin American airlines are 4.2% for each. Asia-Pacific airlines have an increase rate of 4.8%, North American airlines' RPK increase rate is 4.1% and Middle Eastern airlines have a RPK increase rate of 2.4% (IATA, 2019c). Airlines based in Asia-Pacific and Europe are the main contributors of RPK which are followed by the airlines of North America. When compared to other regions, Africa has the least share of RPK contribution to the industry.

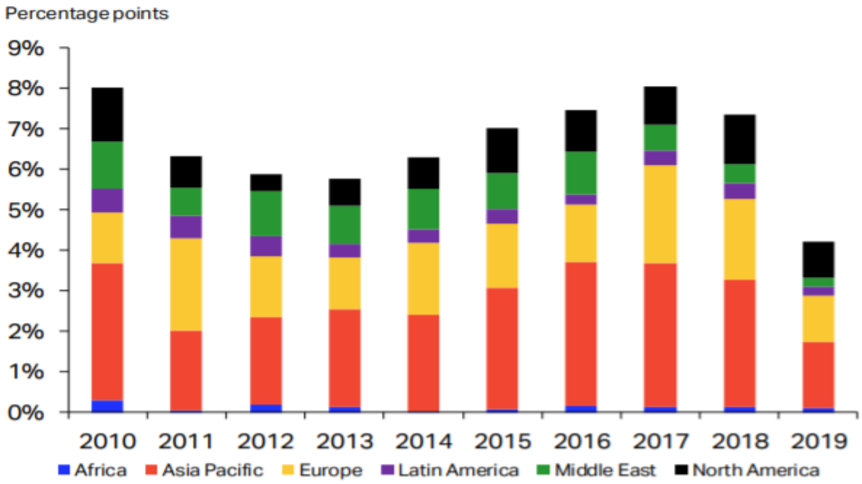

Figure 2.2. Contribution to Annual RPK Growth (Airline Region of Registration)

Source: IATA Air Passenger Market Analysis, December 2019

Figure 2.3 shows that, in December 2019, total market share of Asia-Pacific airlines in terms of RPK is the highest with 34.7%. European airlines fell behind their Asia-Pacific competitors but still have a high share of traffic (26.8%). The market share of North American airlines is 22.3%. There is a dominance of Asia-Pacific, European and North American airlines. Airlines in Middle East have a market share of 9.0% and are followed by the airlines from Latin America and Africa with 5.1% and 2.1% share, respectively. The least share belongs to the airlines from Africa (IATA, 2019c).

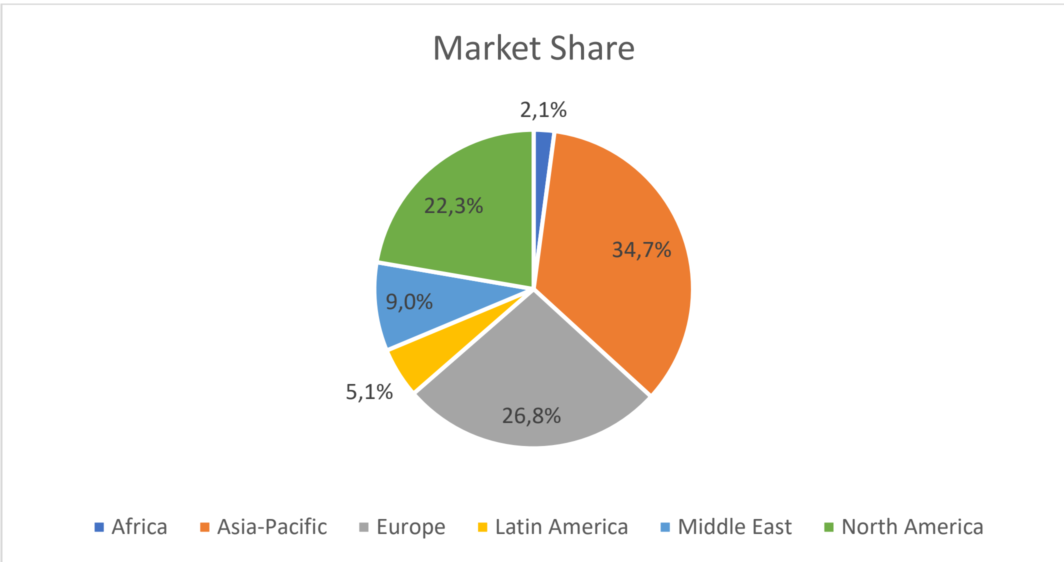

Figure 2.3. Regional Market Share of Airlines in December 2019

Source: Adapted from IATA Air Passenger Market Analysis, December 2019

2.2. Low-Cost Airlines

Liberalization and deregulation of air transport industry have brought passenger growth in the industry for decades. Button, (1998) in his study, revealed that after U.S. deregulation, between 1978 and 1988, there was 55% increase in passenger traffic and revenue passenger mile (RPM) increased over 60%. The increase in passenger numbers and the removal of regulatory barriers by deregulation and liberalization have increased the competition between airlines. Airlines have been forced to improve their performance. Less efficient airlines went bankrupt or merged and the gap was filled with the emergence of new business models like low-cost airlines.

Southwest Airlines was the pioneer of the low-cost airline model. After the launch of Southwest Airlines in 1971, several new brands such as JetBlue, Ryanair and EasyJet emerged. This new business model changed the market and players' inability of adapting to this new changing market brought about the downfall. For these emerging airlines, it was easier to enter the market with competitive prices and gain the route. Low fares offered by low-cost airlines stimulated the demand in the market and created a new generation of passengers. They not only attracted the "low-yield" passengers and "heavy bargainers" who would not have preferred air travel otherwise but also put off the regular and price-sensitive passengers from full-service carriers (FSC) (Franke, 2004). Entry of a new capacity in a market generated new traffic. In 1986, when Ryanair entered Dublin-London market, the demand quadrupled, pushing down the market shares of British Airways and Aer Lingus (Franke, 2004).

Business dynamics of the air transport industry have been changed by LCCs entering into rivalry with once-preeminent FSCs (Pels, 2008). The choice of airport is one of the main differences between LCCs and traditional FSCs. Hub-and-spoke adaptation makes FSCs operate mainly in primary airports. Hubbing has some strategic advantages to its operator and it reduces cost (Oum, Zhang, & Zhang, 1995), but operational complexity of hub airports due to the congestion and delays may increase expenses (Wong, Zhang, Cheung, & Chu, 2019). The traditional service model by FSCs with a hub-and-spoke network organization is under the threat of rapid growth in the number of LCCs (Gillen & Morrison, 2003). LCCs focus their point-to-point network expansion mainly on secondary airports (Reynolds-Feighan, 2010). Another difference between FSCs and LCCs is that LCCs use single-class fleet to minimize costs. The “no frills” approach of LCCs is also another advantage over FSCs because especially in short-haul flights, passengers may not need the services offered by FSCs with high ticket price.

Globally, LCCs are expanding faster than FSCs. The intra-regional seat capacity of LCCs increased 8 points from 25% in 2009 to 33% in 2018. Figure 2.4 illustrates annual intra-regional seat capacity of LCCs have doubled over a nine-year period (2009-2018) from 753 million to 1,564 billion while the capacity increase of FSC is relatively modest with 41% (CAPA, 2019).

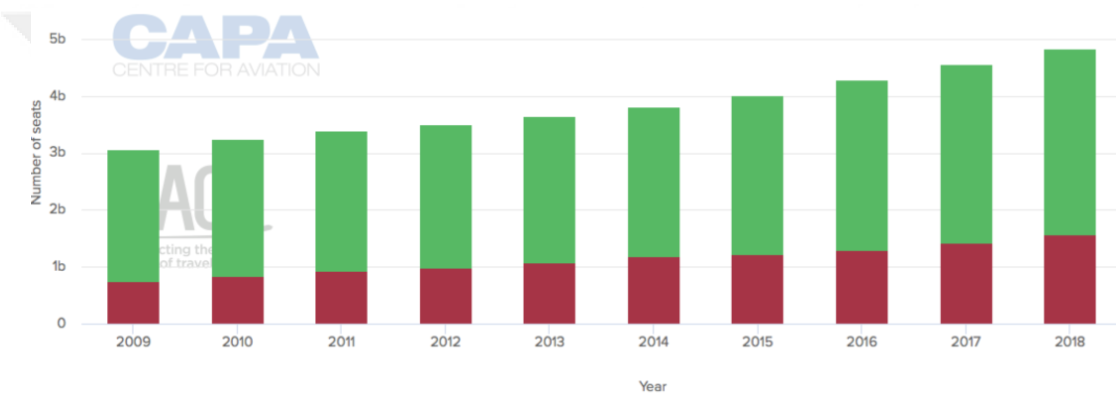

Figure 2.4. Capacity Increase of LCCs (red) and FSC (green) Between 2009-2018

Source: CAPA – Center for Aviation and OAG.

After the emergence of LCCs, the market share of FSCs has started to go down by the increasing share of LCCs. Airbus, (2013) forecasted that in the next 20 years, the global network of air transport will decline from the 62% level to 59%. The market share of charter and regional airlines will decrease 1% from 4% to 3%. Major airlines are forecasted to have 10% share with 1% increase. The global traffic market share of LCCs, which is 17% in 2012, is forecasted to be 21% in 2032 (Figure 2.5).

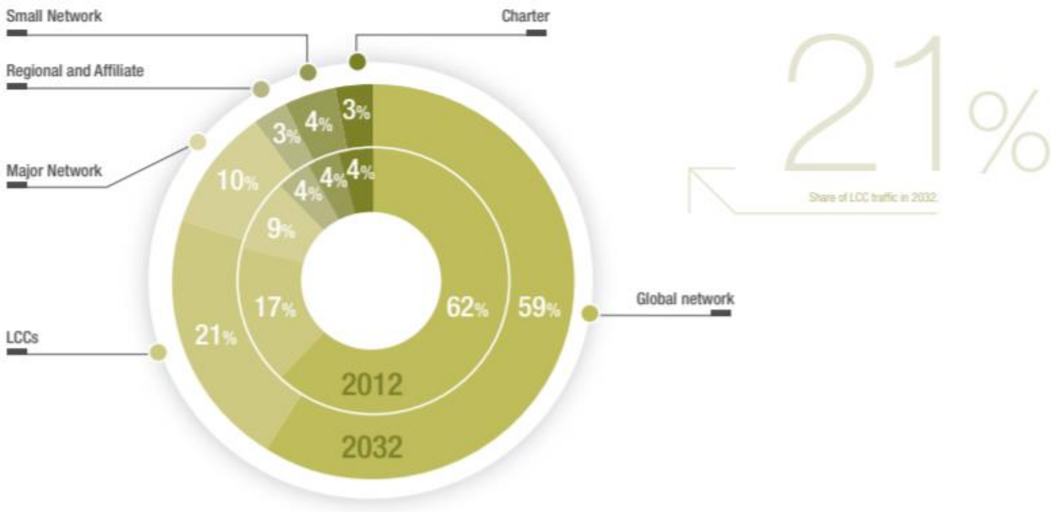

Figure 2.5. Global Traffic Market Share by Airline Types
Source: Airbus Global Market Forecast, 2012-2032

2.3. Alliances

Increased competition after the emergence of low-cost carriers has brought changes to the airline industry. These changes have forced airlines to adapt different strategies to strengthen their performance through mergers, acquisitions, and strategic alliances. The possibility of forming alliances has been considered by airlines since the 1990s (Gaggero & Bartolini, 2012). Any partnership arrangements between two or more airline companies with the aim of enhancing competitiveness and thus improving the performance is known as an alliance (Morrish & Hamilton, 2002). Most of the airlines seek to extend their network beyond the markets they serve but the regulations, ownership and control restrict their market access, and these have pushed airlines to form strategic alliance groups (Iatrou & Alamdari, 2005). Alliances have flexible organization forms, they promise their member airlines a global network and a rapid expansion (Agusdinata & De Klein, 2002). Alliance groups instantly enlarge airlines' market shares by allowing them to add new routes into their networks (Vander Kraats, 2000). Beginning their history with five airlines in 1997 with Star Alliance, three dominant global alliance groups, which are Star Alliance, SkyTeam and OneWorld, serve the industry with their 58 member airlines today.

The reasons behind joining an alliance membership are listed in the study of Oum and Park (1997) as:

- By linking up their networks and providing “seamless” services to their customers, alliances can expand service network.
- By linking up the partner’s networks, alliance membership allows the members to feed traffic to each other and it increases their load factor.
- The advantage of increased traffic density, economies of scale and scope allow alliance partners to decrease their unit costs.
- Increased flight frequencies, more convenient flight schedules and more on-line connections are the major dimensions of service quality which can be achieved by an alliance membership.
- An allied airline can be more able to offer more routing choices to its customers than a non-allied airline.
- Codeshared flights between allied airlines are listed with primacy and more than once on the computer reservation systems. This causes other airlines’ flights to be down below the screen or on the next page.

Alliance membership also gives the advantage of being in a global position to its members without investing in infrastructure or slots in foreign airports (Ramón-Rodríguez, Moreno-Izquierdo, & Perles-Ribes, 2011). According to Kleymann and Seristö (2001), alliance integration requires a certain investment and it brings risk together. Their assumptions on the risk of alliance membership are listed as:

- Airlines have uncertain and ambiguous environment in alliances.
- The value created in alliances is not predestinated.
- Because the relationship between alliance partners can evolve, it cannot be predicted.
- Member airlines which are partners in an alliance can be rival tomorrow because of the unstable field of alliances.
- The success of an alliance membership depends on whether the airline adapts the changes.

Contrary to the assumption that alliance membership help airlines improve their performances, some studies showed that there is no relationship between the operational performance of airlines and alliance membership (Min & Joo, 2016; Kottas & Madas, 2018). Official Aviation Guide's (OAG) executive vice president Data and Market Intelligence, John Grant says: "Alliances are no longer the only means of international competition. Increasingly joint ventures, equity stakes and less formal partnerships are being used, all of which challenge existing structures and operations." (OAG, n.d.).

Figure 2.6 shows that total RPK share of three major alliance groups which was 63.2% in 2015 has decreased to 56.1% in 2019. The dominant share among alliance groups belongs to Star Alliance in both years but the group has 8.8% decrease in its shares from 2015 to 2019. The RPK share of OneWorld group has decreased from 19.3% to 15.4% with a decrease rate of 20.2% over a five-year period. SkyTeam has a relatively lower decrease rate with 5.5% when compared to other two groups. The non-allied airlines have increased their market share from 36.8% in 2015 to 43.9% in 2019 with an increase rate of 19.3% (All Nippon Airways, n.d.).

