ENVIRONMENTAL EFFICIENCY ANALYSIS OF GLOBAL AIRLINES

NURUL SYUHADAH BINTI YAKATH ALI

UNIVERSITI SAINS MALAYSIA

2021

ENVIRONMENTAL EFFICIENCY ANALYSIS OF GLOBAL AIRLINES

by

NURUL SYUHADAH BINTI YAKATH ALI

Thesis submitted in fulfilment of the requirements
for the degree of
Master of Social Science

August 2021

ACKNOWLEDGEMENT

I sincerely thank Allah SWT, the Most Gracious, the Most Merciful, for giving me the opportunity and helping me endlessly finish my master's thesis. I want to express my deepest gratitude and appreciation to my main supervisor, Dr. See Kok Fong, for his expertise, patient guidance, motivation, and tremendous support throughout the study. With his guidance and valuable advice, I have managed to overcome many obstacles to complete this thesis. In addition, I want to express appreciation to my co-supervisor, Dr. Chu Ei Yet, for giving me full support and advice during my research study.

In addition, I would like to express my gratitude to the Jabatan Perkhidmatan Awam (JPA) for providing financial support throughout my study through the "Biasiswa Yang Di-Pertuan Agong (BYDPA)" scholarship.

Last but not least, I would like to express my boundless appreciation to my parents and members of my family for their prayers, unconditional support, motivation, and patience during my master's study. With their support and encouragement, I was able to manage my time and concentrate on writing this thesis in a good environment. My gratitude is also extended to all my friends and colleagues who always supported me at any time and in everything.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

Page

LIST OF ABBREVIATIONS

ANA	All Nippon Airways
ASEAN	Association of Southeast Asian Nations
ASK	Available Seat Kilometres
ASM	Available Seat Miles
ATAG	Air Transport Action Group
ATK	Available Tonne Kilometres
BC	Bias-Corrected
BCC	Banker, Charnes, and Cooper's model
BC-EE	Bias-Corrected Environmental Efficiency
BC-TE	Bias-Corrected Technical Efficiency
BMLI	Biennial-Malmquist Productivity Index
CCR	Charnes, Cooper, and Rhodes' model
CNG2020	Carbon Neutral Growth from 2020
CO_2	Carbon Dioxide
CORSIA	Carbon Offsetting and Reduction Scheme for International Aviation
COVID-19	Coronavirus Disease of 2019
CRS	Constant Return to Scale
CSR	Corporate Social Responsibility
CTK	Cargo Tonne Kilometres
DEA	Data Envelopment Analysis
DMUs	Decision Making Units
EE	Environmental Efficiency
EU	European Union
EU-ETS	European Union Emissions Trading Scheme
FSCs	Full-Service Carriers
FTE	Full-time Equivalent
FTK	Freight Tonne Kilometres
GDP	Gross Domestic Product
GHGs	Greenhouse Gas Emissions
GLS	Generalized Least Square
HFCs	Hydrofluorocarbons

IATA	International Air Transport Association
ICAO	International Civil Aviation Organization
IEA	International Energy Agency
IEP	Input Efficiency Profiling
ITF	International Transport Forum
K-ETS	Korea Emission Trading Scheme
LB	Lower Bound
LCCs	Low-Cost Carriers
LPI	Luenberger Productivity Index
M&As	Mergers and Acquisitions
MLPI	Malmquist-Luenberger Productivity Index
MOLIT	Ministry of Land, Infrastructure and Transport
MPI	Malmquist Productivity Index
NDEA	Network Data Envelopment Analysis
OECD	Organisation for Economic Co-operation and Development
PPP	Purchasing Power Parity
RAM	Range-adjusted Measure
RPK	Revenue Passenger Kilometres
RPM	Revenue Passenger Miles
RTK	Revenue Tonne Kilometres
SBM	Slack-based Measure
SF6	Sulphur Hexafluoride
SFA	Stochastic Frontier Analysis
TE	Technical Efficiency
TFP	Total Factor Productivity
UB	Upper Bound
UNFCCC	United Nations Framework Convention on Climate Change
US	United States
USD	United States Dollar
USM	Universiti Sains Malaysia
VIF	Variance Inflation Factor
VRS	Variable Return to Scale
WATS	World Air Transport Statistics

LIST OF APPENDICES

ANALISIS KECEKAPAN PERSEKITARAN TERHADAP SYARIKAT PENERBANGAN GLOBAL

ABSTRAK

Berikutan Akta Deregulasi Syarikat Penerbangan 1978 di Amerika Syarikat, produktiviti dan kecekapan syarikat penerbangan telah menarik perhatian yang luar biasa daripada kalangan ahli akademik dan penganalisis industri. Hal ini kerana produktiviti dan kecekapan adalah keutamaan bagi syarikat penerbangan untuk meneruskan keberlangsungan operasi dan berkembang sejajar dengan tekanan pasaran yang terus meningkat. Oleh kerana terdapat tanggungjawab sosial korporat (CSR) yang semakin meningkat dalam industri penerbangan, pemahaman dan penambahbaikan impak persekitaran bagi operasi syarikat penerbangan adalah sangat penting. Walau bagaimanapun, sebilangan kecil kajian menggabungkan faktor persekitaran untuk mengukur kecekapan syarikat penerbangan. Kajian ini bertujuan untuk mengisi sebahagian jurang dalam literatur yang lepas. Oleh itu, objektif utama kajian ini adalah untuk menilai kecekapan persekitaran 54 syarikat penerbangan global pada tahun 2017. Kajian ini menggunakan kaedah bootstrap berganda analisis penyusutan data (DEA) dan turut mengintegrasikan pelepasan karbon daripada industri penerbangan sebagai output yang tidak diingini. Kajian ini juga bertujuan untuk mengenal pasti lima pemboleh ubah penjelas (faktor berat beban, pakatan, wilayah geografi, jumlah keberangkatan, dan nisbah pesawat berbadan lebar dengan jumlah armada) sebagai penentu untuk menjelaskan kesan terhadap kecekapan persekitaran syarikat penerbangan di dalam industri. Dapatan kajian mengesahkan bahawa skor kecekapan persekitaran (EE) berat sebelah yang diperbetul (BC) adalah lebih kukuh, kerana skor berada di antara batasan bawah dan atas. Tambahan pula,

British Airways dan Lufthansa adalah dua syarikat penerbangan yang cekap persekitaran, manakala Alaska Airlines dan Air Moldova adalah dua syarikat terbawah. Hasil mengenai penentu kecekapan persekitaran syarikat penerbangan menunjukkan bahawa faktor berat beban mempunyai kesan negatif. Sebaliknya, bagi syarikat penerbangan Eropah, jumlah keberangkatan dan nisbah pesawat berbadan lebar menunjukkan hubung kait positif dengan skor BC-EE. Tertakluk kepada "Skim Perdagangan Pelepasan Kesatuan Eropah (EU-ETS)", hanya memanfaatkan syarikat penerbangan Eropah untuk beroperasi secara cekap persekitaran. Oleh itu, strategi baru pengurangan karbon yang mantap di peringkat antarabangsa dan domestik yang melibatkan semua syarikat penerbangan harus dirancang dan dilaksanakan dengan teliti. Penggunaan pendekatan kuantitatif lanjutan untuk menganalisis syarikat penerbangan global memerlukan pemahaman yang lebih baik mengenai kecekapan industri yang berkaitan dengan pelepasan karbon sebagai output yang tidak diingini.

