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Evaluation of Airline Efficiency and Environmental Impacts Using Data Envelopment Analysis

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EVALUATION OF AIRLINE EFFICIENCY AND ENVIRONMENTAL IMPACTS USING DATA ENVELOPMENT ANALYSIS

By

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This Dissertation was prepared under the direction of the candidate's Dissertation Committee Chair, Dr. Dothang Truong, and has been approved by the members of the dissertation committee. It was submitted to the College of Aviation and was accepted in partial fulfillment of the requirements for the
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ABSTRACT

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Airline efficiency has been a focus of research since the birth of the airline industry. Data envelopment analysis has become a highly accepted methodology for performing efficiency analysis and assessing relative differences between comparable business entities; over the last decade, airline efficiency research has proliferated into this linear programming domain. While early airline efficiency research focused primarily on revenue generation and profitability, growing commercial social responsibility is driving greater investment into understanding and improving the environmental impact of airline operations. This study is intended to partially fill a gap in exigent literature. While limited data envelopment analysis including environmental impacts has been conducted, the models treat environmental impacts as an output, never as an input or intermediate variable in the decision-making models.

This study constructed a linear programming model utilizing the data envelopment analysis methodology to assess the relative efficiencies of thirteen airlines. The model consumes operational and financial performance indicators of the airlines, as well as abatement success measured as a function of the carbon dioxide emissions

produced by the airline operations. The study analyzed airline activities from 2013 to 2015.

The results of the study indicated that the linear programming model was successful in measuring airline operational efficiency, inclusive of: (a) different capacity and cost components of airline operations, (b) carbon dioxide emissions abatement, (c) differing airline business models associated with service levels, and (d) the implications of different routes and networks. Airline-specific recommendations are presented, based on analysis of their 2013-2015 operational performance reviewed in conjunction with airline strategy disclosures included in annual reports.

The study provides theoretical and practical contributions to airline efficiency research. The study is the first to include environmental impact abatement expense as an input into airline decision-making for an overall airline efficiency model, as opposed to an output which is calculated as part of an optimization strategy focused on capacity or revenue generation.

DEDICATION

I dedicate this work to my mother and father.

Mom, your support and perpetual reinforcement have been the wind beneath my wings through this seven-year journey. Thanks for seeing this through with me.

Dad, your memory and achievements continue to influence the course I plot. I will forever be blessed to have so much advice available to me, long after I lost the opportunity to ask you for it.

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I would like to acknowledge everyone that made this dissertation possible. This doctoral program has encompassed a seven-year period, and I would not be at this point without extraordinary support in my academic, professional, and personal life.

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My career has carried me through three very different jobs at Gulfstream Aerospace during this program. In the positions I have held, it has required understanding and accommodation from my leaders for me to survive this journey. Chronologically, I must recognize the support of Mark Sells & Bill Bradley; Greg Collett, Becky Elliott, Jonathan Ringham, & Melissa Grant; and Steve Ritchie.

My family and friends have accepted my absence over the last several years while continuing to provide love and understanding. My mother's support has never wavered. The Saini-Shea's have accepted my aberrant attendance to family gatherings; I hope my two nieces are too young to remember. The Atkinsons, Fosters, Pearlmans, and Shepards continued to include me as the friend they see every day, though I seemed to decline 95% of their invitations.

Finally, a special thanks to Andrea Burkhardt for her support of the dissertation. In the last year of this program, she has literally taken on the responsibility of my day-to-day survival so I could focus on this work.

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CHAPTER I

INTRODUCTION

The perpetual evolution of the operating environment for aviation has produced a steady progression of aircraft development. In commercial aviation, an increase in fuel prices and the introduction of legislation restricting greenhouse gas emissions have driven a need for finding sources of improved operational and environmental efficiency and implementing changes to harness these efficiencies (Beck et al., 2011). The improvements to reduce aircraft operating costs have been implemented, for example, through aircraft design strategies, use of lightweight materials, and incorporation of more efficient and lighter power plant designs. Some of the aforementioned improvement foci may help reduce emissions through reduced fuel consumption. As airlines strive to achieve maximum effectiveness, airline management must understand the specific environmental footprint of each individual airline's business operations. The efficiency of an airline is influenced by all the inputs and outputs of its operations, employee and capital management, and resource consumption. By developing a better understanding of airline efficiency and its relationships to an airline's environmental footprint, the organizational leadership of airlines can better leverage strategies tailored to reduce its environmental impact.