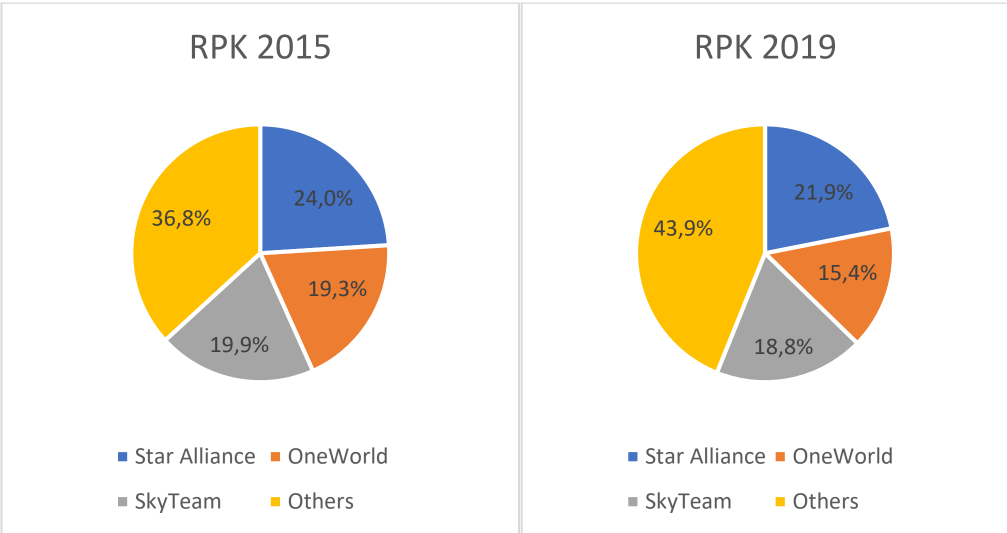

Figure 2.6. RPK Shares by Alliance 2015 vs. 2019

Source: "Annual Report 2015" and "Annual Report 2019" by All Nippon Airways

2.4. The Future of the Airline Industry

The airline industry has faced with several changes over the past years such as increased share of low-cost carriers and hence, the implication of innovative solutions to catch the market trend and become competitive in this changing environment is still of paramount importance. It is forecasted that the global population will reach to 8.5 billion by 2030 and 9.7 billion by 2050, and the growth will come from India, Nigeria, Pakistan, Democratic Republic of the Congo, Ethiopia, Tanzania, the United States, Indonesia and Uganda. This change is the potential for new markets, labor and capital for the airlines (IATA, 2018a).

Europe and North America have been the center of aviation for decades where the air transport activities mostly exist, but Figure 2.7 shows that the direction of air traffic flow has been changing from west to east. Changes in economy, increase in middle-class population over years will move the center of gravity to south and east (Airbus GMF, 2019).

Figure 2.7. Center of Gravity Moving South and East

Source: Airbus GMF, 2019

International Air Transport Association (IATA, 2018) forecasted that in 2037, the Asia-Pacific region will be the largest market with compound annual growth rate (CAGR) of 4.8% and passenger numbers will reach to 3.9 billion with an additional 2,351 million passengers. Second highest CAGR increase will belong Africa region with 4.6% and with an extra 199 million passengers, passenger numbers will reach to 334 million. Total market will increase 4.4% in the Middle East and reach 501 million passengers with an extra 290. The growth will be followed in the Latin America region by a CAGR of 3.6% and total passenger numbers will increase to 731 million with an extra 371 million passengers. North America is already one of the largest markets and it will see an increase of 2.4% annually and carry 1.4 billion passengers in total. Europe will remain as one of the largest markets carrying 1.9 billion passengers in 2037 with a CAGR of 2.0%. The Figure 2.8 shows the 20-year passenger growth outlook for each region. As a result of the changes in the center of aviation gravity and population, European and North American airlines have found themselves in a competition with the carriers from Middle East and Asia-Pacific regions.

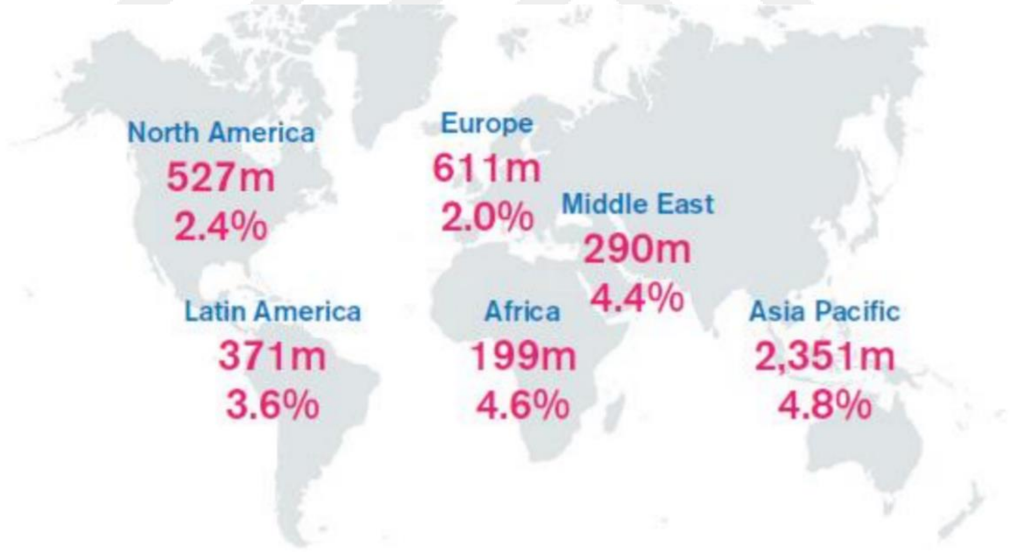

Figure 2.8. 20-Year Passenger Growth Outlook 2017-2037

Source: The Global Air Transport Industry Presentation by IATA, 2018

CHAPTER III

LITERATURE REVIEW

There are various research conducted on the performance evaluation of airlines in the literature. The methodology used to measure the performance of airlines differs according to the aim of the research. One of the most appropriate technique is DEA. The DEA models for measuring the efficiency of airlines also differs. In this study, a review of the previous research dealing with the implementation of DEA in performance evaluation in aviation is performed.

One of the early studies on the performance evaluation of airlines is Oum and Yu's (1996). They divided the dataset to yearly panel data as 5 inputs and 5 outputs to compare the productivity and unit costs of 23 airlines between 1986 and 1993. They analyzed the productivity of airlines with total factor productivity (TFP). Input variables of this research are labor, fuel, materials, flight equipment and ground property and equipment. Output variables are scheduled passenger service measured in RPK, freight service measured in revenue ton kilometer (RTK), mail service measured in RTK, non-scheduled passenger and freight service and incidental services. Their study showed that between the analyzed years, major European and Asian carriers were more productive than the ones in North America.

Scheraga (2004) used both input-oriented CRS and VRS model DEA to analyze 38 airlines from North America, Europe, Asia, and Middle East for the year 2000. The inputs for this analysis are available ton kilometer (ATK), operating cost and non-flight assets. The outputs are RPK and non-passenger RTK. The research revealed that airlines with operational efficiency are vulnerable in point of financial mobility.

Chiou and Chen (2006) used different models of DEA to evaluate 15 Taiwanese air routes from cost efficiency, cost effectiveness and service effectiveness perspectives in 2001. The inputs for cost efficiency analysis are fuel cost, personnel cost, and aircraft cost where the outputs are number of flights and seat-mile. The inputs for service effectiveness are number of flights and seat-mile where the outputs are passenger mile and embarkation passengers. The inputs for cost effectiveness are fuel cost, personnel cost, and aircraft cost where the outputs for cost effectiveness are passenger mile and embarkation passengers. The research found that ten routes were relatively cost efficient, five routes were cost effective and four routes were relatively service effective.

Barbot, Costa, and Sochirca (2008) compared the efficiencies of 49 airlines for the year 2005 using input-oriented VRS DEA model and TFP. The inputs of the research data for DEA are labor, fleet and fuel. The outputs are ASK, RPK and RTK. In TFP analysis, they used number of employees, fleet, fuel, and other operating inputs as input and as outputs RPK, RTK and ancillary outputs, which are the items related to operations other than passenger and cargo, were used. The variables for regression analysis are employees per ASK, block hours per day, fuel consumption per million ASK and airlines' size in billion ASK. The result showed that FSCs are not as efficient as LCCs.

Barros and Peypoch (2009) used output-oriented CRS model DEA to evaluate the operational performance of 29 European airlines between 2000 and 2005. The inputs for DEA are the number of employees, operational cost, and the number of planes. The outputs are RPK and EBIT. The drivers of efficiency such as population and network alliance were evaluated with bootstrap truncated regression. Alliance membership and demographic dimensions of airlines' home countries were found to have importance.

Bhadra (2009) used gallons of jet fuel used, number of full time employees, ratio of flight stage miles to trip stage miles, utilization of aircraft in hours, number of seats per aircraft and number of aircrafts as inputs and available seat mile (ASM) as output for the analysis of 13 US airlines between 1985 and 2006 with output-oriented VRS DEA model. The research revealed that by reducing block hours, airlines tend to be more efficient.

Wing Chow, (2010) utilized output-oriented Malmquist productivity index (MPI) to measure the productivity changes of 16 Chinese airlines between 2003 and 2007. The inputs for the research are full-time employee number, aircraft fuel used and seat capacity, and the output is RTK. It was found that non-state-owned airlines perform better than state-owned airlines.

Carlos Pestana Barros and Couto, (2013) conducted an analysis with 3 inputs (employees, operational cost, and ASK) and 2 outputs (RPK and RTK) to measure the productivity of 23 airlines between 2000 and 2011 with Luenberger productivity indicator (LPI) and MPI. They found that most European airlines did not manage productivity growth between 2001 and 2011.

Carlos P. Barros, Liang, and Peypoch, (2013) used output-oriented B-convex model to evaluate the technical efficiency of 11 US airlines between 1998 and 2010. The inputs for the analysis are total cost, number of employees and fuel used. The outputs are total revenue, RPM, and passenger load factor. Drivers of efficiency were investigated with bootstrap test. Size of the airlines, mergers and acquisitions were revealed to influence the efficiency of US airlines.

Merkert and Williams (2013) measured the efficiency of 18 European public service obligation (PSO) airlines between 2007 and 2009 using input-oriented CRS DEA model. The inputs for the research are ASK and the number of employees. The outputs are RPK and flight departures. The impacts of specific details of the airlines and their 206 PSO contracts were determined with truncated regression analysis. The result of the research showed that airline efficiency is not affected by ownership.

Wu, He, and Cao, (2013) used both input-oriented CRS and VRS model DEA to investigate the operational efficiency of 12 airlines between 2006 and 2012. The inputs for the analysis are full-time equivalents (FTE), operational cost, number of operated aircrafts. The outputs were selected as RTK of passenger and cargo and operating revenue. The impacts of international focus, proportion of cargo traffic and the level of salaries on operational efficiencies of airlines were measured with bootstrapped truncated regression. It was found that international focus negatively affects the performances where level of salaries has a positive impact. A U-shaped relationship was revealed between efficiency and proportion of cargo traffic.

Lee and Worthington (2014) used a bootstrap DEA truncated regression with output-oriented VRS model to measure the performance of 42 international airlines in 2016 and find the sources of efficiency. The inputs of the analysis are average number of employees, total assets and kilometers flown. The output is ATK. It was found in the analysis that operations of mainstream airlines need to be reorganized and rescaled to keep the position in the competitive area. The second stage analysis showed that better organizational efficiency is contributed by the improvements in weight load, private ownership, and status as a low-cost carrier.

Cao, Lv, and Zhang, (2015) divided 29 Chinese airlines as central, local, and private joint airlines and investigated those airlines' productivity efficiency for 2005 by using MPI. The input variables are the number of full-time employees, aircraft fuel used and the amount of aircrafts where the output variables include total flight volume, RTK of passenger and freight. Research findings suggested that after the deregulation of China's air transport industry, non-private-owned airlines improved their productivity efficiency and their performance surpassed state-owned airlines'.

Cui and Li (2015) calculated the energy efficiency of 11 airlines from 2008 to 2012 by using Virtual Frontier Benevolent DEA Cross Efficiency model (VFB-DEA). The inputs for the analysis are number of employees, capital stock and tons of aviation kerosene and the outputs are RTK, RPK, total business income and CO_2 emission decrease index. The results of the analysis showed the remarkable influence of American financial crisis on the change in energy efficiency during the analyzed years and capital efficiency is found to be the factor behind energy efficiency.

Mallikarjun (2015) used an un-oriented VRS DEA model to investigate the organizational efficiencies of 27 US airlines and tried to find out the sources of inadequate operating performance. Airlines were divided into two groups as major and national airlines. Operating expense is the input and operating revenue is the output for DEA. ASM and RPM were used as intermediate products. The analysis revealed the higher efficiency of major US airlines than national ones.

Min and Joo (2016) used output-oriented CRS model DEA to compare the efficiency of the strategic alliances among 59 global airlines between 2006 and 2010. The inputs for the analysis are underutilization and operating expense where the outputs are passengers, operating revenue, RPK and service rating. The efficiency scores of the alliance member and non-alliance member airlines were compared with a post-hoc analysis and no difference was found. The study implied that alliance membership has no impact on the performance of airlines.

Saranga and Nagpal, (2016) used various of indicators such as ASK, RPK, total number of full time employees at a year end, operating revenue per ASK, operating expenses less employee expenditure per ASK, employee expenditure/staff strength, load factor, revenue hours per aircraft, average stage length, passenger per departure, percentage of international operations, yield, operating expenses per RPK to compare the airlines' performances in India for the period 2005-2012. They implied input-oriented VRS model DEA, two-way random effects generalized least squares (GLS) regression and Tobit model. The research suggested that better market performance can be had via technical efficiency in Indian airline industry.

Choi (2017) used output-oriented CRS and VRS DEA models and output-oriented MPI and bootstrap regression analysis to analyze the efficiency of 14 US domestic airlines between 2006 and 2015. The input for the analysis is cost per available seat and the outputs are revenue per available seat, passenger yield and load factor. One of the findings of the research is that network legacy carriers had the highest efficiency where low-cost carriers had the lowest. Another finding is that the effect of fluctuations in technical change was greater than on fluctuations of MPI. In terms of efficiency and economies of scale, mergers and acquisitions between US airlines were found to have both positive and negative effects. Revenue factor had a positive effect on the efficiency of US airlines, but cost environmental factors were found to have negative effects.

Kottas and Madas (2018) conducted an analysis using input-oriented CRS DEA model super-efficiency approach for the evaluation of 30 major international airlines between 2012 and 2016. They also used post-hoc analysis to assess whether alliance membership and freight revenue share have effects on the efficiency of airlines. The inputs of this analysis are number of employees, total operating cost, and number of operating aircraft. The outputs are total operating revenue, RPK, and RTK. The researchers found that there is no efficiency difference between the airlines with and without an alliance membership. It is also found in the research that higher freight revenue share is associated with higher efficiency.

Kuljanin et al., (2019) analyzed 17 airlines operating at European airports during 2008-2012 and efficiencies of those airlines were evaluated according to fuzzy DEA CRS input-oriented model. Input variables of this research are determined as number of employees, number of aircraft in the fleet, cost per available seat kilometer (CASK), employee cost per ASK, ASK, delay and output variables are aircraft per employee, passenger per employee, RPK, load factor, number of passengers, operating revenue and the number of destinations. It was found in the research that Central and South East airlines had lower efficiency than western airlines.

Table 3.1 summarizes all relevant studies conducting the performance evaluation of airlines along with the models, inputs, and outputs used. The researches evaluate the performance of airlines from different regions of the world. Most of them conducted a post-hoc analysis to find the factors affecting the efficiency of airlines. Operating revenue, RPK, operating expense, number of employees and number of aircrafts are the most used inputs and outputs which also shapes the input and output selection of this study.