ENVIRONMENTAL EFFICIENCY ANALYSIS OF GLOBAL AIRLINES

ABSTRACT

Airline productivity and efficiency have emerged as areas of tremendous interest among academics and industry analysts following the 1978 Airline Deregulation Act in the United States because being productive and efficient is essential for airlines to survive and thrive under continually increasing competitive market pressures. As there is growing corporate social responsibility (CSR) in the airline industry, understanding and improving the environmental impact of airline operations are crucial. However, a limited number of studies have incorporated environmental factors into assessments of airline efficiency. This study intends to partially fill this gap in the existing literature. Therefore, this study's main objective is to evaluate the environmental efficiency of 54 global airlines in 2017. The study applies a double-bootstrap data envelopment analysis (DEA) and integrates the airline industry's undesirable output of carbon emissions. This study also aims to capture five explanatory variables (weight load factor, alliances, geographical region, number of departures, and the ratio of wide-bodied aircraft to total fleet) as determinants to explain the impacts on airline environmental efficiency in the industry. The results confirmed that the bias-corrected (BC) environmental efficiency (EE) scores were highly robust, as the scores were within the lower and upper boundaries. Moreover, British Airways and Lufthansa were the top two environmentally efficient airlines, while Alaska Airlines and Air Moldova were the bottom two. The results regarding the determinants of airline environmental efficiency showed that the weight load factor had a negative impact. In contrast, European airlines, the number of departures, and

the proportion of wide-bodied aircraft showed a positive correlation with BC-EE scores. The results also indicated that being subject to the “European Union Emissions Trading Scheme (EU-ETS)” is only useful for European airlines to operate in an environmentally efficient manner. Therefore, a new robust carbon abatement strategy that applies internationally and domestically to all airlines should be planned and executed thoughtfully. The use of advanced quantitative approaches to analyse global airlines calls for a better understanding of the industry's efficiency in terms of carbon emissions, which is considered an undesirable output.

CHAPTER 1

INTRODUCTION

1.1 Research Background

In this era of globalization, the airline industry is one of the world's most significant industries, strongly dominating the economy. The airline industry's growth has direct, indirect, and induced impacts on the airline industry's net revenue. The direct impacts are related to aviation traffic growth, while supplying jobs to industry is associated with indirect and induced impacts. In other sectors, such as tourism and trade, there are also catalytic effects that influence its derivatives. Overall, through the effects mentioned above, the aviation industry affects gross domestic product (GDP) growth (ATAG, 2020).

The growth of aviation has affected the evolution of airline traffic over the years. Figure 1.1 illustrates the growth of passenger and freight traffic from 2010 to 2019. As shown in Figure 1.1, the revenue passenger kilometres (RPK)[1] increased steadily from 2010 to 2019, and the annual growth of RPK increased by 4.9% in 2019. These figures indicate that the demand for air transport continues to grow. Additionally, the annual growth of freight tonne kilometres (FTK)[2] decreased by 2.9% in 2019. The performance of air cargo operations in 2019 was hampered by a 0.9% increase in global trade, and these problems were exacerbated by lower company and consumer trust, as well as a decrease in export orders (IATA, 2020a).

---

[1] Revenue passenger kilometres (RPK) or Revenue Passenger Miles (RPM) is a measurement of real airline service demand, which is also known as airline "traffic" (Jadhav, 2016). RPK is also an indicator of passenger traffic volume of sales (Pietersz, 2005–2020b). The unit of measurement in miles is used in the United States airline industry.
[2] Freight tonne kilometres (FTK), also known as cargo tonne kilometres (CTK), measures actual freight traffic and is the equivalent of RPK for freight (Pietersz, 2005–2020a).

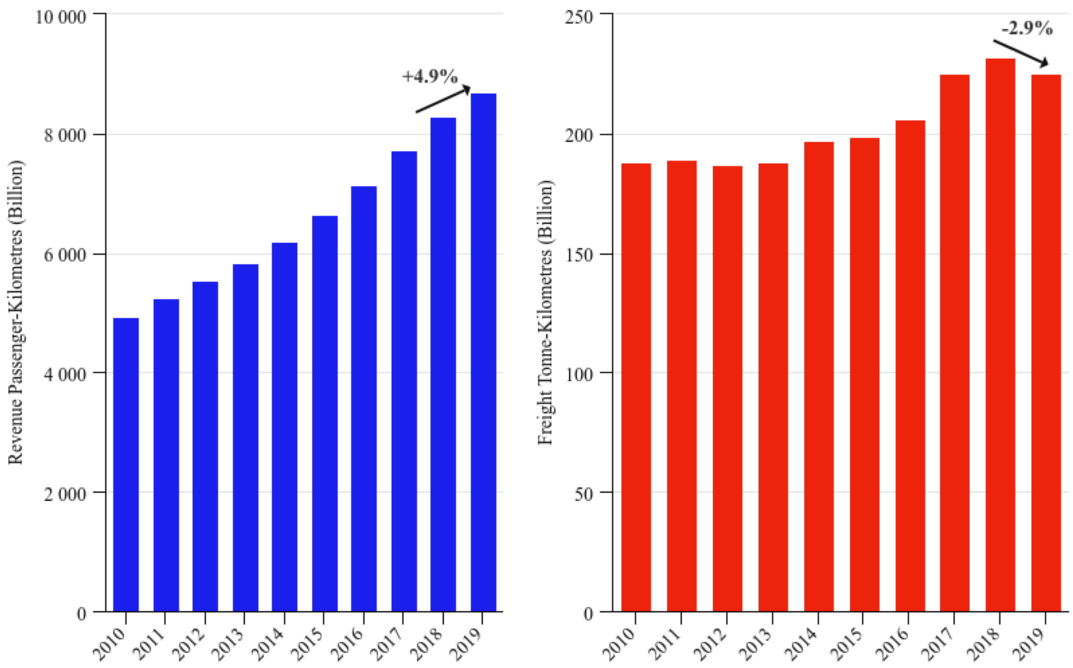

Figure 1.1 Passenger and freight traffic growth
Source: International Civil Aviation Organization (ICAO) (2019).

The growth in the aviation industry has led to an increase in the export of goods and services. Positive growth in the aviation industry contributed to overall economic growth (GDP) by 4.1% in 2010, 3.1% in 2015, and 3.4% in 2017 (ICAO, 2019). However, the contribution of the industry to the GDP was only 2.5% in 2019. Slowing GDP growth in manufacturing-intensive economies also contributed to the sector's underperformance (IATA, 2020a).