The terms *efficiency* or *productivity* are used to describe the ability of an entity to maximize output while minimizing input. Similarly, airline efficiency describes the relative ability of individual airlines to maximize their performance while minimizing their resource consumption (Forsyth et al., 1986). Since the 1980s, significant research has been conducted to define and measure airline efficiencies. Caves et al. (1984)

utilized the translog cost function to compare and contrast legacy carriers employing *hub-and-spoke* operating models versus local service carriers. Early airline performance studies typically focused solely on firm size; Caves et al.'s (1984) research was one of the first airline performance studies to instead consider the impact of differing internal cost between hub-and-spoke and local service models in the post-deregulation environment. The study concluded that local service carriers did bear significantly higher variable costs. However, the study demonstrated that the sample local service carriers were operating with economies of scale; the only opportunities for the local service carriers to reduce costs was by increasing traffic density or stage length – industry and business model factors, not airline operational variables.

As research into the industry evolved, so too did the areas of focus and the research methods used. The original air carrier performance analysis focused on revenue maximization and asset utilization; in the air carrier world, performance is demonstrated by aircraft load factors and revenue-per-seat-miles (Mallikarjun, 2015). Greer's (2009) research explores factors influencing airline efficiencies by examining the impact of unionization. Greer found that there was no statistical evidence (at a ten percent level of significance) that unions negatively impacted efficiencies. At the time of this study, research had begun to recognize the environmental aspect of airline operations, identifying the environment impacts as an output of airline operation. In a special investigation conducted by the Intergovernmental Panel on Climate Change (IPCC), researchers deduced that aviation accounted for 3.5% of CO_2 emissions in the world (IPCC, 1999). The continued growth of the aviation industry, coupled with few barriers to emissions growth, suggests that aviation could represent 15%-40% of the world's CO_2

emissions by 2050 (Gössling & Peeters, 2007). In recent research, Baumeister and Onkila (2017) have suggested that an *eco-label* (a public disclosure summarizing the environmental impact of that good or service available to prospective consumers before purchase) should be developed to provide aviation consumers greater transparency on their airline selection. Embracing the impact of airline operations on the environment, Cui and Li's energy efficiency study (2016) builds on previous research to perform an analysis on airline efficiencies by assessing the comparative effectiveness to transform human and material capital into revenue capability as well as carbon dioxides.

Data envelopment analysis (DEA) was first introduced to airline efficiency analysis in the mid-1990s (Mallikarjun, 2015). DEA is a nonparametric analysis method used to assess the efficiencies of decision-making units (DMUs) that have multiple inputs and outputs (Sengupta, 1999). This methodology allows the comparison of relative DMU efficiencies and enables researchers to establish a benchmark and/or best practice to define the optimal efficiency frontier for that industry environment. A key facet of DEA is that it does not require input and output values to be converted into a financial equivalent or common unit of measure to evaluate the efficiency of the DMU. The analysis method evaluates the consumption of inputs and production of outputs compared to hypothetical optimum performance levels. Sengupta (1999) notes that the ability to perform efficiency analysis without cost information makes DEA a popular choice with public sector enterprises and nonprofit organizations. Merket and Hensher (2011) highlight that this feature of DEA also makes it a popular efficiency tool for research in aviation – an industry that is particularly data sensitive. The current body of knowledge demonstrates that DEA has become useful for modeling and comparing the operations of major airlines for efficiency evaluation; several researchers have chosen this method to analyze airline operations for many different facets (Mallikarjun, 2015).