Table 3.1. Summary of the Studies on the Performance of Airlines

Author(s), Year	Airlines	Study period	Model*	Inputs*	Outputs*
Oum and Yu (1996)	23 International	1986-1993	TFP Index	Total number of employees, Fuel consumed, Materials, Fleet, Ground property and equipment	RPK, RTK (cargo), RTK (mail), Non-scheduled passenger and freight service (measured in RTK), Incidental services
Scheraga (2004)	38 International	2000	Input-oriented VRS, Output-oriented VRS Tobit regression	ATK, Operating cost, Non-flight assets	RPK, Non-passenger RTK
Chiou and Chen (2006)	1 Taiwanese (15 routes)	2001	Integrated CRS, VRS, Tobit regression, Agglomerative hierarchical clustering	Fuel cost, Personnel cost, Aircraft cost (production), Number of flights, Seat miles (service)	Number of flights, Seat miles (production), Passenger miles, Passenger number (service)
Barbot et al. (2008)	49 International	2005	Input-oriented VRS, TFP, Regression analysis	Number of core workers, Fleet, Fuel	ASK, RPK, RTK
Barros and Peypoch (2009)	29 European	2000-2005	Output-oriented CRS, Truncated regression	Number of employees, Operational cost, Number of aircrafts	RPK, EBIT
Bhadra (2009)	13 US*	1985-2006	Output-oriented VRS, Tobit regression	ASM	Fuel, FTE, Ratio of flight stage miles to trip stage miles, Utilization of aircraft, Number of seats per aircraft, Number of aircrafts
Wing Chow (2010)	16 Chinese	2003-2007	Output-oriented MPI	FTE, Aircraft fuel used, Seat capacity	RTK of passenger and cargo

Table 3.1. (Continued)

Author(s), Year	Airlines	Study period	Model*	Inputs*	Outputs*
Barros and Couto (2013)	23 European	2000-2011	LPI, MPI	Number of employees, Operational cost, ASK	RPK, RTK
Barros et al. (2013)	11 US*	1998-2010	Output-oriented B-Convex Model	Total cost, Number of employees, Fuel used	Total revenue, RPM, Passenger load factor
Merkert and Williams (2013)	18 European	2007-2009	Input-oriented CRS, Truncated regression	ASK, Number of employees	RPK, Flight departures
Wu et al. (2013)	12 Chinese and non-Chinese	2006-2010	Input-oriented CRS, VRS, Truncated regression	FTEs, Operational cost, Number of operated aircrafts	RTK of passenger and cargo, Operating revenue
Lee and Worthington (2014)	42 International	2006	Output-oriented VRS Truncated regression	Average number of employees, Total assets in USD, Kilometers flown	ATK
Cao et al. (2015)	29 Chinese	2005-2009	MPI	FTE, Aircraft fuel used, Number of aircrafts	RTK of passengers and cargo, Total flight volume
Cui and Li (2015)	11 International	2008-2012	VFB	Number of employees, Capital stock, Tons of aviation kerosene	RTK, RPK, Total business income, CO_2 emission decrease index
Mallikarjun (2015)	27 US*	2012	Un-oriented network VRS	Operating expenses (1st stage), ASM (2nd stage), RPM (3rd stage)	ASM (1st stage), RPM (2nd stage), Operating revenue (3rd Stage)
Min and Joo (2016)	59 International	2010	Output-oriented CRS, Post-hoc analysis	Operating expenses, Underutilization (load factor subtracted from unity)	Number of passengers, RPK, Operating revenue, Service ratings

Table 3.1. (Continued)

Author(s), Year	Airlines	Study period	Model*	Inputs*	Outputs*
Saranga and Nagpal (2016)	13 Indian	2005-2012	Input-oriented VRS, Two-way random effects GLS regression, Tobit regression	ASK, FTE, Operating expense less employee expenditure/ASK, Employee expenditure per full time employee	RPK, Operating revenue/ASK
Choi (2017)	14 US*	2006-2015	Output-oriented CRS, VRS, Bootstrap regression	CASM	Revenue per ASM, Passenger yield, Load factor
Kottas and Madas (2018)	30 International	2012-2016	Input-oriented CRS, Post-hoc analysis	Number of employees, Total operating cost, Number of aircrafts	Total operating revenue, RPK, RTK
Kuljanin et al (2019)	17 European and Emirates	2008-2012	Input-oriented CRS MPI	Number of employees, Number of aircrafts, cost per ASK, Employee cost per ASK, ASK, Delay	Aircraft per employee, Passenger per employee, RPK, Load factor, Number of passengers, Operating revenue, Number of destinations

Notes: CRS: Constant returns to scale; VRS: Variable returns to scale; VFB: Virtual frontier benevolent; TFP: Total factor productivity; GLS: Generalized least squares; MPI: Malmquist productivity index; LPI: Luenberger productivity indicator; CASM: Cost per available seat mile; ASK: Available seat kilometers; ASM: Available seat miles; ATK: Available ton kilometers; RPK: Revenue passenger kilometers; RPM: Revenue passenger miles; RTK: Revenue ton kilometers; FTE: Full-time equivalent; USD: United States dollar; US: United States.

CHAPTER IV

DATA AND METHODOLOGY

4.1. Data

In this study, the efficiencies of 38 airlines between 2015 and 2019 were measured. The airlines were selected from different regions of the world according to IATA regional classification. 14 airlines from Europe and Russia, 7 airlines from North America, 3 airlines from Latin America, 8 airlines from China and North Asia, 4 airlines from Asia-Pacific and 2 airlines from Middle East and Africa were selected. The aim was to include each region's representative full-service and low-cost airlines. Of 38 airlines, 9 are LCCs from Europe, North and Latin America and Asia-Pacific. In this research, there are 190 Decision Making Units (DMUs) with 38 airline observations for 5 years from 2015 to 2019 (38 airlines x 5 = 190 observations).

One of the critical tasks in DEA is the selection of inputs and outputs. Based on the literature review of previously conducted studies and data availability, 3 inputs and 2 outputs were selected. The inputs can be divided into two subcategories as resources and expense. The number of employees and the number of aircrafts have the aspects of resources where the operating expense is under the category of expense. The outputs which are the indicators of performance were selected as RPK and operating revenue. RPK is the indicator of productivity and operating revenue is the indicator of profitability. The rule of thumb that the minimum number of DMU observations should be greater than three times the inputs plus outputs was respected [$190 \geq 3(3+2)$] (Carlos Pestana Barros & Peypoch, 2009; Carlos Pestana Barros & Couto, 2013; Kottas & Madas, 2018; Lee & Worthington, 2014).

4.1.1. Inputs

Operating expense is the expense occurred while acquiring and utilizing the resources to perform an operation. Operating expense is a popular input measure for airline efficiency evaluation (Mallikarjun, 2015; Min & Joo, 2016). Operating expenses were converted into US dollars for this research using the exchange rates extracted from the annual reports of the airlines.

Employees are personnel involve in all the aspects of performing, planning, managing, and supervising the operations. Number of employees is one of the most used inputs in the literature (Carlos Pestana Barros & Peypoch, 2009; Carlos Pestana Barros & Couto, 2013; Carlos P. Barros et al., 2013; Cui and Li, 2015; Kottas and Madas, 2018; Kuljanin et al., 2019; Merkert & Williams, 2013; Oum & Yu, 1996). There are different references in the literature and in the annual reports of the airlines for number of employees such as number of FTEs (Cao et al., 2015; Chow, 2010; Saranga & Nagpal, 2016; Wu et al., 2013), average number of employees (Lee & Worthington, 2014) and number of core workers (Barbot et al., 2008).

Aircraft is the main means through which airline operations are conducted. Assigning the appropriate number and type of aircraft can help airlines maintain their market share and satisfy their customer needs (Kottas & Madas, 2018). Number of aircrafts is also one of the most used inputs in the literature (Barbot et al., 2008; Carlos Pestana Barros & Peypoch, 2009; Cao et al., 2015; Kottas & Madas, 2018; Kuljanin et al., 2019; Oum & Yu, 1996; Wu et al., 2013).

4.1.2. Outputs

Airlines offer services such as passenger and freights transport and beside those, they have ancillary services like catering, ground handling and maintenance. Operating revenue is the financial earnings extracted by these services. Revenue is one of the most used outputs for the evaluation of airline efficiencies. In some research, it was expressed as total revenue (Barros et al., 2013) and operating revenue (Kuljanin et al., 2019; Mallikarjun, 2015; Min and Joo, 2016; Wu et al., 2013), and total operating revenue (Kottas & Madas, 2018). For practical purposes, operating revenues were converted into US dollars at exchange rates from the annual reports of the airlines to make the data comparable.

RPK is the productivity indicator of an airline and is calculated as the number of paying passengers carried on scheduled flights multiplied by the number of kilometers those seats were flown. RPK is another most widely adopted output measure (Barbot et al., 2008; Carlos Pestana Barros & Peypoch, 2009; Carlos Pestana Barros & Couto, 2013; Cui & Li, 2015; Kottas & Madas, 2018; Kuljanin et al., 2019; Merkert & Williams, 2013; Min & Joo, 2016; Oum & Yu, 1996; Saranga & Nagpal, 2016; Scheraga, 2004). Where the metric system is not used, RPK can be expressed as RPM (Carlos P. Barros et al., 2013; Mallikarjun, 2015). In this research, RPMs were converted into RPKs.

4.2. Methodology

The evaluation of operational performance is an important indicator to the management of the companies. The studies on the performance of airlines reveal important results about each of the evaluated airlines and the industry. Recognizing the factors behind the efficiency/inefficiency can lead airlines to evaluate and improve their performance. Researchers have employed several methodologies to evaluate the performance of airlines. In consideration of the previous studies, DEA was determined as the method of the analysis, which is a powerful nonparametric method allowing post-hoc analysis. However, DEA comes with a shortcoming. The method draws an efficient frontier and assigns an efficiency score of one to all DMUs on the frontier. To discriminate the performance of efficient DMUs, super-efficiency DEA was also used, which enabled post-hoc analysis to be conducted. Furthermore, the effects of operational performance determinants were assessed by utilizing post-hoc analysis. Figure 4.1 shows the main steps of the applied methodology. The rest of this section gives a short background on the methodology.

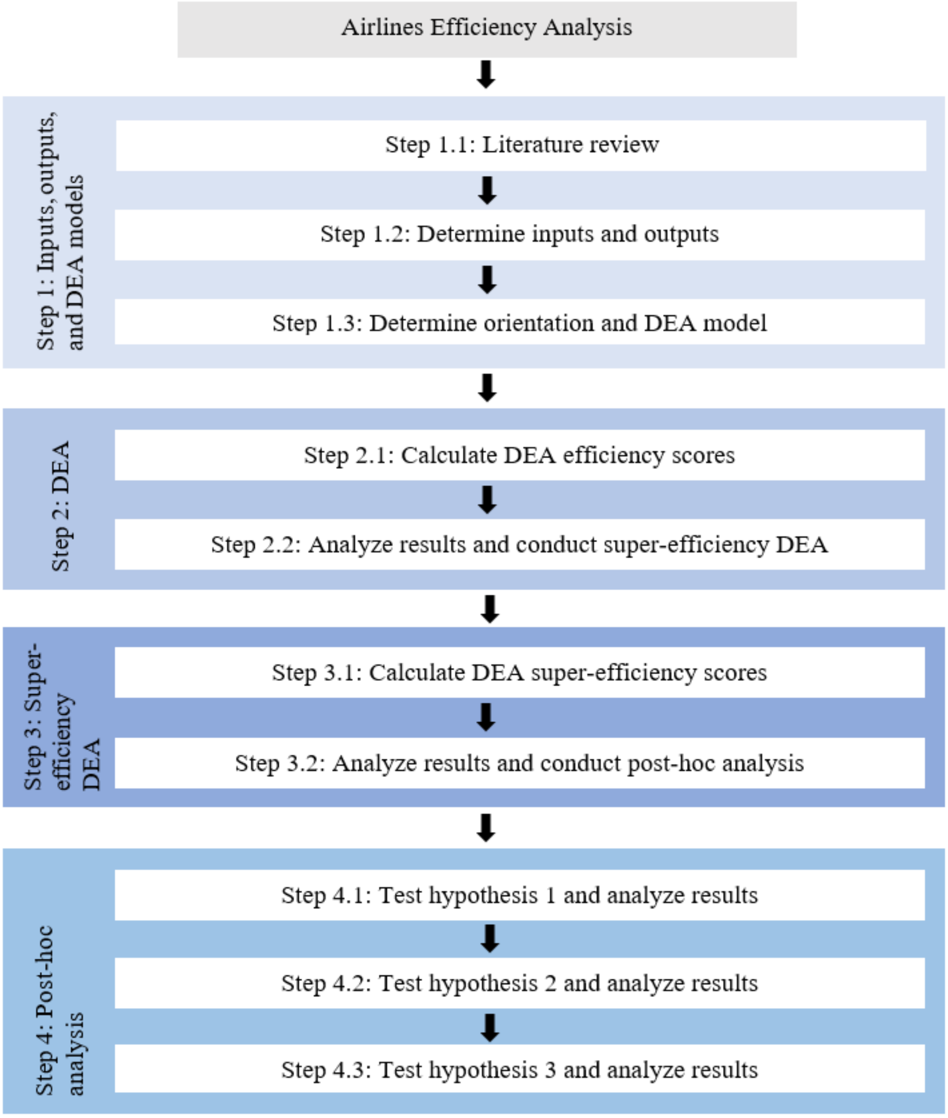

Figure 4.1. Main Steps of the Methodology

4.2.1. Data Envelopment Analysis

DEA is a non-parametric method for measuring efficiency of entities which are known as DMUs. It allows the use of multiple inputs and outputs without requiring any functional form on data. It was initially introduced by Farrell, (1957) and extended by Charnes, Cooper, and Rhodes, (1978) and Banker, Charnes, and Cooper, (1984). The model used by Charnes et al. (1978) is known as CCR (from the initials of the writers' names) which assumes constant returns to scale (CRS) and the model proposed by Banker et al. (1984) is known as BCC (from the initials of the writer' name) which assumes variable returns to scale (VRS). The traditional DEA rates the efficient DMUs as one and the inefficient DMUs are rated between zero and one. DEA consists of different models. CRS model measures the technical efficiency (TE) of a DMU and VRS model measures the pure technical efficiency (PTE). The ratio between TE and PTE reveals the scale efficiency (SE).

An essential element of DEA is the orientation which considers the process of input-to-output transformation and, input-oriented models concern with the reduction of excess inputs. In this model, the efficiency of evaluated DMU depends on its ability to reduce its inputs without decreasing outputs when the inputs are controllable (Kottas & Madas, 2018). In this direction, this study applied input orientation for DEA analysis because it is assumed that airline companies have more control on their inputs than outputs (Saranga & Nagpal, 2016; Wu et al., 2013). In the first stage of DEA analysis, input-oriented models of CRS and VRS were applied to find TE, PTE and SE efficiencies of airlines. In order to calculate the efficiency scores DEAP Version 2 software tool was utilized.

Given *n* DMUs which are evaluated in terms of *r* input and *s* output, the input-oriented efficiency of DMU_q, θ_q is calculated using the following dual linear programming problem:

$$\min_{\theta,\lambda} \theta_q, \tag{1}$$

$$\text{s.t.}$$

$$y_j\lambda - y_{jq} \geq 0 \quad j = 1, \ldots, s \tag{2}$$

$$\theta_q x_{iq} - x_i\lambda \geq 0 \quad i = 1, \ldots, r \tag{3}$$

$$\lambda \geq 0, \tag{4}$$

where $y_j = [y_{j1}, \ldots, y_{jn}]$, $x_i = [x_{i1}, \ldots, x_{in}]$ are *n* dimensional column vectors of *j* output and *i* input factors, respectively. Also, $\lambda = [\lambda_1, \ldots, \lambda_n]^T$ is a *n* dimensional vector of the dual variables of the model. It should be noted that the same problem must be solved *n* times, once for each DMU. The model presented here is referred as the input-oriented CRS model. The model can be extended to account for the VRS situation by adding a convexity constraint to the dual LP model.

$$B\lambda = 1, \tag{5}$$

where B is an n-dimensional vector one.