The positive effect of aviation growth is expected to continue because aviation is a globally relevant and highly competitive industry. ICAO (2013a) reported the predicted changes in RPK and FTK for the 2011–2030 period, predicting 4.5% growth for RPK in the next 20 years and 5.3% growth in FTK. As air travel increasingly becomes a norm in our society, aviation is expected to reach 19,000 billion passenger kilometres in 2050 (ITF, 2017).

For all of its benefits to nations and individuals, transportation imposes large impacts through the release of greenhouse gas emissions (GHGs) and other forms of pollution. Therefore, the growth of the aviation industry has raised global concerns, as the related production of negative externalities (emissions) is also increasing. Greenhouse gas emissions include carbon dioxide, methane, nitrous oxide emissions, and trace gases, such as hydrofluorocarbons (HFCs) and sulphur hexafluoride (SF6). Carbon dioxide (CO_2) is the largest contributor to overall GHGs, representing 73.48% of the total amount (Figure 1.2).

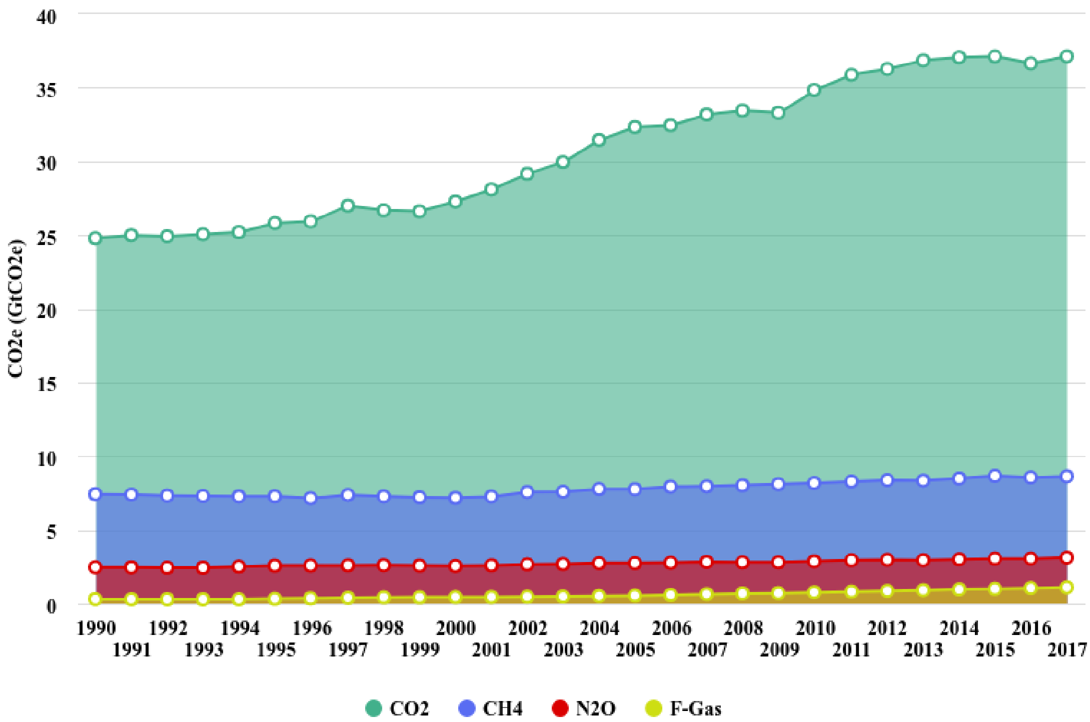

Figure 1.2 Global historical greenhouse gas emissions
Source: Climate Watch Historical GHG Emissions (2020).

The transportation industry is one contributor to carbon emissions. Figure 1.3 shows the carbon emissions by transportation mode, with passenger roads and road freight vehicles ranking first (45.09%) and second (29.45%), respectively, as the highest carbon emissions contributors in 2018. Aviation accounts for just 11.57% of all transportation emissions. However, as most aviation emissions are emitted at heights of 10–12 km between the upper troposphere and lower stratosphere, the impacts on the ozone, cloudiness, and radiative forcing are larger than those of the carbon emissions emitted on the Earth's surface (Penner et al., 1999). The environmental impact is worsening due to the long-lived carbon dioxide in the atmosphere, trapping more heat and radiation and increasing global temperatures.

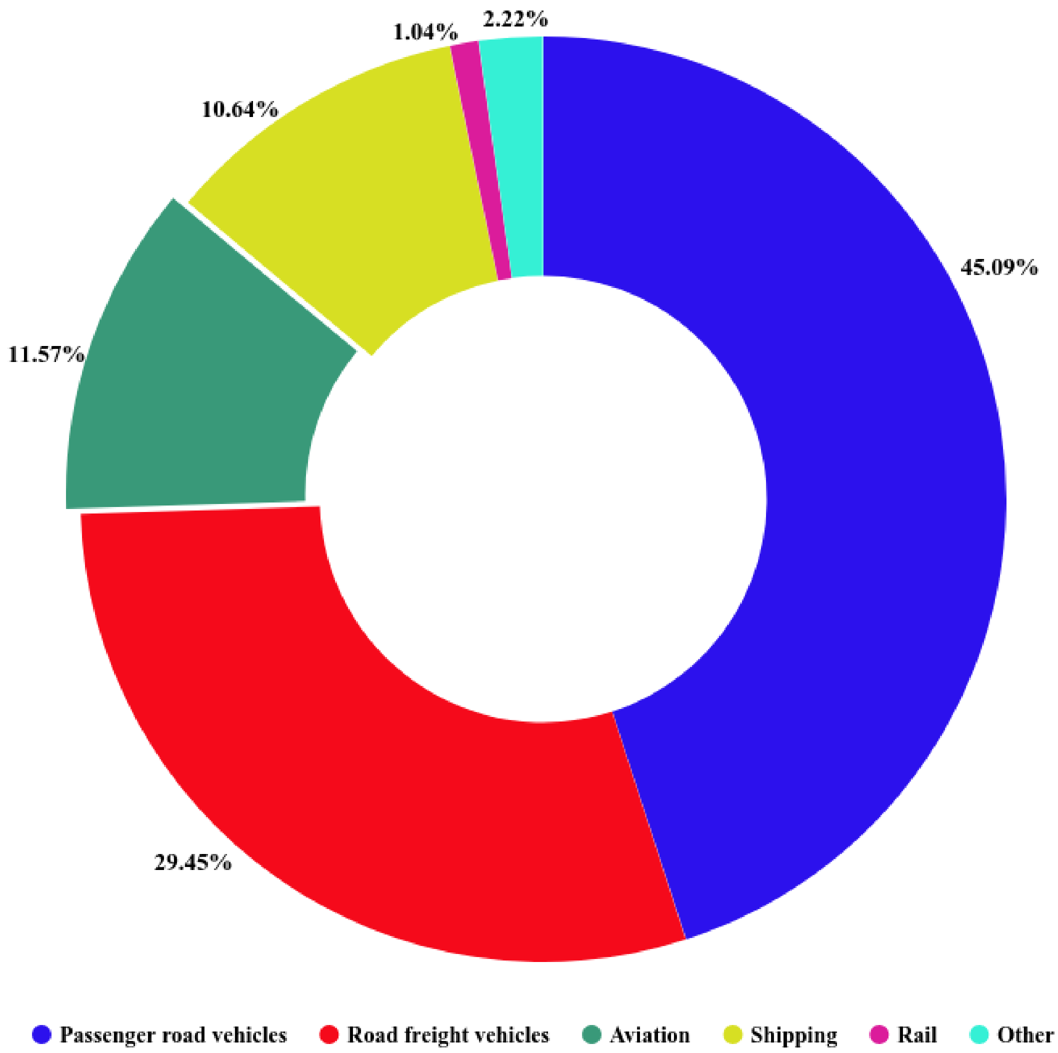

Figure 1.3 Carbon dioxide emissions from the transportation sector in 2018
Source: International Energy Agency (IEA) (2019).