The early airline efficiency analysis using DEA focused on traditional business operations – i.e., translating capital, material, and labor inputs into revenue generation capability. Sengupta (1999) performed a study on 14 international airlines in which he assessed the efficiency of their consumption of aircraft capacity, total operating cost, and total nonflight assets to produce passenger and non-passenger revenue. As the airline industry has embraced environmental impacts, the research applications of DEA have also been extended to the topic of environmental impacts associated with aviation. Cui and Li (2016) leveraged a multi-stage DEA model to evaluate airline efficiencies with respect to carbon dioxide abatement. This research study is one of many examples in recent years of exploring airline efficiencies and their relationship to the environmental impacts of aviation. However, the existing airline operations research focused on environmental implications considers environmental impacts as an output of business operations.

The existing related research does not structure the decision-making units (airlines) to consider environmental impact or abatement expenses in the same total efficiency calculation that includes revenue generation from operations. The focus of this research study builds upon the current body of knowledge to explore airline operations and the effectiveness of airlines to abate their emissions impacts as part of their total business model.

Statement of the Problem

Limited but concentrated research has been conducted in analyzing environmental costs associated with airline efficiencies. The current body of knowledge includes several concentrated evaluations of characteristics which can positively or adversely impact aircraft operating costs. However, the extant literature presents environmental impacts as an output of airline operations. Since the environmental impact – typically defined by pollutant emissions – is an analysis output, the conclusions highlight improvements which can be made by decreasing the aircraft emissions output (newer aircraft) and / or the average emissions per distance traveled (which directly correlates to flying longer legs). Opportunities exist within the current body of knowledge to integrate more organizational and operational factors to comprehensively assess airline efficiencies, inclusive of environmental considerations. Analytical models used to supplement airline operations decision-making should consider environmental impacts earlier in the decision process, which may introduce less capital-intrusive recommendations compared to costly aircraft purchases or upgrades.

The airline industry will benefit from increased awareness in operational decision-making inclusive of environmental concerns – i.e., decision-making models that present environmental impacts as a decision characteristic while also recognizing operational cost and revenue generation. The airline participants within the industry will gain the ability to measure their environmental efficiency relative to their peers. The literature review explores the study of corporate social responsibility in Scandinavian airlines by Lynes and Andrachuk (2008) which highlights how airline management can find value in greater environmental efficiencies. The results of this study can also be used by industry regulators to promote social responsibility by airlines who may choose to conduct operations counter to industry expectations.

Purpose Statement

The purpose of this study was to: (a) develop a measure of airline efficiency that recognizes emissions abatement capability; and (b) evaluate and differentiate the efficiency of current U.S. airlines, exploring their environmental impacts over time, as well as their potential for future emissions abatement. To facilitate a high-fidelity representation of airline business operations (and the decision-making activities required), a two-phase multiplicative two-stage DEA strategy will be utilized to effectively model the different decision-making units of the airline. The stages will incorporate: (a) operations – airline activities transforming capital, material, and labor resources into passenger capacity; (b) services – the choices of consumption by the market of the capacity, influenced by the operating environment of the airline; and (c) revenue realization – the actual sales of the passenger choices realized as revenue, accounting for carbon abatement. The modeling and analysis will use airline operations data available from the Bureau of Transportation Statistics (Bureau of Transportation Statistics, 2017) and public disclosures by the airlines.

Significance of the Study

Investigative studies into airline efficiency have continued since the inception of commercial aviation. Research utilizing DEA techniques to examine airline efficiency was first published in the 1990s (Mallikarjun, 2015). Several of the early studies focused on the operational efficiency of airlines and their consumption of assets to produce revenue – e.g. the previously mentioned research by Sengupta (1999). Similarly, Scheraga (2004) studied the impact of airline spending on passenger services (e.g. in-flight meals and entertainment) and marketing on airline efficiency. In both cases, the focus of efficiency research was on the traditional business practice of maximizing revenue. In recent years, the awareness of the environmental ramifications of airline operations has increased substantially. A few airline efficiency models have begun to incorporate environmental impacts (Cui & Li, 2016); however, the current body of knowledge lacks a focused assessment that models the primary airline operating DMUs in conjunction with the costs of limiting environmental impacts.