4.2.2. Super-Efficiency Data Envelopment Analysis

Andersen and Petersen (1993) proposed a radial super-efficiency method which allows the efficient DMUs to have scores greater than one and the inefficient DMUs remain unchanged and hence, the super-efficiency DEA models can discriminate between efficient airlines. This study employed input-oriented CRS model for super-efficiency assessment of airlines using EMS Version 1.3 software tool. It is assumed that there are n DMUs. Each DMU_j ($j = 1, 2, \ldots, n$) consumes a vector of inputs, x_j, to produce a vector of outputs, yj. The linear programming of the CRS input-oriented super-efficiency model is:

$$\min \rho \tag{6}$$

$$\text{s.t.}$$

$$\sum_{\substack{j=1 \\ j \neq 0}}^{n} \lambda_j x_j \leq \rho x_{0;} \tag{7}$$

$$\sum_{\substack{j=1 \\ j \neq 0}}^{n} \lambda_j y_j \geq y_{0;} \tag{8}$$

$$\rho, \lambda_j \geq 0, j \neq 0; \tag{9}$$

Where (x_0, y_0) represents DMU_0. The difference between the traditional and super-efficiency DEA models is that the efficient DMU is excluded from the reference set.

4.2.3. Post-hoc Analysis

Post-hoc analysis was used to assess whether there are statistically significant mean efficiency differences between two groups such as large and small airlines (according to their ASKs), full-service and low-cost airlines, and lastly, the airlines with alliance membership and without an alliance membership.

H_1: Large airlines and small airlines have identical mean efficiency.

H_2: Full-service airlines and low-cost airlines have identical mean efficiency.

H_3: Allied airlines and non-allied airlines have identical mean efficiency.

The statistical tests were performed utilizing IBM SPSS software tool Version 26. Mann-Whitney rank-sum test, which is a popular non-parametric test to compare the outcomes of two independent groups, was employed to compare the mean efficiency scores of two groups.

The formula for the test is:

$$U = n_1 n_2 + \frac{n_2(n_2+1)}{2} - \sum_{i=n_1+1}^{n_2} R_i \tag{10}$$

Where:

U = Mann-Whitney U test.

n_1 = Sample size one.

n_2 = Sample size two.

R_i = Rank of the sample size.

CHAPTER V

EMPIRICAL FINDINGS

In order to evaluate the efficiency scores of airlines, given the data availability, 3 inputs and 2 outputs were selected in the consideration of the previous studies. Operating expense, number of employees and number of aircrafts were used as inputs. The outputs are operating revenue and RPK. The data was collected from the annual and financial reports of airlines. As aforementioned, airlines process their data with diverse approaches. Thus, some required conversions were performed. More specifically, operating expense and operating revenue were converted into US dollars using the exchange rates in the annual reports of airlines. Additionally, non-metric traffic figures (e.g., ASM, RPM) were converted into metric system (e.g., ASK, RPK). ASK was not used as either input or output but it was needed for grouping the airlines according to their size for post-hoc analysis. Table 5.1 presents the descriptive statistics of inputs and outputs used in the evaluation. The results can be listed as:

- Average operating expense has risen with a rate of 19.4% within five years.
- As the industry grows, airlines need to hire more people, which allows an increase in the average number of employees. The mean of number of employees has risen from 32,370 employees in 2015 to 36,438 employees in 2019.
- The number of aircrafts that airlines have for their operations has also increased from average 335 aircrafts to 380 aircrafts at the end of 2019.
- The average operating revenue of airlines which was US$ 11,681 million in 2015 has increased 15.7% to average US$ 13,514 million in 2019.
- There is an increase of 25.4% in average RPKs from 2015 to 2019 which proves that demand for air traffic is increasing.

Table 5.1. Descriptive Statistics of Inputs and Outputs for Airlines

Year		Operating revenue (million USD)	RPKs (million seat-kilometers)	Operating expense (million USD)	Number of employees	Number of aircrafts
		Output	Output	Input	Input	Input
2015	Mean	11,681	109,407	10,458	32,370	335
	SD*	10,284	88,596	8,804	28,079	345
2016	Mean	11,466	114,934	10,257	33,166	346
	SD	9,898	90,021	8,558	28,736	347
2017	Mean	12,154	122,781	11,080	34,126	357
	SD	10,214	92,170	9,165	29,427	351
2018	Mean	13,271	130,992	12,255	35,339	372
	SD	10,964	96,341	10,076	30,110	360
2019	Mean	13,514	137,244	12,486	36,438	380
	SD	11,394	100,991	10,314	30,939	365

Notes: SD = Standard deviation.

Table A.1 (in Appendix) shows the descriptive statistics of inputs and outputs for each airline over the five-year period. The highest average operating revenue and operating expense belong to American Airlines with $US 47,737 million and $US 38,484 million, respectively. American Airlines has also the highest RPK mean with 368,540 million RPK. The airline, with its employee (average 126,000) and aircraft numbers (average 1,542), is the largest airline company among other airlines under evaluation. Kenya Airways has the lowest average operating revenue and operating expense which are $US 1,166 million and $US 1,184 million, respectively. It has also the smallest fleet with average 46 aircrafts. Wizz Air has the least number of employees with an average of 3,141 employees (see Appendix).

5.1. DEA Results

In this study, the efficiency scores of 38 major airlines between 2015 and 2019 were measured. TE, PTE and SE of these airlines were assessed using input-oriented CRS and VRS models. TE measures the overall or managerial efficiency combining pure technical and scale efficiencies (TE = PTE x SE). It reflects the efficiency of converting inputs into outputs. PTE measures only the pure technical or managerial efficiency which depends on managerial factors for instance, the degree of customer satisfaction, advertising activities, cost-cutting, and load factor, but it misses the scale efficiency. Based on these differentiations, the ratio between TE and PTE enables the estimation of SE assuming efficiency is due to managerial abilities and scale effects. SE reflects the economies of scale to reach the efficiency frontier (Carlos Pestana Barros & Peypoch, 2009; Kottas & Madas, 2018; Min & Joo, 2016).

5.1.1. Results for 2015

TE reflects the success of managerial practices in terms of pure managerial and scale efficiencies. Table 5.2 shows the efficiency scores of 38 airlines in the year 2015. There are efficiency score variations among airlines and these variations can be derived from their adaptation of different strategies and having different resources (Carlos Pestana Barros & Peypoch, 2009). The number of TE efficient airlines is 11 and these are British Airways, EasyJet, Ryanair, Wizz Air, Alaska Airlines, Delta Airlines, Air Asia, Japan Airlines, Singapore Airlines, Emirates and JetBlue Airlines. All TE efficient airlines are also PTE efficient indicating that the scale is the source of efficiency. The lowest TE score belongs to Kenya Airways with 0.710.

PTE reflects the ideal utilization of resources by management. Total number of PTE efficient airlines is 17. Except for abovementioned 11 airlines, 6 of them (SouthWest Airlines, United Airlines, Eva Airways, Kenya Airways, Vueling Airlines and American Airlines) are only PTE efficient. Although pure managerial factors were satisfactory to be efficient, these airlines could not catch the efficiency frontier for TE due to their economies of scale; they were either too large or too small to be efficient. Gol Transportes Aeros has the lowest PTE score with 0.830.

The “returns to scale” column shows the position in the frontier of scale efficiency. 27 airlines suffer from economies of scale. 16 of these with decreasing returns to scale (DRS) are too large in dimension and they could have reduced their scale dimensions to reach the efficiency frontier. 11 of SE inefficient airlines with increasing returns to scale (IRS) are too small and they could have increased their dimensions to be efficient. 11 airlines with constant returns to scale (CRS) have the adequate dimensions.

Benchmarking is an appropriate procedure for inefficient entities to adopt the required procedure for approaching “the best practice” frontier (Carlos Pestana Barros & Peypoch, 2009). “Peer” columns in the Table 5.2 show the peer DMUs for the analyzed DMU based on the CRS and VRS models. Alaska Airlines and British Airways are the most significant peers since the times that they were taken as peers for TE inefficient airlines is greater than for other peers with 17 times. They are followed by Wizz Air and Emirates, which were taken as peers 13 times. EasyJet, Delta, Japan Airlines, Singapore Airlines and JetBlue were taken as peers 9, 6, 4, 4 and 3 times, respectively.

Emirates is the most significant peer under VRS efficiency assumption since it was taken as a peer 13 times for PTE inefficient DMUs. It is followed by Wizz Air and British Airways which were taken as peers 12 times each. Ryanair 10 times, Alaska Airlines 8 times, Delta, and Singapore Airlines 5 times each, EasyJet, Eva and SouthWest 4 times each, United and Japan Airlines 2 times each, were taken as peers. JetBlue was taken as a peer only once which indicates that it has a specialty regarding its inputs and outputs.

Table 5.2. Airlines Efficiency Scores, 2015

Airline number	Airline	TE	PTE	SE	Returns to Scale	Peer CRS	Peer VRS
1	Aeroflot	0.938	0.945	0.993	DRS	13,16,37	9,13,16,37
2	Air France	0.905	0.906	0.999	DRS	3,16,32	19,3,32
3	British Airways	1.000	1.000	1.000	CRS	3	3
4	EasyJet Airlines	1.000	1.000	1.000	CRS	4	4
5	Finnair	0.879	0.913	0.962	IRS	3,4,13,37	3,13,33,37
6	KLM	0.922	0.925	0.997	IRS	3,16,37	3,13,34
7	Lufthansa German Airlines	0.895	0.960	0.932	DRS	3,4,33	24,33,37
8	Norwegian Air Shuttle	0.899	0.908	0.990	DRS	4,13,33,37	4,9,13,33
9	Ryanair	1.000	1.000	1.000	CRS	9	9
10	Vueling Airlines	0.980	1.000	0.980	IRS	4,13	10
11	Scandinavian Airlines	0.881	0.897	0.982	IRS	3,4,19	3,4,13,16
12	Swiss International Airlines	0.963	0.978	0.984	IRS	3,4,33	3,13,33,37
13	Wizz Air	1.000	1.000	1.000	CRS	13	13
14	Turkish Airlines	0.928	0.932	0.996	DRS	3,4,13,19	3,4,9,13,37
15	Air Canada	0.912	0.916	0.996	DRS	3,13,16,21	3,9,16,19,23
16	Alaska Airlines	1.000	1.000	1.000	CRS	16	16
17	American Airlines	0.926	1.000	0.926	DRS	3,16,32	17
18	Avianca	0.820	0.830	0.988	IRS	16,32	13,16,32
19	Delta Airlines	1.000	1.000	1.000	CRS	19	19

Table 5.2. (Continued)

Airline number	Airline	TE	PTE	SE	Returns to Scale	Peer CRS	Peer VRS
20	Gol Transportes Aeros	0.796	0.797	0.999	DRS	13,16,37	9,13,16,37
21	JetBlue Airways	1.000	1.000	1.000	CRS	21	21
22	LATAM Airlines	0.886	0.890	0.995	DRS	13,16,37	9,16,23,37
23	SouthWest Airlines	0.994	1.000	0.994	DRS	3,16,19,21	23
24	United Airlines	0.959	1.000	0.959	DRS	3,4,19	24
25	Air Asia	1.000	1.000	1.000	CRS	25	25
26	Air China	0.940	0.949	0.991	DRS	13,16,37	9,16,23,37
27	All Nippon Airways	0.936	0.939	0.998	IRS	3,16,32	3,13,34
28	Cathay Pacific	0.987	0.987	0.999	DRS	3,4,33,37	3,4,19,33,37
29	China Airlines	0.932	0.959	0.971	IRS	3,16,37	3,13,34,37
30	China Eastern Airlines	0.871	0.879	0.991	DRS	13,16,37	9,16,23,37
31	China Southern Airlines	0.888	0.930	0.954	DRS	13,16,37	9,19,24,37
32	Japan Airlines	1.000	1.000	1.000	CRS	32	32
33	Singapore Airlines	1.000	1.000	1.000	CRS	33	33
34	Eva Airways	0.959	1.000	0.959	IRS	3,16,37	34
35	Thai Airways	0.918	0.923	0.994	IRS	13,16,37	3,13,34,37
36	Qantas	0.925	0.926	0.999	DRS	3,13,19,21	3,4,9,19,21
37	Emirates	1.000	1.000	1.000	CRS	37	37
38	Kenya Airways	0.710	1.000	0.710	IRS	3,16,19	38

5.1.2. Results for 2016

Table 5.3 shows the efficiency scores of 38 airlines in the year 2016. The number of TE efficient airlines is 11 and these are British Airways, EasyJet, Ryanair, Vueling Airlines, Wizz Air, Alaska Airlines, JetBlue Airways, Air Asia, Japan Airlines, Singapore Airlines and Emirates. All TE efficient airlines are also PTE efficient which indicates that scale is the source of efficiency. The lowest TE score in 2016 is 0.782 and it belongs to Kenya Airways.

Total number of PTE efficient airlines is 17. Except for abovementioned airlines, 6 of these airlines are only PTE efficient (American Airlines, Delta Airlines, SouthWest Airlines, United Airlines, Eva Airways and Kenya Airways). Since PTE shows the pure managerial efficiency, the reason behind TE inefficiency of these airlines is their scale dimension; they are either too large or too small to be efficient in TE. The lowest TE score in 2016 belongs to Turkish Airlines with a score of 0.829.

KLM, Turkish Airlines and Cathay Pacific are SE efficient, but they could not catch the frontier for TE. This shows that although they had adequate dimensions to be efficient, due to their pure managerial inefficiencies, they could not be TE efficient. Kenya Airways has also the lowest SE score of 2016 which is 0.782.

The “returns to scale” column shows the position in the frontier of scale efficiency. 24 airlines are SE inefficient. Of 15 airlines with DRS are too large in dimension and they could have reduced their dimension to become TE efficient. 9 airlines with IRS are too small in dimension and they could have increased their dimensions. There are 14 airlines with CRS whose dimensions are adequate.

In the Table 5.3, “Peer” columns show the peer DMUs for evaluated DMU based on the CRS and VRS model in 2016. For those TE inefficient airlines, JetBlue Airlines was taken as a peer 16 times which is the most significant one among other peer DMUs. Japan Airlines and Ryanair were taken as peers 14 times each. Singapore Airlines, Emirates, Wizz Air, British Airways, and Alaska Airlines were peers 11, 9, 8, 7 and 5 times, respectively.

Emirates is the most significant airline in terms of the times (14 times) it was taken as a peer for other PTE inefficient DMUs. Wizz Air, Ryanair, Singapore Airlines, British Airways, Japan Airlines, Delta, JetBlue, Alaska Airlines and Kenya Airways were taken as peers 12, 11, 10, 9, 7, 6, 5, 2 and 3 times, respectively. United Airlines and Eva Airways were the special DMUs in terms of inputs and outputs because they were taken as peers only once under VRS assumption.