The rapid growth of the industry makes global climate goals unachievable; for example, it has led to an approximate annual increase in CO_2 emissions of 250 million tonnes from 2010 to 2019 (a 37.65% increase). Worldwide, 914 million tonnes of CO_2

in 2019 were emitted by flights, accounting for approximately 2.1% of total global CO_2 emissions (i.e., 43.1 billion tonnes) (ATAG, 2020). At the same time, the number of passengers is forecast to double to 8.2 billion in 2037, resulting in increased pollution (IATA, 2018a).

However, in 2019, the world was shocked by the outbreak of the Coronavirus Disease of 2019 (COVID-19) pandemic. COVID-19 has had a great impact on the aviation industry; country borders have been closed, and international flights have been halted. However, air traffic is expected to recover, similar to previous shocks (ATAG, 2020). According to the International Air Transport Association (IATA), the availability of COVID-19 vaccines and screening processes worldwide by mid-2021 will allow countries to reopen their borders. Passengers are forecast to increase to 2.8 billion, and the passenger load factor is bound to grow to 72.7% by 2021. These results show that the CO_2 emissions from aviation only temporarily dropped due to the COVID-19 crisis but that once the industry recovers, carbon emissions will rise again. As a result, as part of COVID-19 crisis recovery policies, halting or relaxing environmental protection measures will be ineffective at reducing CO_2 emissions (ITF, 2021).

The growing airline industry has negative environmental consequences and at the same time faces difficulties from changes in environmental laws and policies (Zhang et al., 2010). To reduce carbon emissions, a few actions have been taken. First, CO_2 emissions from aviation have been included in the EU-ETS, where each international flight taking off or landing in the European Union (EU) is required to obtain an emissions permit beginning January 1, 2012. However, due to significant controversy worldwide, the EU suspended pollution taxes on non-EU airlines, implementing them only for EU airlines. Second, the Paris Agreement under the United Nations Framework Convention on Climate Change (UNFCCC) was put into practice in 2016. However, international flights, which are responsible for CO_2 emissions of approximately 65% within the industry, are not covered by the Paris Agreement but by the International Civil Aviation Organization (ICAO) (ICAO, 2016). Later, the ICAO developed the "Carbon Offsetting and Reduction Scheme for International Aviation (CORSIA)" to complement the UNFCCC Paris Agreement. The process towards achieving the goals set by the Paris Agreement and CORSIA will put the airlines under considerable pressure.

1.2 Problem Statement

The aviation industry faces challenges in mitigating CO_2 emissions to meet international requirements (CORSIA). Operational or economic efficiency is strongly correlated with environmental efficiency, as efficient engines consume less fuel and reduce costs and emissions (Payán-Sánchez et al., 2019). The improvement in airline environmental efficiency will reduce the environmental impact and reduce operating expenses. CO_2 emissions are undesirable output products associated with a desirable output. Undesirable outputs negatively affect the production process, and ignoring them would inaccurately represent the airline's overall production process. Thus, incorporating CO_2 emissions into measuring efficiency is vital, as this will provide comprehensive results to airlines for planning and managing their resources effectively.

Previous studies have revealed that airline productivity and efficiency emerged as an area of tremendous interest among academics and industry analysts following the 1978 Airline Deregulation Act in the United States because productivity and efficiency became essential for airlines if they were to survive and thrive under continually increasing competitive market pressures. In more recent years, a growing number of studies have melded airline productivity and efficiency with carbon emissions (e.g., Arjomandi and Seufert, 2014; Scotti & Volta 2015). Although a number of airline efficiency and productivity studies focused on CO_2 emissions have been carried out, there are still two problems that need to be addressed.

First, studies on the airlines' environmental efficiency have used a nonparametric approach, namely, data envelopment analysis (DEA). This method is preferable because it does not impose an a priori functional form, and it is able to handle multiple outputs and multiple inputs. However, the deterministic DEA approach suffers from a failure to provide statistical inference. This issue can only be solved by using the bootstrap procedure proposed by Simar and Wilson (1998; 2000). The use of the DEA bootstrap method to model environmental efficiency is limited to Arjomandi and Seufert (2014). Their study focuses on 48 international airlines during the period from 2007–2010. However, the inclusion of new airline efficiency studies with recent data adds value to airline efficiency research. Hence, this study takes this opportunity to measure the airlines' environmental efficiency by using the DEA bootstrap method with a more comprehensive sample of studies.

Second, the study of the determinants of airline environmental efficiency is very important, as it can capture the exogenous factors that affect airline performance. Airline companies can identify which factors improve or decrease performance and can prioritize these factors. Moreover, the lack of consideration of factors that significantly impact airline efficiency will cause efficiency measurements to be biased (Daraio and Simar, 2005). In addition, studies exploring the impact of determinants on airlines, especially those related to carbon emissions, are limited to country-specific airlines and to productivity analyses. Moreover, these studies measured the determinant variables of airline efficiency and productivity by using the conventional two-step procedure, which is usually carried out using a Tobit regression. However, this approach will cause inconsistency in the analysis due to the lack of a well-defined data generating process and misleading inference. Simar and Wilson (2007) proposed the double-bootstrap DEA approach to solve this issue. Additionally, Cui and Li (2016) stated that the study on the determinants of airline environmental efficiency was a gap for future research. Hence, this study adopts this approach and the variables used in previous studies to assess the influence of these explanatory variables on airline environmental efficiency.

1.3 Research Questions

This study aims to address the following research questions:

i. How can airline environmental efficiency be measured using a nonparametric approach?

ii. How do the influencing factors affect airline environmental efficiency?

1.4 Research Objectives

This research focuses on the following objectives:

i. To examine global airline environmental efficiency using a nonparametric approach.

ii. To investigate the determinants of global airline environmental efficiency.

1.5 Significance of the Study

This research study adds to the emerging body of literature in both theoretical and practical ways. From a theoretical perspective, this study contributes by using a double-bootstrap DEA approach to assess airline environmental efficiency and the determinants of efficiency; namely, this study incorporates undesirable outputs into a double-bootstrap DEA to measure airline environmental efficiency. This analysis enables the simulation of data for hypothetical testing and statistical inferences to obtain more precise results. This study also incorporates undesirable output into overall airline efficiency by using an algorithm #1 double-bootstrap DEA approach.