The focus of this research study has both theoretical and practical contributions to the current body of knowledge. From a theoretical perspective, this study is the first to model airline efficiency with environmental considerations utilized for both input and output variables. Utilizing environmental variables for both consumption and as a product from the DMUs has the potential to identify new facets of airline efficiency for future research. From a practical perspective, this study should provide a basis for an effective assessment of the environmental efficiency of an airline's operations. The results of this research study can be applied by academic or regulatory institutions to drive future improvements in aviation carbon particulate emissions abatement. Additionally, commercial entities could use the model or results from this study to analyze efficiencies and identify opportunities to improve profitability.

The research study is original for published scholarly work. The goal of this study is to provide an understanding of the industry as air carriers are further incentivized to improve their fleet emissions. The aircraft-specific data sources utilized in this research study are publicly available through the Bureau of Transportation Statistics and the public disclosures of the included airlines.

Research Questions

Three research questions (RQs) were explored in the interest of better understanding the relationship between the abatement of detrimental impacts to the environment and the business operations of an airline.

RQ1: Can airline efficiency be modeled to incorporate the cost and responsibility for abating environmental impacts in addition to traditional operating and revenue generating effectiveness?

RQ2: To what extent does the cost of environmental abatement affect the efficiency of airline operations in the United States?

RQ3: What are the relative differences among airlines compared to an optimal efficiency benchmark when considering all facets of airline efficiency – i.e., inclusive of operational constraints, environmental impacts, and revenue generating effectiveness?

Delimitations

This research study focuses on the fleet operations of U.S. and foreign carriers operating through the United States. The source of air carrier operational and revenue data was obtained from the U.S. Bureau of Transportation Statistics (2017). The data sample includes all commercial revenue-generating air carrier operations in the United States – inclusive of international operations that are arriving or departing from U.S. airports. From this dataset, the large carrier segment was chosen for the focus of the analysis because the air carriers in this business segment possess more similar business characteristics (almost all the carriers conduct operations across the country, serving large and small airports in domestic and international destinations). However, while the sample includes large air carriers, it still includes differing business models – e.g., *full-servic*e carriers (FSCs), *low-cost carriers* (LCCs), and even non-LCC *point-to-point* carriers (e.g. JetBlue Airways).

The sample also includes both U.S.-owned and non-U.S.-owned carriers. This facet of the sample definition also creates a *domestic market* dichotomy between the airlines included in the study. Some of the air carriers within the study population are U.S. airlines whose domestic markets are included in the study (and represent a significant portion of their operations). Other members of the population are foreign carriers with significant capacity inside and outside of the United States. Although the flight data for international carriers operating within the sample will mostly represent international flight legs, short international routes by these carriers are equivalent to regional or transcontinental domestic operations for the U.S carriers. Inclusion of these carriers: (a) strengthens the external validity of the data collection; and (b) provides the ability to compare U.S. and non-U.S. carriers with respect to air carrier efficiency.

In order to mitigate the influence of changing airline composition due to merger and acquisition (M&A) activity, the data collection for this proposed study focuses on airline operations no earlier than the first quarter of 2013. Analysis of mergers and acquisitions in the commercial aviation industry show that several airline mergers or buyouts occurred through 2012 (including the United Airlines acquisition of Continental Airlines in 2012). By restricting the study period to begin with first quarter of 2013, only one airline merger will have to be addressed in the study period: American Airlines merged with U.S. Airways (incorporating under the American Airlines name) in 2013; however, the two airlines continued to report separate earnings through 2015.

The airlines included in the study have different reporting timing for their annual corporate sustainability reports. Due to the differences in reporting cycles, the study bounds the analysis for airline operations through the fourth quarter of 2015. The 2015 limit ensures every airline has published its operating information for every year reviewed in the study.