Table 5.3. Airlines Efficiency Scores, 2016

Airline number	Airline	TE	PTE	SE	Returns to Scale	Peer CRS	Peer VRS
1	Aeroflot	0.943	0.944	0.999	DRS	13,21,37	9,13,21,37
2	Air France	0.887	0.892	0.995	DRS	21,32,37	3,19,32,37
3	British Airways	1.000	1.000	1.000	CRS	3	3
4	EasyJet Airlines	1.000	1.000	1.000	CRS	4	4
5	Finnair	0.880	0.927	0.949	IRS	9,32,33	13,33,38
6	KLM	0.939	0.939	1.000	CRS	3,21,32,37	3,13,21,32,37
7	Lufthansa German Airlines	0.949	0.984	0.965	DRS	9,32,33	24,33,37
8	Norwegian Air Shuttle	0.923	0.927	0.996	DRS	3,21,32,37	9,13,33,37
9	Ryanair	1.000	1.000	1.000	CRS	9	9
10	Vueling Airlines	1.000	1.000	1.000	CRS	10	10
11	Scandinavian Airlines	0.884	0.887	0.997	IRS	9,32,33	9,13,32,33
12	Swiss International Airlines	0.954	0.973	0.980	IRS	9,32,33	13,33,37,38
13	Wizz Air	1.000	1.000	1.000	CRS	13	13
14	Turkish Airlines	0.828	0.829	1.000	CRS	3,9,13,33	3,9,13,33,37
15	Air Canada	0.908	0.910	0.998	DRS	3,9,21,32	3,9,19,32
16	Alaska Airlines	1.000	1.000	1.000	CRS	16	16
17	American Airlines	0.921	1.000	0.921	DRS	16,21	17
18	Avianca	0.846	0.855	0.990	IRS	16,21	13,16,21
19	Delta Airlines	0.995	1.000	0.995	DRS	9,32,33	19

Table 5.3. (Continued)

Airline number	Airline	TE	PTE	SE	Returns to scale	Peer CRS	Peer VRS
20	Gol Transportes Aeros	0.855	0.872	0.980	IRS	9,16,21	13,16,21
21	JetBlue Airways	1.000	1.000	1.000	CRS	21	21
22	LATAM Airlines	0.880	0.883	0.996	DRS	13,21,37	3,9,21,37
23	SouthWest Airlines	0.982	1.000	0.982	DRS	16,21	23
24	United Airlines	0.957	1.000	0.957	DRS	9,32,33	24
25	Air Asia	1.000	1.000	1.000	CRS	25	25
26	Air China	0.944	0.965	0.978	DRS	9,16,21	3,9,19,37
27	All Nippon Airways	0.974	0.986	0.987	DRS	32,33,37	19,32,33,37
28	Cathay Pacific	0.902	0.902	1.000	CRS	3,13,33,37	3,9,13,33,37
29	China Airlines	0.894	0.925	0.967	IRS	3,21,32,37	13,34,37
30	China Eastern Airlines	0.861	0.878	0.980	DRS	9,13,21	3,9,19,32
31	China Southern Airlines	0.868	0.971	0.894	DRS	9,13,21	9,37
32	Japan Airlines	1.000	1.000	1.000	CRS	32	32
33	Singapore Airlines	1.000	1.000	1.000	CRS	33	33
34	Eva Airways	0.929	1.000	0.929	IRS	21,32,37	34
35	Thai Airways	0.918	0.950	0.966	IRS	13,21,37	13,33,37,38
36	Qantas	0.953	0.954	0.999	DRS	3,9,32,33	3,9,19,32,33
37	Emirates	1.000	1.000	1.000	CRS	37	37
38	Kenya Airways	0.782	1.000	0.782	IRS	21,32	38

5.1.3. Results for 2017

The results in the Table 5.4 show that in 2017 the number of TE efficient airlines is 8 which are British Airways, Ryanair, Vueling Airlines, Swiss International Airlines, Wizz Air, Air Asia, Singapore Airlines and Emirates. All TE efficient airlines are also PTE efficient indicating that the scale is the source of efficiency. The lowest TE and PTE scores belong to China Eastern Airlines in 2017 with a score of 0.836 and 0.849, respectively.

16 airlines are PTE efficient. EasyJet, Lufthansa German Airlines, American Airlines, Delta Airlines, SouthWest Airlines, United Airlines, Eva Airways and Kenya Airways are only PTE efficient airlines. These airlines could not catch the efficiency frontier for TE due to their scale dimensions; they are either too large or too small to be efficient.

"Peer" columns in the Table 5.4 show the peer DMUs for evaluated DMU based on the CRS and VRS models. For those TE inefficient airlines, British Airways was taken as a peer 26 times, which is the most significant one among other peers. Ryanair, Swiss International Airlines, Emirates, Wizz Air, Singapore Airlines and Vueling Airlines were taken as peers 22, 10, 6, 5, 5 and 4 times, respectively.

British Airways is again the most significant peer since it was taken as a peer 18 times also for PTE inefficient DMUs. It is followed by Ryanair with 15 times, Emirates 10 times, Kenya Airways 9 times, Lufthansa German Airlines 5 times, Singapore Airlines 4 times and Eva Airways 2 times. Swiss International Airlines, Wizz Air and Delta Airlines were taken as peers 5 times each. EasyJet was a peer only once indicating that it was a special DMU in terms of inputs and outputs.

30 airlines suffer from SE inefficiency. 17 airlines with DRS are too large, 13 airlines with IRS are too small in dimension to be efficient. Only 8 airlines with CRS have adequate dimension.

Table 5.4. Airlines Efficiency Scores, 2017

Airline number	Airline	TE	PTE	SE	Returns to Scale	Peer CRS	Peer VRS
1	Aeroflot	0.868	0.881	0.985	DRS	3,9,13	3,9,13,37
2	Air France	0.908	0.921	0.987	DRS	3,37	3,19,37
3	British Airways	1.000	1.000	1.000	CRS	3	3
4	EasyJet Airlines	0.983	1.000	0.983	DRS	9,10,12,13	4
5	Finnair	0.922	0.969	0.951	IRS	9,10,12	12,13,38
6	KLM	0.975	0.978	0.997	IRS	3,33,37	3,12,34,37
7	Lufthansa German Airlines	0.989	1.000	0.989	DRS	9,10,12	7
8	Norwegian Air Shuttle	0.877	0.897	0.977	DRS	10,13,33	4,9,13,33
9	Ryanair	1.000	1.000	1.000	CRS	9	9
10	Vueling Airlines	1.000	1.000	1.000	CRS	10	10
11	Scandinavian Airlines	0.921	0.923	0.997	IRS	3,9,12	3,9,12,13
12	Swiss International Airlines	1.000	1.000	1.000	CRS	12	12
13	Wizz Air	1.000	1.000	1.000	CRS	13	13
14	Turkish Airlines	0.927	0.935	0.991	DRS	3,9,12,13	3,7,9,33,37
15	Air Canada	0.935	0.939	0.995	DRS	3,9,12	3,7,9,19
16	Alaska Airlines	0.971	0.972	0.998	IRS	3,9	3,9,38
17	American Airlines	0.912	1.000	0.912	DRS	3,9	17
18	Avianca	0.873	0.880	0.993	IRS	3,9	3,9,38
19	Delta Airlines	0.987	1.000	0.987	DRS	3,9,12	19

Table 5.4. (Continued)

Airline number	Airline	TE	PTE	SE	Returns to Scale	Peer CRS	Peer VRS
20	Gol Transportes Aeros	0.913	0.924	0.988	IRS	3,9	3,9,38
21	JetBlue Airways	0.962	0.964	0.997	IRS	3,9	3,9,38
22	LATAM Airlines	0.899	0.900	0.999	IRS	3,9	3,9,38
23	SouthWest Airlines	0.989	1.000	0.989	DRS	3,9	23
24	United Airlines	0.951	1.000	0.951	DRS	3,9,12	24
25	Air Asia	1.000	1.000	1.000	CRS	25	25
26	Air China	0.912	0.929	0.981	DRS	3,9	3,9,19,37
27	All Nippon Airways	0.965	0.968	0.997	DRS	3,33,37	3,7,33,37
28	Cathay Pacific	0.910	0.931	0.977	DRS	3,33,37	7,33,37
29	China Airlines	0.932	0.953	0.978	IRS	3,12,33	3,12,34,38
30	China Eastern Airlines	0.836	0.849	0.985	DRS	3,9	3,9,19,37
31	China Southern Airlines	0.854	0.933	0.916	DRS	3,9	9,19,37
32	Japan Airlines	0.982	0.984	0.999	IRS	3,9	3,9,38
33	Singapore Airlines	1.000	1.000	1.000	CRS	33	33
34	Eva Airways	0.990	1.000	0.990	IRS	3,37	34
35	Thai Airways	0.971	0.985	0.985	IRS	3,13,37	3,13,37,38
36	Qantas	0.932	0.932	0.999	DRS	3,9,12	3,7,9,12
37	Emirates	1.000	1.000	1.000	CRS	37	37
38	Kenya Airways	0.955	1.000	0.955	IRS	3,9	38

5.1.4. Results for 2018

Airline efficiency scores for the year 2018 are shown in the Table 5.5. The number of TE efficient airlines is 6 and these are British Airways, Ryanair, Vueling Airlines, Wizz Air, Singapore Airlines and Emirates. All these TE efficient airlines are also PTE efficient, which shows that the source of efficiency is scale. The lowest TE score which is 0.806 belongs to Kenya Airways.

Total number of PTE efficient airlines is 13 in 2018. Except for abovementioned airlines, of 7 airlines are only PTE efficient, which are Lufthansa German Airlines, Swiss International Airlines, American and Delta Airlines, United Airlines, Eva Airways and Kenya Airways. This indicates that these airlines are not in the efficiency frontier for TE due to their scale inefficiencies; they are either too large or too small in dimension. The lowest PTE score (0.859) belongs to China Eastern Airlines.

32 airlines are SE inefficient. 17 airlines with DRS are too large in dimension and they could have decreased their dimensions to be efficient. 15 airlines with IRS are too small and they could have increased their dimensions. 6 airlines with CRS have adequate dimension.

“Peer” columns in the Table 5.5 show the peer DMUs for the evaluated DMU based on the CRS and VRS models. For those TE inefficient airlines, British Airways was taken as a peer 29 times which is the most significant one. It is followed by Ryanair with 23 times, Singapore Airlines 15 times, Emirates 8 times and Wizz Air 5 times. Vueling Airlines was taken as a peer only once which indicates that it is a distinctive DMU in terms of its inputs and outputs.

For PTE inefficient airlines, British Airways was taken as a peer 18 times and followed by Ryanair with 17 times, Wizz Air 11 times, Singapore Airlines and Emirates 9 times each, Delta Airlines 5 times, Kenya Airways and Lufthansa German Airlines 4 times each, and Vueling Airlines 2 times. Swiss International Airlines and United Airlines were taken as peers only once.

Table 5.5. Airlines Efficiency Scores, 2018

Airline number	Airline	TE	PTE	SE	Returns to Scale	Peer CRS	Peer VRS
1	Aeroflot	0.905	0.908	0.996	DRS	3,9,13	3,9,13,37
2	Air France	0.886	0.892	0.993	DRS	3,37	3,19,37
3	British Airways	1.000	1.000	1.000	CRS	3	3
4	EasyJet Airlines	0.914	0.979	0.934	DRS	9,10,33	9,10,33
5	Finnair	0.914	0.984	0.929	IRS	3,9,33	10,33,38
6	KLM	0.970	0.974	0.996	IRS	3,33,37	3,33,34
7	Lufthansa German Airlines	0.972	1.000	0.972	DRS	3,9,33	7
8	Norwegian Air Shuttle	0.879	0.951	0.924	DRS	13,33,37	9,13,33,37
9	Ryanair	1.000	1.000	1.000	CRS	9	9
10	Vueling Airlines	1.000	1.000	1.000	CRS	10	10
11	Scandinavian Airlines	0.925	0.934	0.990	IRS	3,9,33	3,9,12,13
12	Swiss International Airlines	0.996	1.000	0.996	IRS	3,9,33	12
13	Wizz Air	1.000	1.000	1.000	CRS	13	13
14	Turkish Airlines	0.932	0.940	0.992	DRS	3,9,13,33	3,7,9,33,37
15	Air Canada	0.898	0.904	0.993	DRS	3,9,33	3,7,9,33
16	Alaska Airlines	0.871	0.877	0.994	IRS	3,9	3,9,13
17	American Airlines	0.867	1.000	0.867	DRS	3,9	17
18	Avianca	0.846	0.866	0.977	IRS	3,9	3,9,13
19	Delta Airlines	0.946	1.000	0.946	DRS	3,9,33	19

Table 5.5. (Continued)

Airline number	Airline	TE	PTE	SE	Returns to Scale	Peer CRS	Peer VRS
20	Gol Transportes Aeros	0.914	0.956	0.956	IRS	3,9	3,9,13
21	JetBlue Airways	0.853	0.862	0.990	IRS	3,9,33	3,9,13
22	LATAM Airlines	0.883	0.887	0.996	IRS	3,9	3,9,13
23	SouthWest Airlines	0.948	0.999	0.950	DRS	3,9	3,9,19
24	United Airlines	0.922	1.000	0.922	DRS	3,9,33	24
25	Air Asia	0.994	0.995	0.999	DRS	13	9,13
26	Air China	0.883	0.926	0.954	DRS	3,9	3,9,19,37
27	All Nippon Airways	0.947	0.964	0.982	DRS	3,33,37	3,7,19,37
28	Cathay Pacific	0.939	0.990	0.948	DRS	3,33,37	7,33,37
29	China Airlines	0.907	0.953	0.951	IRS	3,33,37	3,33,34,38
30	China Eastern Airlines	0.827	0.859	0.963	DRS	3,9	3,9,19
31	China Southern Airlines	0.829	0.955	0.868	DRS	3,9	9,24,37
32	Japan Airlines	0.972	0.979	0.993	IRS	3,9	3,34,38
33	Singapore Airlines	1.000	1.000	1.000	CRS	33	33
34	Eva Airways	0.971	1.000	0.971	IRS	3,37	34
35	Thai Airways	0.887	0.924	0.961	IRS	3,13,37	13,33,37,38
36	Qantas	0.920	0.922	0.998	IRS	3,9	3,9,13
37	Emirates	1.000	1.000	1.000	CRS	37	37
38	Kenya Airways	0.806	1.000	0.806	IRS	3,9	38

5.1.5. Results for 2019

In 2019, the number of TE efficient airlines is 8, which are British Airways, Ryanair, Vueling Airlines, Wizz Air, Delta Airlines, Gol Transportes Aeros, Singapore Airlines and Emirates. It can be seen from the Table 5.6 that all TE efficient airlines are also PTE efficient. Avianca has the lowest TE and PTE scores with 0.762 and 0.773, respectively.

In addition to abovementioned airlines, Finnair, Norwegian Air Shuttle, American Airlines, United Airlines, China Southern Airlines, Eva Airways and Kenya Airways are also PTE airlines, but they suffer from their scale dimensions to become TE efficient. These airlines are too large or too small to catch up the efficiency frontier for TE. Here it can be assumed that scale is the source of their TE inefficiency.

Only SE efficient airlines are Air Canada, Alaska Airlines and Qantas. The reason behind their inefficiencies in TE is their managerial skills because they have adequate dimension to be efficient. It can be suggested that to become efficient in overall, they should practice their peers' pure managerial efficiency procedures.

Of 38 airlines, only 11 airlines with CRS have adequate dimension to be SE efficient. 16 airlines with DRS are too large in dimension and they could have decreased their dimensions to become efficient. 11 airlines with IRS are too small in dimension and they could have increased their dimensions.

"Peer" columns in the Table 5.6, show the peer DMUs for the DMU under evaluation according to both CRS and VRS model in 2019. British Airways is the most distinctive DMU since the times it was a peer for other DMUs is the highest among other peers with 24 times. Wizz Air is the second most significant DMU by being taken as a peer 17 times. Singapore Airlines, Gol Transportes Aeros and Delta Airlines were taken as peers 16, 10 and 8 times, respectively. Ryanair and Emirates were peers 2 times each. Vueling Airlines was taken as a peer only once signifying that it has special characteristics regarding its inputs and outputs in 2019.

Under VRS model assumption, British Airways is again the most significant airline in terms of its count as a peer which is 18 times. Ryanair and Delta Airlines were taken as peers 12 times each. They are followed by Wizz Air with 11 times, Singapore Airlines with 10 times. Emirates, Gol, Eva, and Kenya Airways were taken as peers 10, 9, 4, 3 and 4 times, respectively.