From a practical perspective, this study is significant to the aviation industry, including airline companies, aircraft manufacturers, and government agencies. This work provides important information to improve airline environmental efficiency by understanding what factors affect CO_2 emissions from airlines. Based on the results, airline companies can plan their fleet purchases and determine route networks, among other benefits. Indirectly, airlines can improve environmental efficiency alongside economic efficiency in the future. This research should serve as a foundation for a thorough evaluation of the environmental efficiency of airlines. Moreover, aircraft manufacturers can use these findings to match the aircraft supply based on airline demand. Manufacturers can also focus on producing the most environmentally efficient aircraft according to market demand.

This research aims to better understand the airline industry, as air carriers are increasingly driven to reduce fleet emissions. This research will provide quantitative information to industry players (e.g., aircraft manufacturers, airline companies) and the government (e.g., regulators) for performance assessment and policy analysis. For example, the government should amend landing fee policies and airport slot allocation rules by taking factors, such as the aircraft type, distance flown, and frequency of flights, into consideration. Altogether, the results of this work can make environmental policy decisions more scientific, analytical, and systemic.

1.6 Scope of the Study

The scope of this study was restricted to full-service and low-cost passenger airlines that operate internationally and domestically; the data were retrieved from World Air Transport Statistics (WATS) reports and the Airbus and Boeing webpage. The data in the WATS reports were collected from all airlines operating worldwide and comprise domestic, international and cargo operations data. Thus, the information provided by WATS is comprehensive. However, information about labour, the maximum take-off weights of aircraft, and carbon emissions are not provided WATS. The total sample includes 54 airlines out of 262 airlines in the study, and the focal year is 2017. This time span was chosen to ensure the most comprehensive collection of analytical data, while the sample chosen involves airlines that reported their 2017 operations data completely to the IATA. Four input variables were included for the environmental efficiency measurement: labour, capital, fuel consumption, and other operating inputs. Other operating inputs are represented by residual operating expenses (total expenses excluding the flight crews' salaries and benefits, fuel costs, and capital costs as measured by aircraft depreciation and aircraft leasing costs). The available tonne kilometres (ATK) were considered the desirable output, and carbon emissions were considered the undesirable output. This study also included explanatory variables, namely, the weight load factor, alliance, region, number of departures, and ratio of wide-bodied aircraft to total fleet, to measure the impact of these factors on the environmental efficiency of airlines. This research focused on the fundamental factors affecting the airlines' environmental efficiency in terms of the time involved.

1.7 Research Process

To measure the environmental efficiency of 54 global airlines in 2017 through incorporating carbon emissions as an undesirable output, a double-bootstrap DEA approach was applied (Figure 1.4). This study also investigated the factors that contribute to airline efficiency, and a comparison between the original DEA efficiency scores and bias-corrected efficiency scores is presented. The airline environmental efficiency results are discussed, and policy recommendations are provided.

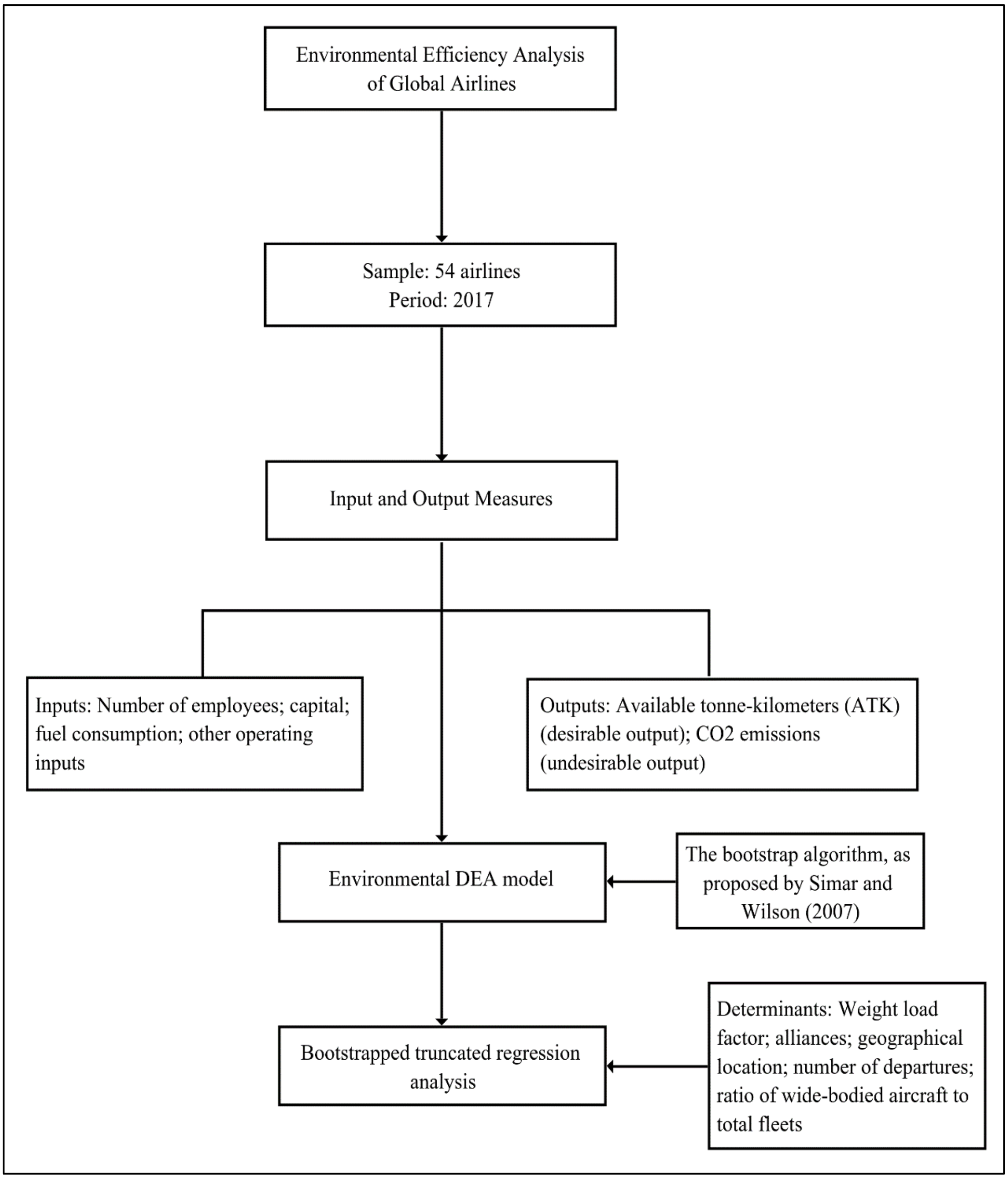

Figure 1.4 Research framework

1.8 Thesis Structure

The thesis is organized as follows: Chapter 2 offers a review of the literature, discussing the current state of the literature in terms of different performance assessment approaches. This constitutes the basis of this thesis. The literature on performance assessment, the assessment of airline efficiency, and other performance evaluation approaches is considered, and a performance assessment model is built based on this analysis. The research methodology used when developing and conducting this analysis is defined in Chapter 3 and involved identifying and collecting data, selecting samples, selecting and validating software, and analysing the data. For each of the airlines evaluated, Chapter 4 presents the results of a double-bootstrap DEA approach and the performance goals needed to achieve the maximum efficiency equivalent for each airline. The findings on the factors that affect airline efficiency are also included. Chapter 5 summarizes the study's findings and shortcomings and offers suggestions for future studies.