The DEA technique was used to assess the efficiency of airlines in managing their business requirements while successfully implementing emissions abatement. The emissions abatement characteristics are defined by public disclosures made by the individual airlines. Therefore, this analysis does not consider emissions abatement activities that airlines are not disclosing (for proprietary reasons) or tertiary emissions abatement from other activities.

Limitations and Assumptions

All airline operating and aircraft-specific data is obtained from the Bureau of Transportation Statistics (2017) or publicly disclosed annual airline reports. After the data population was collected, a data reduction effort was executed to eliminate incomplete data points. The sample representativeness was then confirmed via qualitative demographical analysis as part of the data examination phase.

As defined in the Delimitations section, the study encompasses all large carriers operating within or through the U.S. national air system that disclose their carbon dioxide emission due to operations. While excluding smaller carriers excludes a segment of the commercial air transportation population from study, the strategy is in support of the research objectives. Smaller carriers (e.g. regional airlines) are utilized – and sometimes owned – by legacy air carriers to help feed traffic into the larger hubs. The regional carrier business model may not always constitute an equivalent profit-focused model operated by a full airline – i.e. the carrier may operate at worse margins than normally acceptable and mitigate these lower margins by: (a) lowering direct operating costs (e.g. through lower pilot and crew wages); (b) obtaining subsidies afforded to regional carriers under the Essential Air Service program created to ensure air service to small communities after the Airline Deregulation Act of 1978; and (c) improving economies of scale by avoiding competition with legacy carriers by feeding the legacy carrier hubs on routes to small communities and markets.

The Methodology section discusses the inclusion of additional models to observe the impacts of time to carrier efficiency performance; specifically, in addition to aggregate analysis models, efficiency models are created to analyze the sample annually. It is assumed that all airlines are working to operate as efficiently as possible in each individual year, and any investments or efforts to improve efficiencies do not have a detrimental effect in the year of implementation (i.e. decreasing efficiency in the short-term with the interest of improving efficiency in the long-term). As corporate entities have a fiduciary and ethical responsibility to their stakeholders to promote consistency and stability in their business operations (which includes cost and revenue management), this assumption is considered justified.

The nature of DEA methodology allows the evaluation of efficiencies within decision-making units without requiring the inputs and outputs to be quantified via financial measures or in the same units. However, DEA is susceptible to bias depending on the data sampling versus the efficiency measurement imposed. When modeling a DMU operating with variable returns to scale, the production frontier is modeled as a convex boundary of the observation sets in the input / output space (Simar & Wilson, 1998). This frontier model is therefore an estimate of the true production frontier, dependent on the finite sampling methods used to define the convex boundary. Any efficiency measurements relative to this frontier are therefore susceptible to validity threats if an inappropriate – i.e., inconsistent or too low frequency – sampling strategy is deployed.

Some research in the DEA domain has employed bootstrapping as a strategy to prevent the validity risks associated with data sampling. Bootstrapping effectively uses an algorithm to create a new sample and then reprocess the data based on the model equations and the original estimator. Depending on the bootstrapping algorithm used, the data generation process can be repeated several times with new samples. Unfortunately, bootstrapping possesses its own limitations and validity risks. In more complex models (e.g. non-parametric frontiers or multi-stage DEA), the bootstrapping algorithm may or may not output a distribution reflective of the original sample. When the distribution is not reflective of the original sample, the bootstrapping algorithm is actually degrading the fidelity of the original results, as opposed to augmenting the fidelity of those results (Simar & Wilson, 1998).

To mitigate validity threats due to this limitation of DEA, the sample size utilized in this research study has been defined to avoid any sampling-based bias or need for a bootstrapping algorithm. As previously mentioned, the sample selection includes all large carriers operating within the commercial air market that the sample reviews. By maximizing inclusion of market participants, any concern about sampling bias should be mitigated.