Table 5.6. Airlines Efficiency Scores, 2019

Airline number	Airline	TE	PTE	SE	Returns to Scale	Peer CRS	Peer VRS
1	Aeroflot	0.945	0.971	0.973	DRS	3,13,20	3,9,13,37
2	Air France	0.896	0.901	0.993	DRS	3,33	3,19,37
3	British Airways	1.000	1.000	1.000	CRS	3	3
4	EasyJet Airlines	0.963	0.982	0.980	DRS	10,13,33	9,13,19,33
5	Finnair	0.925	1.000	0.925	IRS	3,13,19,33	5
6	KLM	0.953	0.956	0.997	IRS	3,33	3,33,34
7	Lufthansa German Airlines	0.935	0.974	0.960	DRS	3,19,33	19,33,37
8	Norwegian Air Shuttle	0.977	1.000	0.977	DRS	13,33,37	8
9	Ryanair	1.000	1.000	1.000	CRS	9	9
10	Vueling Airlines	1.000	1.000	1.000	CRS	10	10
11	Scandinavian Airlines	0.920	0.930	0.990	IRS	13,19,33	3,13,19,33
12	Swiss International Airlines	0.971	0.989	0.981	IRS	3,19,33	3,13,33,38
13	Wizz Air	1.000	1.000	1.000	CRS	13	13
14	Turkish Airlines	0.909	0.919	0.989	DRS	3,13,19,33	3,9,19,33,37
15	Air Canada	0.938	0.938	1.000	CRS	3,9,13	3,9,13,19
16	Alaska Airlines	0.972	0.972	1.000	CRS	3,9,20	3,9,13,20
17	American Airlines	0.915	1.000	0.915	DRS	3,2	17
18	Avianca	0.762	0.773	0.986	IRS	3,2	3,13,20,38
19	Delta Airlines	1.000	1.000	1.000	CRS	19	19

Table 5.6. (Continued)

Airline number	Airline	TE	PTE	SE	Returns to Scale	Peer CRS	Peer VRS
20	Gol Transportes Aeros	1.000	1.000	1.000	CRS	20	20
21	JetBlue Airways	0.952	0.952	0.999	IRS	3,19	3,13,20
22	LATAM Airlines	0.919	0.923	0.996	DRS	3,13,20	3,9,20
23	SouthWest Airlines	0.984	0.988	0.995	DRS	3,2	3,9,19
24	United Airlines	0.975	1.000	0.975	DRS	13,19,33	24
25	Air Asia	0.899	0.907	0.992	DRS	13	9,13
26	Air China	0.923	0.945	0.976	DRS	3,13,20	3,9,19,37
27	All Nippon Airways	0.958	0.965	0.993	DRS	3,33	3,19,33,37
28	Cathay Pacific	0.935	0.940	0.995	DRS	3,13,33	3,9,19,33,37
29	China Airlines	0.918	0.960	0.956	IRS	3,33	33,34,38
30	China Eastern Airlines	0.871	0.885	0.984	DRS	3,13,20	3,9,19,37
31	China Southern Airlines	0.885	1.000	0.885	DRS	3,13,20	31
32	Japan Airlines	0.984	0.987	0.997	IRS	3,33	3,33,34
33	Singapore Airlines	1.000	1.000	1.000	CRS	33	33
34	Eva Airways	0.974	1.000	0.974	IRS	3,33	34
35	Thai Airways	0.885	0.937	0.944	IRS	13,33,37	13,37,38
36	Qantas	0.933	0.933	1.000	CRS	3,13,19	3,9,13,19
37	Emirates	1.000	1.000	1.000	CRS	37	37
38	Kenya Airways	0.846	1.000	0.846	IRS	3, 20	38

5.1.6. 5-Year Overview

In consideration that TE identifies the overall or managerial efficiency where PTE measures the pure managerial efficiency, TE, PTE and SE scores reveal the reason behind inefficiency. The mean efficiency scores in the Table 5.7 brief the five-year period process for each airline. British Airways, Ryanair, Wizz Air, Singapore Airlines and Emirates are efficient for all the analyzed years in terms of TE, PTE and SE scores.

Vueling, American Airlines, Delta Airlines, United Airlines, Eva Airways and Kenya Airways are only PTE efficient airlines which indicates that the reason behind their TE inefficiencies is their scale dimensions. They could not have the adequate dimension to become TE efficient. According to their position in the frontier as DRS and IRS, they should arrange their dimensions.

The airline with the lowest mean TE score which is 0.820 is Kenya Airways. The airline has also the lowest SE score. Avianca has the lowest PTE mean which shows that it has the worst managerial practices. The details about the mean TE, PTE and SE scores of each airline for the five-year period are demonstrated in the Table 5.7.

Table 5.7. Mean Efficiency Scores of Each Airline

Airline	TE_{mean}	PTE_{mean}	SE_{mean}
Aeroflot	0.920	0.930	0.989
Air France	0.896	0.902	0.993
British Airways	1.000	1.000	1.000
EasyJet Airlines	0.972	0.992	0.979
Finnair	0.904	0.959	0.943
KLM	0.952	0.954	0.997
Lufthansa German Airlines	0.948	0.984	0.964
Norwegian Air Shuttle	0.911	0.937	0.973
Ryanair	1.000	1.000	1.000
Vueling Airlines	0.996	1.000	0.996
Scandinavian Airlines	0.906	0.914	0.991
Swiss International Airlines	0.977	0.988	0.988
Wizz Air	1.000	1.000	1.000
Turkish Airlines	0.905	0.911	0.994
Air Canada	0.918	0.921	0.996
Alaska Airlines	0.963	0.964	0.998
American Airlines	0.908	1.000	0.908
Avianca	0.829	0.841	0.987
Delta Airlines	0.986	1.000	0.986
Gol Transportes Aeros	0.896	0.910	0.985
JetBlue Airways	0.950	0.955	0.995
LATAM Airlines	0.893	0.897	0.996
SouthWest Airlines	0.979	0.997	0.982
United Airlines	0.953	1.000	0.953
Air Asia	0.979	0.980	0.998
Air China	0.920	0.943	0.976
All Nippon Airways	0.956	0.964	0.991
Cathay Pacific	0.935	0.950	0.984
China Airlines	0.917	0.950	0.965
China Eastern Airlines	0.853	0.870	0.981
China Southern Airlines	0.865	0.958	0.903
Japan Airlines	0.988	0.990	0.998
Singapore Airlines	1.000	1.000	1.000
Eva Airways	0.965	1.000	0.965
Thai Airways	0.916	0.944	0.970
Qantas	0.933	0.933	0.999
Emirates	1.000	1.000	1.000
Kenya Airways	0.820	1.000	0.820

Figure 5.1 demonstrates the percentage of the airlines having scale efficiencies and inefficiencies in each year. The airlines with CRS are SE efficient which means that they have adequate dimension for the efficiency frontier. The airlines which are too large in dimension are positioned in the frontier as DRS, and which are too small in dimension are positioned in the frontier as IRS. The five-year summary can be listed as:

- In 2015, the percentage of the airlines with IRS is 29% while the percentages of airlines with DRS and CRS are 42% and 29%, respectively. Most of the airlines in 2015 suffer from large dimension and by decreasing their economies of scale, they could have improved their performances.
- In 2016, the percentage of airlines with IRS is 24% while the percentages of airlines with DRS and CRS are 39% and 37%, respectively. Most of the airlines in 2016 are too large in dimension.
- The percentage of the airlines with IRS is increased to 34% in 2017. 45% and 21% of the airlines have DRS and IRS, respectively. Most of the airlines in 2017 are too large to have an adequate dimension and they could have decreased their dimension.
- The percentage of the airlines faced with IRS in 2018 is 39% while 45% of the airlines are too large in dimension and only 16% of the airlines have adequate dimension.
- The percentages of the airlines with IRS and CRS in 2019 are equal to 29%, 29%, respectively.
- In a five-year period, 74% of the evaluated airlines suffer from scale inefficiency. The mean percentage of the airlines with IRS is 31% and with DRS is 43%. Only 26% of them have achieved to be scale efficient.

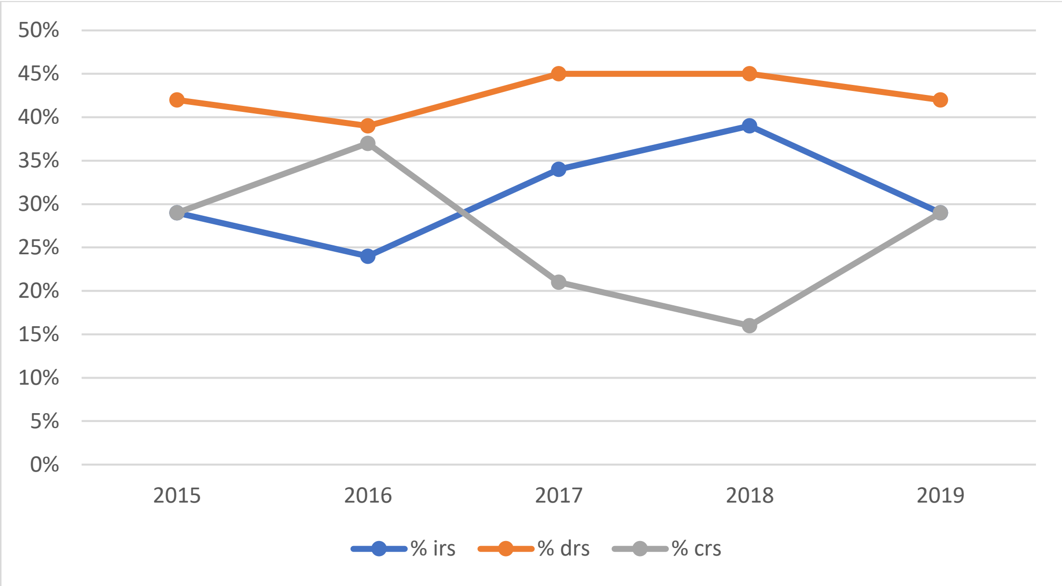

Figure 5.1. Percentage of Airlines With IRS, DRS and CRS Conditions

Figure 5.2 illustrates the mean TE, PTE and SE of airlines from 2015 to 2019. Highest TE mean belongs to the year 2017 with the score of 0.947. Airlines have increased their average PTE scores to 0.964 in 2019 which is the highest average PTE score among the analyzed years. There is a decrease in average SE scores to 0.978 in 2019.

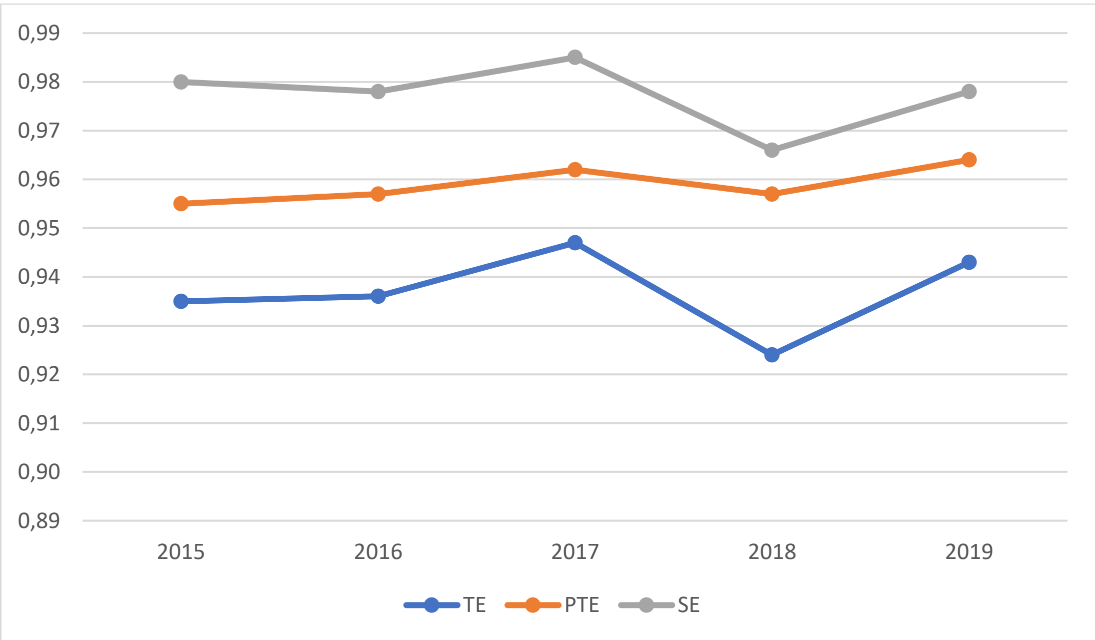

Figure 5.2. Mean TE, PTE and SE Scores of Airlines From 2015 to 2019

Figure 5.3 illustrates the percentage of TE and PTE efficient airlines from 2015 to 2019. The percentage of TE and PTE efficient airlines are the same in the first two years of the analysis with 29% and 45%, respectively. There is a decreasing trend both in the percentage of TE and PTE efficient airlines from 2017 to 2018. Some of the airlines have improved their performance in 2019 and the percentages of TE and PTE efficient airlines have increased to 21% and 39%, respectively. The results revealed that the percentage of PTE efficient airlines is always higher than TE efficient airlines indicating that the main reason behind TE is the scale of airlines.

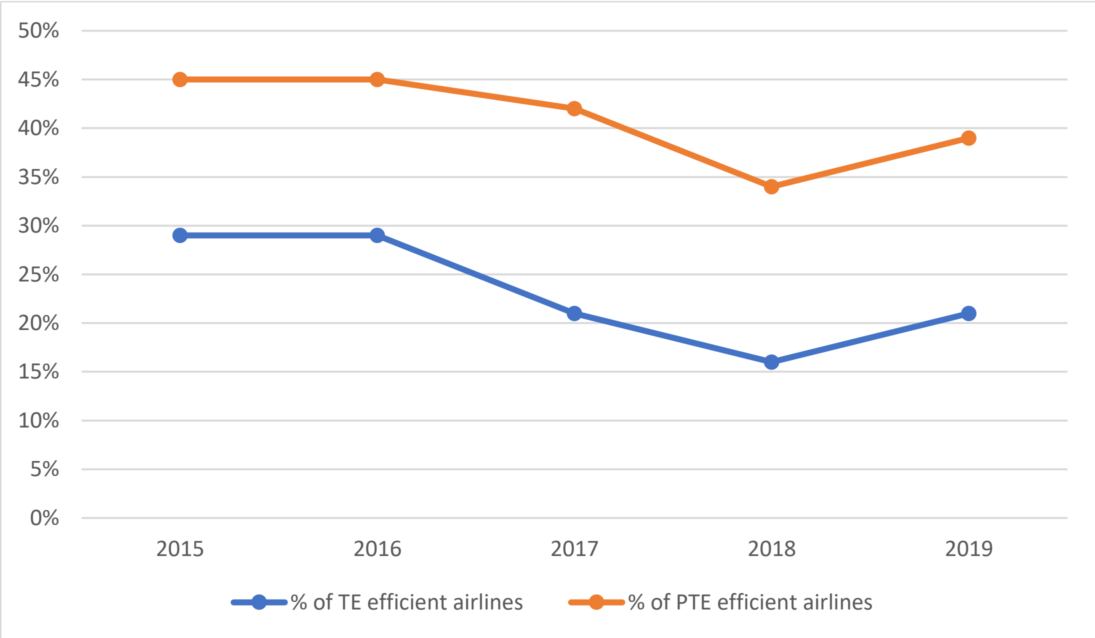

Figure 5.3. Percentage of TE and PTE Efficient Airlines (i.e., Airlines With TE = 1 and PTE = 1)

The average PTE and SE scores are 0.959 and 0.977, respectively while the mean TE score is 0.937. The fluctuations in the mean efficiency scores of airlines may be derived from the changes in the industry itself and the environmental factors. The results in the Table 5.8 show that the mean SE scores are relatively high in the first three years of the analysis and this indicates that majority of the airlines were close to be scale efficient. In five years, 41% of airlines are PTE efficient whereas only 23% of airlines are TE efficient which implies that scale is the main reason behind TE inefficiency.