1.9 Operational Definitions

Term	**Definition**
Bootstrapping	Bootstrapping is a statistical procedure to estimate the sampling distribution by resampling the original sample 2000 times to create many simulated samples (Simar & Wilson, 1998).
Efficiency	Efficiency is the measurement between the observed and the optimal output and input values. For instance, efficiency can be calculated by comparing the observed output to the maximum potential output obtainable from the input under the output orientation (Fried et al., 2008).
Environmental Efficiency	"Environmental efficiency" or "eco-efficiency" refers to an efficiency measurement that includes the undesirable output that harms the environment[3] (Dyckhoff & Allen, 2001). Environmental efficiency is used to illustrate how the airline allocates capital to produce good outputs while reducing undesirable outputs (Graham, 2004; Lee et al., 2017).
Full-Service Carriers (FSCs)	Airlines that follow a standard operating model and serve full meal services, amenities, and facilities.
Hub-and-spoke	Airline operating strategy where all passengers, except for those whose origin or destination is the hub, switch to a second flight to their destination at the hub (Cook & Goodwin, 2008).

[3] When undesirable outputs have no environmental effect, efficiency is referred to as operational or technical efficiency. There are five other eco-efficiency definitions provided by Koskela and Vehmas (2012).

Low-Cost Carriers (LCCs)	Airlines that generally offer a lower fare than full-service carriers. However, such airlines come with extra fees on other items, such as in-flight beverages and carry-on bags.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter addresses the theoretical framework and empirical studies on airline efficiency and is divided into six sections. Section 2.2 will present the theoretical framework on efficiency measures. Section 2.3 will present efficiency measurement tools. Previous studies of airline efficiency will be discussed in Section 2.4. The input-output variables used in previous studies will be discussed in Section 2.5. Section 2.6 concludes the chapter.

2.2 Theoretical Framework

In this section, based on Farrell's definition of efficiency introduced in 1957, the study will analyse the theoretical framework of the efficiency measures in the production frontier. Moreover, the study reviews the main efficiency measurement tools, which are known as parametric and nonparametric approaches. Stochastic frontier analysis (SFA) is a parametric approach, whereas data envelopment analysis (DEA) is a nonparametric approach.

2.2.1 Concept of Efficiency

A classical paper by Koopmans[4] and Debreu[5], which defines the current definition of efficiency, was expanded by Farrell (1957). Previous work defines a basic

---

[4] The definition of technical efficiency by Koopmans (1951) was interpreted by Fried et al. (2008), asserting that if "to increase one output, either the input is increased or another output has to be reduced whereas to reduce one input, either another input is increased or the other output is reduced, the firm is technically efficient".

[5] An efficiency measurement proposed by Debreu (1951) and based on the "coefficient of utilization" can be thought of as a distance measurement between the outputs generated and the outputs that should have been produced provided the inputs.

firm efficiency measurement that accommodates multiple inputs and demonstrates the efficiency assessment of United States agriculture. To evaluate the economic efficiency of the industry, there are two general efficiency measurements: technical efficiency and allocative efficiency (Farrel, 1957). The former refers to the firm's ability to maximize the production of output while using fewer inputs, whereas the latter refers to the firm's ability to use the optimal proportion of inputs and/or output combinations given the respective prices (Coelli et al., 2005). To illustrate the concept of efficiency, Figure 2.1 shows the feasible production set of the operator given the combination of a single input and output. The production frontier is constructed at line f(x), where the firms produce the potential maximum output given a set of inputs consumed. The firm is inefficiently operating at point B, while points F and H are considered technically efficient, as they are located along the production frontier. The firm at point B could achieve technical efficiency by increasing the output produced and moving to point H. This is known as output orientation, which refers to output maximizing using the given input (Charnes et al., 1994). GB/GH represents the Farrell output-oriented measure of TE. Meanwhile, the input orientation refers to inputs minimizing the production of the given output (moving from point B to point F) (Charnes et al., 1994). The EF/EB ratio is the Farrell input-oriented calculation of technical efficiency (TE). Essentially, the model's orientation should be determined by which variables the decision making units (DMUs) can control effectively. For example, the input-orientation model is suitable if the firm's inputs are flexible to be changed to satisfy market demand (Ramanathan, 2003). However, the model's orientation minimally affects the efficiency score (e.g., see Coelli and Perelman, 1999).

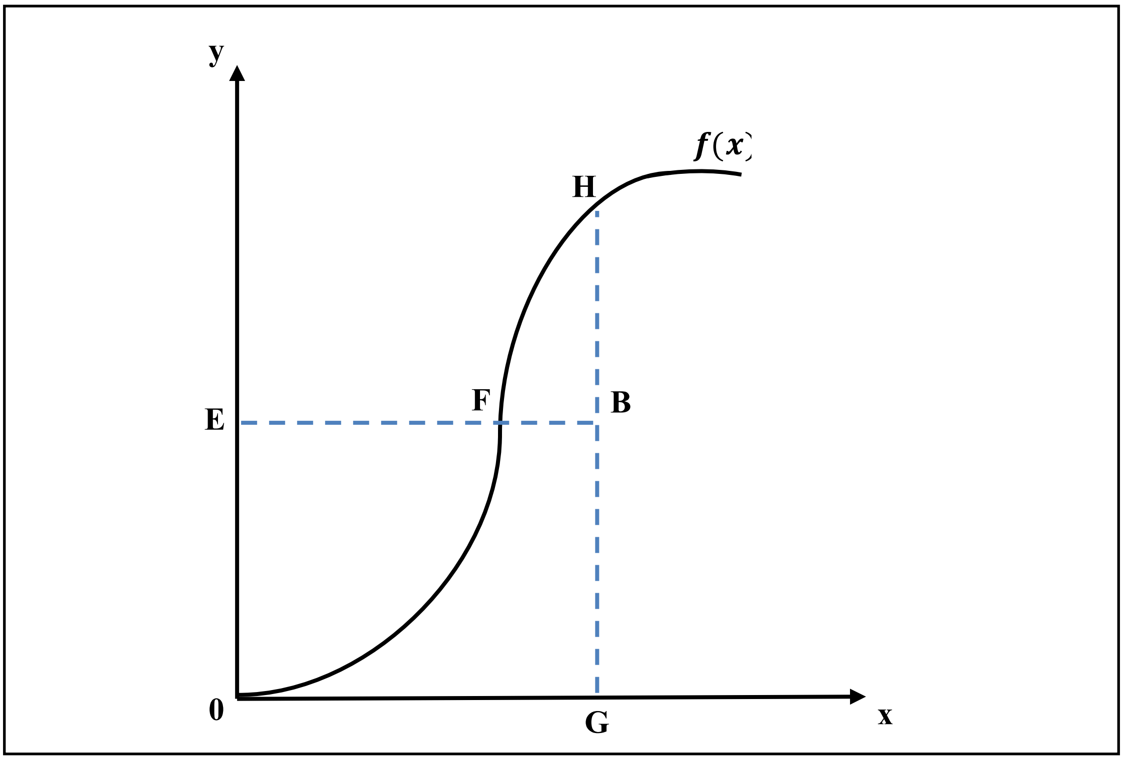

Figure 2.1 The production frontier and technical efficiency measures
Source: Coelli et al. (2005).