Definitions of Terms

Airline Energy Efficiency	Measure of airline's effectiveness in consuming energy resources (e.g. fuel) to produce revenue-generating outputs (e.g. passenger capacity) relative to environmentally-harmful emissions (Cui & Li, 2016).
Bias-corrected	A dataset or data point that has already had a transformation or cleaning step applied to address bias-related concerns. Bootstrapping is suggested as a possible method to apply bias-correction.
Bootstrapping	Bootstrapping is a method of repeating the data generation cycle by utilizing additional data points from the sample (replacing those in the original dataset).
Efficiency	A measure of the ability of an entity to maximize its output while minimizing its input.
Efficient Production Frontier	The collective set of operating parameters which defines efficient production for a specific DEA model. Also referred to as "Efficient Frontier", "Benchmark Production Frontier", and "Benchmark Frontier".
Full-service Carriers	Airlines operating a traditional business model with full offering of meal service, entertainment, and amenities.

Green	An adjective describing practices or policies that have reduced negative impacts to the environment.
Large Air Carriers	For the purpose of this study, this term refers to airlines serving at least 5,000,000 passengers annually.
Low-cost Carriers	Airlines operating a business model with fewer free amenities (sometimes available at an additional fee) but lower fares than full-service carriers.
Point-to-Point	Airline operating strategy where routes are operated with direct flights, as opposed to routing passengers through hub airports.
Productivity	A measure of the ability of an entity to maximize its output while minimizing input.
Service Effectiveness	Ability of an airline to transform operating capacity (e.g. ASMs) into customer consumable products – e.g. RPMs – based on its routes and schedules (Mallikarjun, 2015).
Slacks-based Measure	Slacks-based measures (SBMs) are methods of reviewing DEA results, specifically the excesses in input consumption and shortfalls in output production.
Super SBM	SBM methodology that removes the target DMU from the calculation of the sample DMU average performance.
Technical Efficiency	Similar to *airline energy efficiency*, this term refers to the airline's ability to create consumable services through consumption of inputs, realizing the detrimental creation of

environmentally-impacting emissions (Arjomandi & Seufert, 2014).

List of Acronyms

ASK	Available Seat Kilometer
ASM	Available Seat Miles
CRS	Constant Returns-to-Scale
DEA	Data Envelopment Analysis
DMU	Decision-Making Unit
FSC	Full Service Carrier
GRI	Global Reporting Initiative
IPCC	Intergovernmental Panel on Climate Change
LCC	Low Cost Carrier
M&A	Merger and Acquisition
OE	Operating Expenses
P2P	Point-to-Point Carrier
RPM	Revenue Passenger Mile
RQ	Research Question
SBM	Slacks-Based Method
VRS	Variable Returns-to-Scale

CHAPTER II

REVIEW OF THE RELEVANT LITERATURE

Review of Research in Airline Efficiency

The study of airline efficiency has been a focus of the airline industry since its inception in the early 1900s, specifically by its participants. However, as a highly regulated industry with rapid evolution of technology, the focus on efficiency and its measures was not fully embraced until decades later (Marti et al., 2015). As the aviation industry has evolved, the efficiency measures have increased in complexity to consider not only revenue generation versus fixed and variable costs, but also other tertiary effects such as socioeconomic impacts.

Most literature in the airline efficiency domain highlight publications by Caves et al. (1981) as the origins of academic research into airline efficiency analysis. Caves had previously published works focusing on transportation efficiencies in the railroad industry. The 1981 research study compared 11 U.S. airlines based on their inputs (resources, capital, etc.), outputs (revenues, passengers served) and total factor productivity (TFP) over a period from 1972-1977.

Airline efficiency utilizing total factor productivity (TFP). TFP is a measure of productive efficiency calculated as the aggregate output produced by a unit of aggregate input (Oum et al., 2005). After the initial usage by Caves et al. (1981), the TFP methodology continued to be a primary focus for evaluating airline efficiency. Caves and his fellow researchers extended their original analysis to include both U.S. and non-U.S. airlines over a period from 1970-1983. In a related work, Caves collaborated with other researchers (Caves et al., 1984) to focus on the cost structures associated with large traditional air carriers versus the operations of smaller regional businesses.