Table 5.8. Summary of Efficiency Analysis on Airlines

Year	TE_{mean}	PTE_{mean}	SE_{mean}	% of TE efficient airlines	% of PTE efficient airlines	% of SE efficient airlines	% IRS	% DRS	% CRS
2015	0.935	0.955	0.980	29%	45%	29%	29%	42%	29%
2016	0.936	0.957	0.978	29%	45%	37%	24%	39%	37%
2017	0.947	0.962	0.985	21%	42%	21%	34%	45%	21%
2018	0.924	0.957	0.966	16%	34%	16%	39%	45%	16%
2019	0.943	0.964	0.978	21%	39%	29%	29%	42%	29%
Mean	0.937	0.959	0.977	23%	41%	26%	31%	43%	26%

5.2. Super-Efficiency DEA Results

The traditional DEA conducted in the first stage of this study evaluated the performance of airlines according to their TE, PTE and SE which makes it possible to find the source behind inefficiency. In this section, to determine the best performing airline and discriminate the efficient ones, super-efficiency DEA is applied under the assumption of input-oriented CRS model. A 5-year window (2015-2019) was created by pooling all DMUs from all years to evaluate the efficiencies over a particular timeframe.

The number of efficient DMUs which have the efficiency scores greater than or equal to 1 is 44 out of 190 DMUs (see Table 5.9). As aforementioned, British Airways, Ryanair, Wizz Air, Singapore Airlines and Emirates are efficient for all the analyzed years. The highest super-efficiency score is 1.3864, which has been reached by the DMU representing Emirates for the year 2019. The lowest observed efficiency score for inefficient DMUs is 0.7099 and it belongs to the DMU representing Kenya Airways in 2015. Emirates is the most efficient airline of 4 analyzed years except for 2016. The most efficient airline in 2016 is Singapore Airlines.

The column “Business Model” in the Table 5.9 differentiates the airlines according to their business model such as full-service and low-cost carrier. 29 of 38 airlines are full-service carriers and 9 are low-cost carriers.

The column “Alliance Group” shows the alliance membership of the airlines. The number of airlines which have maintained their alliance membership for the evaluated five-year period is 26. China Southern Airlines terminated its SkyTeam membership in 2019.

Table 5.9. DEA Super-Efficiency Scores of Airlines

Airline	Alliance Group	Business Model	Year				
			2015	2016	2017	2018	2019
Aeroflot	SkyTeam	Full-Service	0.9377	0.9432	0.8679	0.9049	0.9447
Air France	SkyTeam	Full-Service	0.9050	0.8872	0.9081	0.8862	0.8955
British Airways	Oneworld	Full-Service	1.0176	1.0015	1.0538	1.0524	1.0491
EasyJet Airlines	-	Low-Cost	1.1136	1.0479	0.9834	0.9139	0.9627
Finnair	Oneworld	Full-Service	0.8785	0.8800	0.9225	0.9142	0.9250
KLM	SkyTeam	Full-Service	0.9225	0.9390	0.9754	0.9701	0.9530
Lufthansa German Airlines	Star Alliance	Full-Service	0.8946	0.9491	0.9886	0.9718	0.9353
Norwegian Air Shuttle	-	Low-Cost	0.8992	0.9226	0.8770	0.8795	0.9772
Ryanair	-	Low-Cost	1.0509	1.0718	1.0917	1.1083	1.0007
Vueling Airlines	-	Low-Cost	0.9804	1.0453	1.1460	1.2482	1.0298
Scandinavian Airlines	Star Alliance	Full-Service	0.8806	0.8844	0.9206	0.9250	0.9203
Swiss International Airlines	Star Alliance	Full-Service	0.9628	0.9537	1.0205	0.9961	0.9708
Wizz Air	-	Low-Cost	1.1602	1.2091	1.2129	1.2282	1.2150
Turkish Airlines	Star Alliance	Full-Service	0.9280	0.8285	0.9268	0.9323	0.9090
Air Canada	Star Alliance	Full-Service	0.9116	0.9078	0.9350	0.8980	0.9383
Alaska Airlines	-	Full-Service	1.0286	1.0102	0.9706	0.8715	0.9721
American Airlines	Oneworld	Full-Service	0.9262	0.9212	0.9120	0.8674	0.9151
Avianca	Star Alliance	Full-Service	0.8199	0.8463	0.8735	0.8461	0.7621
Delta Airlines	SkyTeam	Full-Service	1.0132	0.9950	0.9873	0.9459	1.0128

Table 5.9. (Continued)

Airline	Alliance Group	Business Model	Year				
			2015	2016	2017	2018	2019
Gol Transportes Aeros	-	Low-Cost	0.7958	0.8545	0.9132	0.9139	1.0147
JetBlue Airways	-	Low-Cost	1.0008	1.0107	0.9615	0.8532	0.9517
LATAM Airlines	Oneworld	Full-Service	0.8861	0.8798	0.8989	0.8834	0.9188
SouthWest Airlines	-	Low-Cost	0.9936	0.9818	0.9894	0.9484	0.9835
United Airlines	Star Alliance	Full-Service	0.9594	0.9567	0.9507	0.9219	0.9754
Air Asia	-	Low-Cost	1.1006	1.2873	1.0602	0.9937	0.8989
Air China	Star Alliance	Full-Service	0.9404	0.9441	0.9121	0.8833	0.9226
All Nippon Airways	Star Alliance	Full-Service	0.9365	0.9735	0.9651	0.9471	0.9583
Cathay Pacific	Oneworld	Full-Service	0.9866	0.9022	0.9100	0.9386	0.9355
China Airlines	SkyTeam	Full-Service	0.9316	0.8939	0.9319	0.9069	0.9178
China Eastern Airlines	SkyTeam	Full-Service	0.8715	0.8610	0.8362	0.8272	0.8710
China Southern Airlines*	SkyTeam	Full-Service	0.8875	0.8683	0.8539	0.8292	0.8853
Japan Airlines	Oneworld	Full-Service	1.0012	1.0288	0.9824	0.9721	0.9841
Singapore Airlines	Star Alliance	Full-Service	1.2780	1.3690	1.2450	1.2240	1.2162
Eva Airways	Star Alliance	Full-Service	0.9587	0.9287	0.9901	0.9713	0.9739
Thai Airways	Star Alliance	Full-Service	0.9179	0.9181	0.9705	0.8872	0.8851
Qantas	Oneworld	Full-Service	0.9250	0.9533	0.9317	0.9197	0.9326
Emirates	-	Full-Service	1.2912	1.1971	1.2989	1.2968	1.3864
Kenya Airways	SkyTeam	Full-Service	0.7099	0.7818	0.9554	0.8055	0.8456

Notes: China Southern Airlines has left SkyTeam group in January 2019.

As mentioned before, in this study, the selection of the airlines depends on the regional classification of IATA. 14 airlines from Europe and Russia, 7 airlines from North America, 3 airlines from Latin America, 8 airlines from China and North Asia, 4 airlines from Asia-Pacific and 2 airlines from Middle East and Africa were selected. The aim was to include each region's representative full-service and low-cost airlines. Under the consideration that super-efficiency score calculation allows to discriminate the efficient entities, the Table 5.10 provides an abstract of five-year period. Each region's best and worst performing airline can be detected and listed as:

- The most efficient airline from Europe and Russia is Wizz Air with an average score of 1.2051.
- There is no efficient airline from North America according to average scores. Among other airlines, Delta Airlines has a relatively higher mean efficiency score than others with an average score of 0.9908.
- Latin America is another region that has no efficient airlines. The mean efficiency scores of Latin American airlines are relatively lower than the ones from other regions. Of 3 airlines, Gol Transportes Aeros has the highest mean efficiency score which is 0.8984.
- Singapore Airlines with an average score of 1.2664 is the best performing airline of its region.
- The best performing airline of Asia-Pacific is Air Asia with its average score of 1.0681.
- Emirates is the leader of both its region and other regions with an average score of 1.2941.

Table 5.10. Mean Efficiency Scores of Each Airline

Region	Airline	Mean Efficiency
Europe and Russia	Aeroflot	0.9197
	Air France	0.8964
	British Airways	1.0349
	EasyJet Airlines	1.0043
	Finnair	0.9040
	KLM	0.9520
	Lufthansa German Airlines	0.9479
	Norwegian Air Shuttle	0.9111
	Ryanair	1.0647
	Vueling Airlines	1.0899
	Scandinavian Airlines	0.9062
	Swiss International Airlines	0.9808
	Wizz Air	1.2051
	Turkish Airlines	0.9049
North America	Air Canada	0.9181
	Alaska Airlines	0.9706
	American Airlines	0.9084
	Delta Airlines	0.9908
	JetBlue Airways	0.9556
	SouthWest Airlines	0.9793
	United Airlines	0.9528
Latin America	Avianca	0.8296
	Gol Transportes Aeros	0.8984
	LATAM Airlines	0.8934
China and North Asia	Air China	0.9205
	All Nippon Airways	0.9561
	Cathay Pacific	0.9346
	China Airlines	0.9164
	China Eastern Airlines	0.8534
	China Southern Airlines	0.8648
	Japan Airlines	0.9937
	Singapore Airlines	1.2664
Asia-Pacific	Air Asia	1.0681
	Eva Airways	0.9645
	Thai Airways	0.9158
	Qantas	0.9325
Middle East and Africa	Emirates	1.2941
	Kenya Airways	0.8196

5.3. Post-hoc Analysis

Airlines have different resources, capabilities, and characteristics. The differences in resources and capabilities may result in a competitive advantage for the airlines which perform the best (Carlos Pestana Barros & Peypoch, 2009). Under the consideration of this, the post-hoc analysis is an appropriate tool to assess the effects of operational performance determinants. In this analysis, airlines were divided into two subsets as large and small; full-service or low-cost; allied or non-allied to detect the effects of size, business model and alliance membership on the operational efficiency.

ASK is a measure of capacity. The fact that 74% of airlines under evaluation suffer from scale inefficiency and most of them experience decreasing returns to scale (DRS) begs the question of whether there is a significant performance difference between large and small airlines. In answering this question, airlines were divided into two groups as large and small airlines according to their ASKs. Airlines with 100 billion and more ASKs were labeled as large, and the remaining airlines were labeled as small. There are 111 samples representing large airlines and 79 samples representing small airlines.

- Mean efficiency of large airlines = 96.92% (n = 111)
- Mean efficiency of small airlines = 96.23% (n = 79)

To assess whether there is a statistically significant difference between the mean efficiency scores of these large and small airlines, Mann-Whitney rank-sum test is performed at 0.05 significance level. The hypothesis that is investigated to assess the above calculated efficiency difference between large and small airline groups is the following:

H_1: Large airlines and small airlines have identical mean efficiency.

Mann-Whitney rank-sum test was performed to test the above hypothesis. The acquired test results show that Z-value is equal to -0.031 and p-value is equal to 0.975 (see Table 5.11 for more details). Hence, H_1 is not rejected at 0.05 significance level.

There is no statistically significant mean efficiency difference between two groups; large and small airlines operate at the same level of efficiency.

Table 5.11. Mann-Whitney Test for H_1

Group	N	Mean Rank	Sum of Ranks
1	111	95.60	10612.00
2	79	95.35	7533.00
Total	190		
Mann-Whitney U	4373.00		
Wilcoxon W	7533.00		
Z	-0.031		
p-value	0.975		

As stressed before in the study, low-cost and full-service airlines have distinctive characteristics. To assess the impact of business model on the operational efficiency, airlines were divided into two groups as full-service airlines and low-cost airlines. There are 145 samples representing full-service airlines for the five-year period (29 full-service airlines x 5 years). The number of samples representing low-cost airlines is 45 (9 low-cost airlines x 5 years).

- Mean efficiency score of full-service carriers = 94.98% (n = 145)
- Mean efficiency score of low-cost carriers = 101.96% (n = 45)

To assess whether there is a statistically significant difference between the mean efficiency scores of these two groups, Mann-Whitney rank-sum test is performed at 0.05 significance level. The hypothesis that is investigated to assess the above calculated efficiency differentiation between full-service and low-cost carriers is the following:

H_2: Full-service airlines and low-cost airlines have identical mean efficiency.

Running the Mann-Whitney rank-sum test, a Z-value equal to - 4.234 and p-value equal to 0.000 were acquired (see Table 5.12 for more details). The hypothesis H_2 is rejected at 0.05 significance level, thus assuming that there is a statistically significant mean efficiency difference between two groups; low-cost carriers outperform full-service carriers.

Table 5.12. Mann-Whitney Test for H_2

Group	N	Mean Rank	Sum of Ranks
1	145	86.09	12483.00
2	45	125.82	5662.00
Total	190		
Mann-Whitney U	1898.00		
Wilcoxon W	12483.00		
Z	-4.234		
p-value	0.000		

Under the assumption that building strategic groups affects the structural characteristics of units within an industry and this can cause the performance differences (Caves & Porter, 1977), to assess the impact of alliance membership on the operational efficiency, airlines were divided into two groups as allied and non-allied. There are 134 samples representing airlines with alliance membership for the five-year period [26 alliance member airlines x 5 years + 4 years (for the membership period of China Southern Airlines)]. The number of samples representing airlines without alliance membership is 56 [11 airlines without an alliance membership x 5 years + 1 year (for China Southern Airlines)].

- Mean efficiency score of airlines with alliance membership = 93.66% (n =134)
- Mean efficiency score of airlines without alliance membership = 103.73% (n=56)

To assess whether there is a statistically significant difference between the mean efficiency scores of these two groups, Mann-Whitney rank-sum test is performed at 0.05 significance level. The hypothesis investigated to assess the above calculated mean efficiency difference between airlines with and without alliance membership is the following:

H_3: Allied airlines and non-allied airlines have identical mean efficiency.

Mann-Whitney rank-sum test was utilized to test the above hypothesis. The results acquired from the test are Z-value is equal to -5.355 and p-value is equal to 0.000 (see Table 5.13 for further details). Hence, hypothesis H_3 is rejected at 0.05 significance level assuming that there is a statistically significant mean efficiency difference between two groups; non-allied airlines outperform allied airlines.

Table 5.13. Mann-Whitney Test for H_3

Group	N	Mean Rank	Sum of Ranks
1	134	81.69	10946.50
2	56	128.54	7198.50
Total	190		
Mann-Whitney U	1901.50		
Wilcoxon W	10946.50		
Z	-5.355		
p-value	0.000		

Table 5.14 shows the mean efficiency scores of each airline group. The number of samples representing Star Alliance member airlines is 60 (12 airlines x 5 years). The mean efficiency of the Star Alliance group members is 95.55%. There are 39 SkyTeam member samples [7 airlines x 5 years + 4 years (for China Eastern Airlines). The mean efficiency score of SkyTeam member airlines is 90.27%. 35 samples represent 7 OneWorld member airlines (7 airlines x 5 years). The mean efficiency score of OneWorld members is 94.35%. Star Alliance is the alliance group that has the highest mean efficiency score.