2.3 Efficiency Measurement Tools

Under the production frontier method, there are two fundamental approaches to measuring efficiency: econometric approaches, also known as parametric approaches, and nonparametric or mathematical programming approaches. Sharma et al. (1999) stated that the two most important methods used in efficiency analysis are SFA and DEA. SFA is a parametric stochastic frontier analysis approach (Aigner et al., 1977; Meeusen & van den Broeck, 1977), whereas DEA is a nonparametric mathematical programming approach (Charnes et al., 1978). One of the most favourable features of the stochastic frontier approach is that it can handle random noise and errors, and it allows the statistical testing of production structure hypotheses and the inefficiency rate. However, the crucial issue is selecting the parametric model for the technology involved, and the distributional inference for the inefficiency term has no a priori justification (Coelli, 1995; Sharma et al., 1999). DEA has advantages in avoiding these crucial issues. However, owing to the deterministic nature of DEA, the possibility of measurement errors or other noise that could affect the data is not taken into consideration in a frontier calculated by DEA (Coelli, 1995).

2.3.1 Data Envelopment Analysis

DEA, a frontier method, was inspired by the nonparametric technique developed by Farrell (1957) to evaluate the overall productive efficiency of firms by accounting for several inputs and a single output of all sorts. Unlike the parametric approach, DEA is more flexible for small sample sizes, with neither market price nor a priori underlying functional form assumptions (Zhu, 2014). DEA aims to evaluate a group of DMUs; it is not intended to serve as a regression analysis and can be extended to several applications. The analysis methodology can easily process multiple inputs and their relationships with outputs for decision making (Zhu, 2014).

Based on Farrell (1957), two classical DEA models have been proposed: CCR (Charnes, Cooper, & Rhodes, 1978) and BCC (Banker, Charnes & Cooper, 1984). The CCR model refers to a constant-returns to scale (CRS) model. This is defined by assuming that DMUs are operating at an optimal scale and that the efficiency score explains whether the DMUs are efficient or inefficient. DMUs are inefficient when the efficiency score is less than one, while DMUs are fully efficient when the efficiency score is equal to one.

However, the performance of DMUs might not be at the optimal scale due to factors other than production efficiency, such as deregulations, global agreements and financial constraints. As a result, Banker et al. (1984) improved the CCR model by relaxing the CRS assumption and assuming variable returns to scale instead (VRS). The VRS-DEA model suggested an efficiency measure that relying on scale efficiency, only compares DMUs of similar sizes. The CRS provides a technical efficiency score, while the VRS model only provides a pure technical efficiency score, which distinguishes the CCR and BCC models. The scale efficiency of the DMUs can be evaluated when the CRS and VRS of the production technologies are determined (technical efficiency/pure technical efficiency). Even if the DMUs are technically efficient, they do not work at an optimal scale (scale inefficiency) if the production technologies' CRS and VRS differ (Thanassoulis, 2001).

Figure 2.2 illustrates the difference between the scale and pure/technical efficiency measures of the DMUs. The DMU at point N is both technically efficient (CRS frontier) and purely technically efficient (VRS frontier). However, DMU Z is inefficient in both the CRS and VRS models because it is not located at any efficient frontier. In contrast, DMUs M and P are purely technically efficient, although they are not technically efficient. To measure the scale efficiency, referring to the DMU at point Z, its technical efficiency (under CRS) is $\frac{RS}{RZ}$, while its pure technical efficiency (under VRS) is $\frac{RP}{RZ}$. Thus, its scale efficiency is $\frac{RS}{RZ} \div \frac{RP}{RZ} = \frac{RS}{RP}$. However, the DMUs at points P and M operate at scale inefficiency when examined with the VRS model. The DMU at point P is operating at increasing returns to scale, and the productivity can be optimized by increasing the scale of operations to point N. In contrast, the DMU at point M is operating at decreasing returns to scale and should reduce its scale of operations to point N to become more productive.

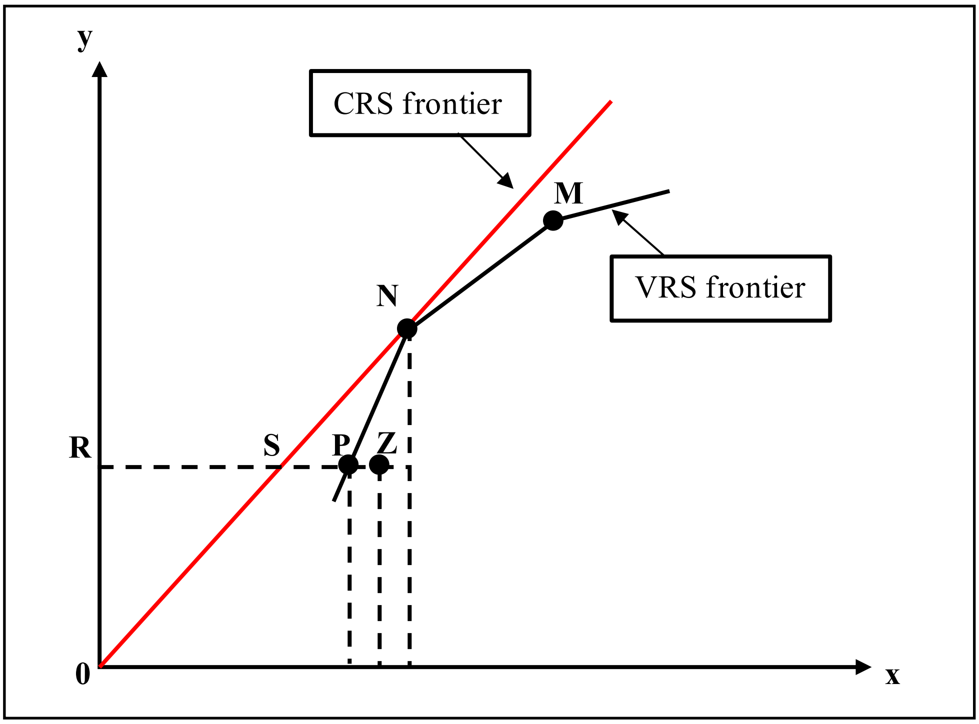

Figure 2.2 Scale and technical efficiency measurements
Source: Coelli et al. (2005).