Traditional carriers were capable of a more efficient cost per passenger-mile than the smaller operations; from an economic perspective, this would make it seem highly unlikely that regional carriers could compete, but historical data demonstrated that they were able to secure market share for the major carriers (Caves et al., 1984). In this study, the authors reviewed all U.S. carrier data (major and regional) between 1970 and 1981. The research study analyzed the different cost components of both the major and regional operations as well as the destinations served and average load factor of the aircraft. The results of the study were surprising in that the variable cost benefits of the large certificated carriers were greater than realized: the major carriers enjoyed over a 40% cost advantage. However, regional carriers did have some advantages; certain unit costs (e.g. wages) were lower. Caves et al. (1984) also recognized that the data substantiated the perspective that there are fixed costs associated with the airline network size, i.e. even if there are economies of scale associated with larger volumes of service, the size of the service network will influence the fixed costs.

Gillen et al. (1985) utilized TFP to evaluate seven Canadian air carriers. The data generated by their research would become a recurring analysis sponsored by the Canadian government to help substantiate policy decisions. Oum et al. (2005) contributed to the proliferation of TFP as a measure of airline efficiency. In their analysis of a period from 1990-2001, the authors reviewed 10 major airlines in North America for operational performance and efficiency. The authors identified a limitation in comparing airlines only on TFP. In developing their research strategy, the authors focused on extending the analysis of airline operations beyond productive efficiency.

Oum et al. (2005) did not want to limit their analysis to productive efficiency (which evaluates how efficiently inputs are converted to outputs), but also intended to include the cost competitiveness of the airlines and effectiveness of the airlines to market their services to maximize yields. Due to the analytical strategy deployed, the input and output variables were each combined into indices which were then used to evaluate efficiency. For example, multiple inputs – including labor, fuel, materials, aircraft / flight equipment, and group equipment – were consolidated into a single input index. The productive efficiency for each airline was calculated by analyzing the consumption of the input index relative to the output index – consisting of airline consumables such as passenger and freight revenue-tonne-kilometers (RTKs), mail, and incidental services (e.g. catering, ground handling, billable support services for other airlines).

The input versus output analysis described above defines the productive efficiency of the airlines – i.e., the analysis yielded a TFP index. The authors (Oum et al., 2005) extended the analysis to cost efficiency by evaluating the airlines' attention to the prices of inputs. A unit cost index artifact was created by subtracting the total input price index from the residual TFP index values. This unit cost index was then used to evaluate the cost competitiveness between the sample airlines.

The final facet of the extension to airline efficiency by Oum et al. (2005) was to focus on the yield performance (i.e. actual profitability) of airlines. The authors presented that while an airline could be efficient in their production and price competitive by managing inputs, neither of the previous two analysis steps evaluated the ability to successfully market the airline services for revenue. Oum et al. (2005) evaluated the average yields per airline demand (i.e. the RTKs) consumed. Reviewing airline performance in the 1990s showed that the majority of airlines had falling yields when reviewed by the relationship above. This trend matched expectations as a number of airlines were combined through merger and acquisition activity during the period of time in analysis (and was captured in the authors' data). The authors also confirmed the impacts of stage length, recognizing that it was inappropriate to generally compare the airlines based on the average yield data, as longer flight stages would enjoy economies of scale for costs and therefore show higher yields. The authors successfully extracted the stage length effects from the yield data, which then presented airlines known to be profitable as having positive average yields.

The research study by Oum et al. (2005) provides a good philosophical framework for examining airline efficiency as they looked at multiple aspects of airline business operations: (a) internal operational efficiency; (b) input cost management; and (c) effectiveness of sales and revenue generation. However, the analytical method employed by the study demonstrated deficiencies in enabling high fidelity understanding of the operations of each of the firms. The reduction and consolidation of all variables to indices forced the analysis to provide general comparison of the different entities involved. From an operations management perspective, the need for greater understanding of every input and output helps promote the consideration of DEA as an analytical tool to be leveraged for airline efficiency analysis.