Table 5.14. Descriptive Statistics of Super-Efficiency Scores of Alliance Groups

	N	Mean	Std. Deviation
Star Alliance	60	95.55	10.62
SkyTeam	39	90.27	6.34
OneWorld	35	94.35	5.30

5.4. Managerial Implications

Evaluation of performance is a vital indicator to the management of the companies. This study provides a guidance to the managers of 38 airlines about what actions to be taken to improve the operational performance. In the light of the findings, some inferences can be made. The first is that the efficiency of poor performing airlines can be increased by focusing the economies of scale. Second, the performance inefficiency caused by the low quality of managerial practices can be eliminated with upgrades on pure managerial procedures. Third, benchmarking is a guide for airline managers to evaluate their position and apply the appropriate managerial procedures to be in the efficiency frontier. Forth, variations in efficiency scores may derive from the capacity differences, the characteristics depending on business models, and the strategic actions such as membership of alliance groups. These differences may result in a competitive advantage for airlines and hence, market-oriented practices should be adopted according to the analysis on the effects of efficiency determinants in this study to remain competitive and efficient.

Other than applying the proper strategies to reach efficiency, airlines need to publish their operational data in a proper framework in order to introduce transparency. All airlines in the industry use different terminologies while reporting their information, and this may lead bias in data and hence, results. The legal authorities can prepare a template for airlines to publish their reports. Transparency in sharing the data may increase competition contributing the industry and promote more research in the field.

Europe and North America have been the center of aviation for decades, but with the regional changes in economic facilities and demographics, the center of gravity has moved from west to east. As a result of this transformation, European and North American carriers have found themselves in a competition with their easterner counterparts. Figure 5.4 illustrates the regional differentiation of average efficiency scores. As a proof of the competition between airlines from different regions, Middle East and Africa was found to be the region that has the highest mean efficiency score thanks to the high performance of Emirates. European and Russian airlines hold the field over their competitors, but it seems that the throne of them can be shaken by Asia-Pacific airlines; the mean efficiency score of airlines from Asia-Pacific is very close to European and Russian ones. North American airlines lose their superiority over even Chinese and North Asian airlines. The lowest mean efficiency score belongs to the airlines from Latin America. This changing environment necessitates the implications of innovative solutions for airlines to remain competitive and efficient.

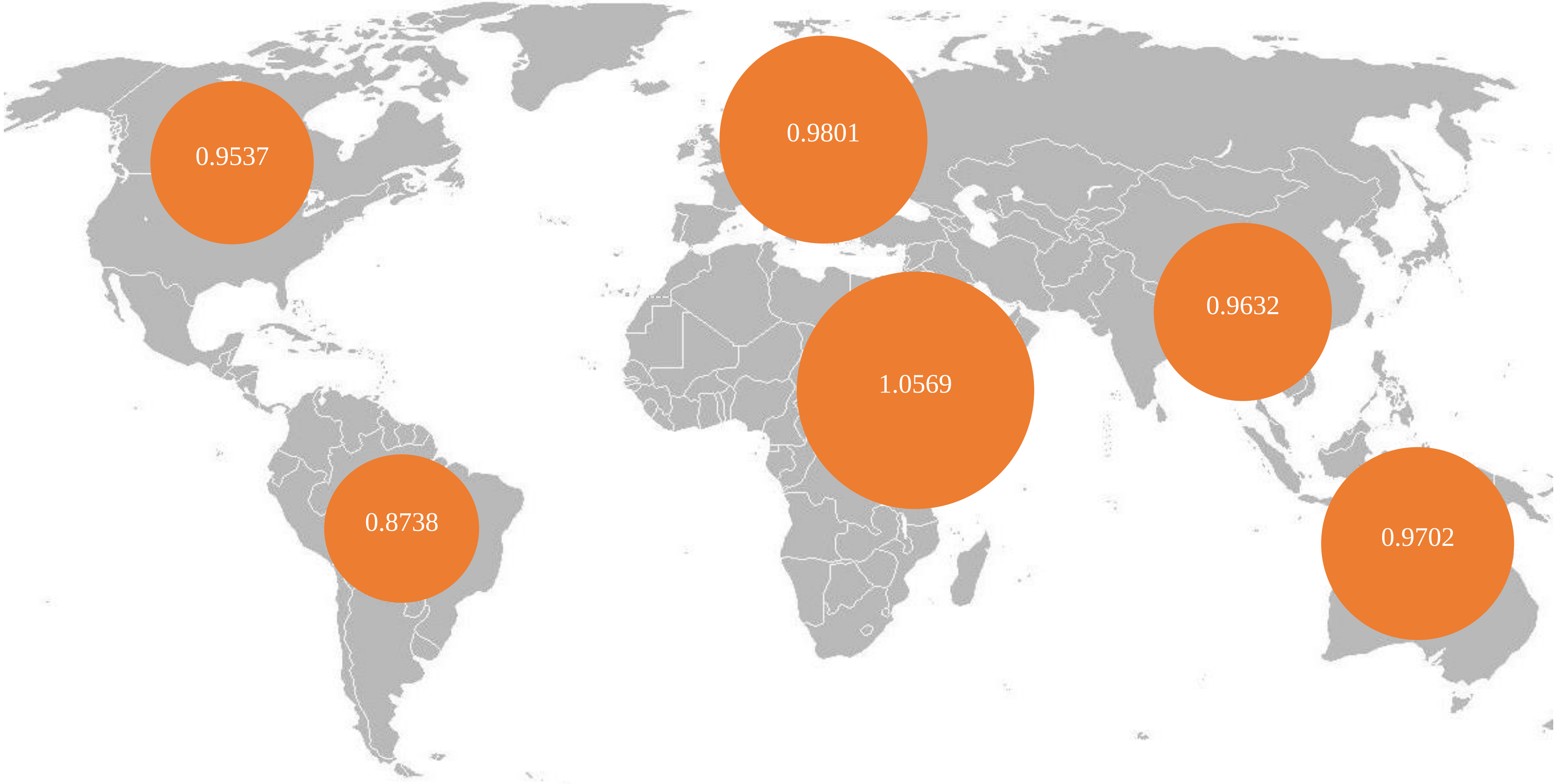

Figure 5.4. Regional Mean Efficiency Scores

CHAPTER VI

CONCLUSIONS

Economic growth, deregulations, liberalizations, and open skies policies in air transport industry have expanded air traffic and these all have brought growth to the airline industry. Over the past decades, with the growth of the industry, airlines have been faced with several transformations in response to the changing and increasingly competitive environment. They have always needed to improve their operational efficiency to gain a seat in the industry. In the past, inefficiency of some major airlines resulted in bankruptcy, their downfall opened a gap in the industry which was filled with the emergence of low-cost carriers. The emergence of LCCs has become a threat to traditional service carriers which are referred to as full-service carriers. FSCs have needed to set a course for this threat and they have formed strategic groups known as alliances. Since all these changes may have an impact on the operational performance of airlines, and hence, evaluation of performance is a crucial indicator of the management, this study evaluated the performance of 38 major airlines from different regions of the world between 2015 and 2019. The effects of the operational performance determinants such as size, business model and alliance membership were also assessed.

Based on the common practice followed by the previous studies, the efficiency of airlines was evaluated using input-oriented CRS and VRS model DEA with the selection of 3 inputs and 2 outputs. To make the discrimination between efficient airlines and to prepare the data for post-hoc analysis, super-efficiency DEA method was also implemented. To assess the effects of size, business model and alliance membership, post-hoc analysis was utilized.

First stage results showed that average TE, PTE and SE scores are 0.94, 0.96 and 0.98 over the five-year period. On average 77% of and 59% of evaluated airlines could not reach the CRS and VRS-frontier, respectively; thus, they are subject to a varying degree of inefficiency. Majority of evaluated airlines suffer from economies of scale and their performance could have been improved by reduction.

British Airways, Ryanair, Wizz Air, Singapore Airlines and Emirates are found to be efficient for all the analyzed years. The super-efficiency results revealed that Emirates is the most efficient airline among the evaluated airlines with its average score of 1.29 and Kenya Airways is the least efficient airline with an average score of 0.82.

The super-efficiency analysis enabled to see the mean efficiency scores of different regions. Middle East and Africa region has the highest mean efficiency score thanks to the high performance of Emirates. It was followed by airlines from Europe and Russia. The main competitors of European airlines are from the Asia-Pacific region whose efficiency scores are very close to European airlines. North American airlines has relatively lower scores than their competitors. Latin American airlines could not catch up the frontier to be efficient and they have poorer performance.

Assuming the fact that most of the airlines are too large in dimension to be efficient, to assess the size effect on the performance, airlines were divided into two subsets as large and small airlines according to their ASKs. The results obtained from Mann-Whitney rank-sum test proved that size has no statistically significant impact on the performance.

The effect of business model on the performance was assessed by dividing the airlines into two groups as full-service and low-cost carriers. Mann-Whitney rank-sum test results showed that low-cost airlines outperform their full-service counterparts. This reveals that the status of being a low-cost airline is a competitive advantage.

To verify the premise that strategic alliances help airlines improve their operational performances by supplying them different opportunities, it was examined whether alliance membership could be translated into a competitive advantage. The result obtained from Mann-Whitney test revealed a statistically significant mean efficiency difference between allied and non-allied airlines. Non-allied airlines outperformed allied airlines. This implies that alliance membership does not help airlines improve their efficiency.

In summary, this study contributes to the literature being one of the few attempts to assess the impacts of size, business model and airline alliances on the performance of airlines. The results obtained from the analyses can be a guidance for airline managers also. They can evaluate their position in the frontier and take actions accordingly. This study can be extended by selecting different determinants to evaluate to what extent the airlines are sensitive to determinants.

The new trend in the airline industry is to adopt innovative technologies for minimizing the environmental impacts of operations. These implications are not only beneficial for decreasing the environmental impacts but also for improving the operational performance. The relationship between the operational performance and the environmental politics of airlines is an attractive research topic for further studies.

Assuming that the airline industry is very fragile and sensitive to the changes, the impact of coronavirus disease (Covid-19) pandemic is inevitable for airlines. The operational performance of airlines may be affected by this process. The impact of Covid-19 on the operational performance of airlines is another topic that is worth further analysis.

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APPENDIX

Table A.1. Descriptive Statistics of Inputs and Outputs for Each Airline

Airlines		Operating revenue (million USD)	RPKs (million seat-kilometers)	Operating expense (million USD)	Number of employees	Number of aircrafts
		Output	Output	Input	Input	Input
Aeroflot	Mean	8,713	127,874	7,940	38,410	322
	SD*	1,557	23,489	1,558	3,143	45
Air France	Mean	18,141	145,935	17,699	54,095	346
	SD	734	5,281	808	4,939	9
British Airways	Mean	16,597	148,301	14,342	38,652	294
	SD	878	5,485	846	542	8
EasyJet Airlines	Mean	7,732	91,013	7,042	11,749	279
	SD	493	12,328	691	2,273	40
Finnair	Mean	2,966	31,320	2,901	5,722	78
	SD	423	5,349	366	817	5
KLM	Mean	11,762	102,321	10,877	30,040	206
	SD	897	6,800	655	470	5
Lufthansa German Airlines	Mean	18,462	157,876	17,579	35,887	367
	SD	1,046	8,568	1,521	2,673	27
Norwegian Air Shuttle	Mean	3,930	65,628	4,005	7,564	136
	SD	981	19,942	1,164	2,371	28
Ryanair	Mean	7,617	146,373	6,092	12,719	403
	SD	1,134	25,271	1,026	2,796	62
Vueling Airlines	Mean	2,483	29,466	2,291	3,421	109
	SD	289	3,390	241	637	10

Table A.1. (Continued)

Airlines		Operating revenue (million USD)	RPKs (million seat-kilometers)	Operating expense (million USD)	Number of employees	Number of aircrafts
		Output	Output	Input	Input	Input
Scandinavian Airlines	Mean	4,928	38,024	4,612	10,583	156
	SD*	207	2,689	129	445	3
Swiss International Airlines	Mean	5,370	46,266	5,038	9,554	96
	SD	390	5,435	276	550	9
Wizz Air	Mean	1,919	39,394	1,639	3,141	81
	SD	513	12,360	454	1,008	22
Turkish Airlines	Mean	11,471	137,098	10,895	25,292	329
	SD	1,499	14,357	1,214	2,882	19
Air Canada	Mean	12,363	133,752	11,307	28,320	390
	SD	1,804	17,934	1,800	3,177	14
Alaska Airlines	Mean	7,301	75,249	6,179	20,984	293
	SD	1,440	16,968	1,641	3,807	49
American Airlines	Mean	42,737	368,540	38,484	126,000	1,542
	SD	2,362	12,153	3,743	5,874	8
Avianca	Mean	4,491	40,536	4,401	19,405	187
	SD	283	3,883	517	1,781	10
Delta Airlines	Mean	42,606	355,061	36,056	86,635	1,313
	SD	3,041	17,959	3,559	3,432	19
Gol Transportes Aeros	Mean	3,142	38,371	2,867	15,534	129
	SD	278	2,206	172	767	11

Table A.1. (Continued)

Airlines		Operating revenue (million USD)	RPKs (million seat-kilometers)	Operating expense (million USD)	Number of employees	Number of aircrafts
		Output	Output	Input	Input	Input
JetBlue Airways	Mean	7,163	76,903	6,240	16,730	239
	SD*	702	7,414	1,045	1,609	18
LATAM Airlines	Mean	10,123	116,886	9,474	44,465	328
	SD	358	5,100	303	3,798	11
SouthWest Airlines	Mean	21,162	204,663	17,651	55,760	726
	SD	1,071	10,111	1,525	4,403	22
United Airlines	Mean	39,344	355,431	35,225	73,142	1,283
	SD	2,816	21,480	3,086	5,179	57
Air Asia	Mean	2,204	46,966	1,827	13,167	204
	SD	569	14,176	681	6,342	33
Air China	Mean	18,454	202,931	16,502	83,777	650
	SD	1,600	24,600	2,070	5,267	45
All Nippon Airways	Mean	16,599	87,881	15,338	39,166	284
	SD	1,894	12,328	1,611	3,624	31
Cathay Pacific	Mean	12,535	127,500	12,400	26,254	196
	SD	886	5,024	655	1,034	7
China Airlines	Mean	5,043	43,990	4,862	12,476	95
	SD	607	3,247	641	173	4
China Eastern Airlines	Mean	15,720	184,064	15,069	75,957	642
	SD	1,536	29,254	1,829	3,641	73

Table A.1. (Continued)

Airlines		Operating revenue (million USD)	RPKs (million seat-kilometers)	Operating expense (million USD)	Number of employees	Number of aircrafts
		Output	Output	Input	Input	Input
China Southern Airlines	Mean	19,288	234,101	18,316	96,255	765
	SD	2,534	38,695	2,877	6,533	85
Japan Airlines	Mean	12,192	65,242	10,572	32,663	229
	SD	968	4,236	954	959	4
Singapore Airlines	Mean	8,826	95,963	8,402	14,631	116
	SD	626	3,839	509	799	7
Eva Airways	Mean	5,213	43,824	4,933	18,212	77
	SD	835	5,691	811	1,672	6
Thai Airways	Mean	5,698	67,796	5,780	22,131	99
	SD	406	5,627	605	548	4
Qantas	Mean	12,310	121,416	11,261	29,345	308
	SD	200	6,132	222	613	7
Emirates	Mean	24,085	271,894	23,202	61,067	256
	SD	1,448	26,588	1,899	2,952	16
Kenya Airways	Mean	1,166	10,858	1,184	4,027	46
	SD	83	1,264	190	447	5

Notes: SD = Standard deviation

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