2.3.2 Dealing with Undesirable Factors in DEA

The conventional DEA approach is formulated to improve efficiency by either raising output or lowering input levels. Nevertheless, in the real world, the industry produces both desirably (good) and undesirably (bad) output. Some examples of undesirable outputs include flight delays (Tsionas et al., 2017) and pollutants from industrial processes (Färe et al., 1996; Arjomandi & Seufert, 2014; Zhou et al., 2008).

Consider a Canadian pulp and paper industry that produces desirable outputs, such as pulp, paper, and paperboards, as well as undesirable outputs, such as biochemical oxygen demand and total suspended solids (Hailu & Veeman, 2001). The increased emissions of a pollutant that is not a desirable byproduct in the manufacturing process may reduce production performance. Environmental efficiency is another term for the performance that is calculated. The term "environmental efficiency" refers to the assessment of efficiency that incorporates the undesirable output that harms the environment[6] (Dyckhoff & Allen, 2001).

Hence, an efficiency measurement that fails to include undesirable outputs would be incomplete and will distort the results (Färe et al., 1989; Seiford & Zhu, 2002). Therefore, it is important to include undesirable outputs together with desirable outputs when measuring efficiency, but they should be treated differently (Seiford & Zhu, 2002).

However, the traditional DEA model (output- and input-orientation) only allows the output to be increased and the input to be reduced. One of the most popular methods for using DEA to assess environmental efficiency is to first include undesirable outputs in the standard DEA context and then quantify the undesirable output orientation (environmental) efficiencies. Previous studies, such as those using the data translation method (Seiford & Zhu, 2002, 2005) and environmental DEA technology (Färe et al., 1989; Färe & Grosskopf, 2004), have attempted to investigate the inclusion of undesirable factors in DEA. However, the principle of environmental DEA technology, in which the outputs are considered to be weakly disposable, appears to be more common in the sense of environmental efficiency calculation, as shown by Chung et al. (1997), Färe et al. (1996), Färe and Grosskopf (2004), and Zhou et al. (2008). As environmental issues have become a major concern and have been treated as undesirable outputs in the production process, environmental efficiency has grown in popularity.

---

[6] There are another five definitions of environmental efficiency or eco-efficiency provided by Koskela and Vehmas (2012), and these definitions depend on the application context and subjective influences.

2.4 Previous Studies of Airline Efficiency

Since the airline industry's establishment in the early 1900s, the study of airline efficiency has attracted the attention of scholars and airline industry members[7]. Inspired by the growing number of airline efficiency studies, this section reviews the studies that measure pure airline efficiency, regardless of whether undesirable outputs have been included in the study. This section will also discuss the studies that measure the impact of determinants on airline efficiency.

2.4.1 Airline Pure Efficiency Studies

Airline efficiency and productivity have increased; to the best of our knowledge, 23 previous studies have measured pure airline efficiency without undesirable outputs. These are listed in Appendix A.

The implementation of the Airline Deregulation Act of 1978 in the United States (US) airline industry stimulated a global shift in thinking about regulation. However, the impact of deregulation might differ according to country. Chan and Sueyoshi (1991) specifically compare the efficiency of 53 US airlines between 1973 and 1984, i.e., prior and post-deregulation, by adopting the DEA approach. The study found that post-deregulation major carriers were less efficient than small carriers. This is due to the reduction in employees. On the other hand, small carriers enjoy the benefit of mergers and acquisitions (M&As) to gain high efficiency.

[7] There are several articles related to the literature surveys that have been conducted on airline efficiency and productivity. For more details on the studies of airline efficiency and productivity, refer to Rich (2004), Heshmati and Kim (2016), and Yu (2016). Mallikarjun (2015) offers a rich summary of the literature on airline productivity and efficiency, although it is not a survey paper.

Following deregulation of the US airline industry, the European airline industry took the same path by implementing three "liberalization packages" in 1988, 1990, and 1993 (Button, 2001). Fethi et al. (2001) employed stochastic DEA to examine the efficiency of 17 European countries from 1991 to 1995 to determine the impact of post-liberalization. Three inputs (ATK, operating cost, and nonflight assets) and two outputs (RPK and nonpassenger revenue) were selected in this study. In their major study, Fethi et al. (2001) found that state-owned airlines are efficient post-liberalization relative to privately owned airlines. A similar result was found by Savolainen and Hilmola (2008), who measured the efficiency of 19 European freight carriers between 1996 and 2004 by using input-oriented DEA. Following the industry's deregulation, the publicly owned freight airlines' efficiency is greater than that of privately owned freight airlines (Savolainen & Hilmola, 2008).

With the entry of non-state-owned airlines after the Chinese aviation industry was deregulated in 2005, the Chinese airline industry's competitive market changed. Chow (2010) used DEA and the output-oriented Malmquist productivity index (MPI) approach to measure the efficiency and productivity of 16 Chinese airlines from 2003 to 2007. Three inputs (full-time employee number, aircraft fuel used, and seat capacity) and one output (RTK) were selected in this study. The findings revealed that non-state-owned airlines outperform state-owned airlines. This conclusion was supported by Cao et al. (2015), who discovered that after the deregulation policy, non-state-owned airlines outperform state-owned airlines in terms of efficiency. Additionally, the changes in the competitive environment in the industry led the government to merge the ten major state-owned airlines. Therefore, Chow and Fung (2012) employed the translog output distance function (SFA) and output-oriented MPI to measure the productivity of Chinese airlines before and after mergers. Medium-sized state-owned airlines were found to be most efficient before and after M&As. Chen et al. (2018) used MPI to assess the productivity of 11 Chinese airlines from 2006 to 2016, concluding that the Chinese airline industry's reform pressured the airlines to improve both their catching-up and innovation capabilities.

After the deregulation of the industry, the airline industry faced a large shock from the events of September 11, 2001, and fuel price fluctuations started in 2004. These events affected the efficiency and productivity of airlines. Greer (2008) employed input-oriented MPI to evaluate the productivity of US passenger airlines from 2000 to 2004. The input variables for the model were labour, fuel, and passenger seating capacity, whereas available seat miles (ASM) was used as the output variable. Despite the challenges, the findings showed that airline productivity improved significantly, owing primarily to the inefficient airlines starting to catch up with the efficient airlines.

Additionally, Assaf (2009) found that the US airlines' technical efficiency has decreased substantially, which was attributed to the increase in oil prices and the long-term effect of September 11. A Bayesian random stochastic frontier was employed to measure 12 major US airlines' efficiency from 2002 to 2007. Because of the external environment's impact and the airlines' management and organization, Barros and Couto (2013) also found no increase in most European airlines' productivity between 2001 and 2011. This study assesses the productivity of 25 European airlines from 2000–2011 by employing the LPI.

Michaelides et al. (2008) employed the SFA Cobb-Douglas production function and DEA to measure the technical efficiency of 24 airlines from 1991–2000. Three inputs (total annual labour in persons employed, total annual available aircraft capacity (representing capital) and total annual energy expended, i.e., fuel and oil) and one output