Application of DEA in measuring airline efficiencies. Good et al. (1995) utilized both a stochastic frontier model (utilizing regression analysis) and DEA to examine European and U.S. air carriers operating between 1976 - 1986. The study was performed to evaluate U.S. air carrier performance post-deregulation, compare the operations between air carriers from the different regions, and then to hypothesize the effects to European carrier efficiencies if they were to similarly deregulate. This study presents a dichotomy in analytical methodology as the authors utilized a more traditional analysis and DEA in parallel. The stochastic frontier approach imposes assumptions on the data distribution but frames the analysis and results so that the results may be generalized for conclusions against the population. The DEA method allowed a more open evaluation of the efficiencies of each decision-making unit, but as previously reviewed in Zhu (2011), DEA allows an effective evaluation of a DMU against a benchmark; it is limited in its capacity to be used to compare the efficiency of several DMUs against each other.

Supplementing the productive efficiency measure. As the research study by Oum et al. (2005) demonstrated, the evaluation of airline efficiencies beyond productive efficiency enables better modeling of firm decision making. The DEA methodology has enabled research in air carrier operational efficiency to include tertiary variables to complete a more secular perspective.

Scheraga (2004) employed a DEA model to explore air carrier management responsibilities to balance investment between productive efficiency goals and customer-focused improvements. The literature review compiled by Scheraga highlights key foci for airline operations that have become choices in airline offerings. In-flight passenger services (e.g. meals, beverages, and airline memorabilia) in certain markets and operating models have transitioned from being inclusive in the base fare to becoming an extra charge. In a separate facet of customer-focus, the ticketing, sales, and promotion aspects of the airline model has evolved to embrace greater value-based segmentation. Specifically, the airlines have started to implement mediums (e.g. online ticketing), choices (e.g. fare-structures, code sharing) and customer-focused initiatives (e.g. improved delay communication, baggage delivery time commitments) to help maximize their attraction to customers who are most desired by the airline along the dimensions of monetary value and travel frequency.

In this study, Scheraga (2004) utilizes an input-oriented DEA model to compute relative efficiency scores for each of 38 global airlines under study. Model orientation describes how a DEA model will seek determination of the optimal production frontier for the DMUs presented in the model. An *input-oriented* model will focus on minimizing input consumption by a DMU to achieve the same output level. An *output-oriented* model will seek to maximize outputs while maintaining the same levels of input consumption. A *base-oriented* (sometimes called unoriented) DEA model equally optimizes both inputs and outputs – or can have weighting applied to establish a relative priority in optimization between the input consumption and output production.

After efficiency scores were established for each airline, the scores were regressed against several variables (both operational and environmental in nature) to promote the ability to compare efficiencies. In line with the aforementioned research study by Oum et al. (2005), the efficiencies were regressed against flight stage length in order to eliminate influences from the cost economies of scale associated with longer flights. Another operational variable that was utilized for the regression was the average load factor. As presented by Caves et al. (1984), comparing airline efficiencies for operations with very different load factors will not result in actionable data. Two of the other variables utilized in the regression activities helped to normalize the revenue structure of the airline: passenger revenues as a percentage of total revenues and scheduled service revenues as a percentage of total revenues. To consider other environmental influences, the efficiencies were also regressed against the percentage state-ownership of the airline – i.e. the extent to which an airline's flag country was supporting the airline's business.

Augmenting DEA with regression analysis. As previously discussed, DEA possesses positive characteristics which enables the evaluation of productive efficiency without requiring assumptions associated with the cost frontier, or pricing information. However, the nature of these benefits results in an evaluation that compares a DMU against a benchmark – i.e. a comparison between DMUs may possess threats to validity. A strategy to provide a more comprehensive evaluation of DMU efficiency relative to the peer group is to augment the DEA with a successive analysis technique.

Merkert and Hensher (2011) employ this strategy via a two-stage DEA analysis to compare 58 airlines from 2007-2009. The goal was to not only evaluate technical efficiency – the efficiency focus of prior DEA research and the evaluation originally constructed by Charnes et al. (1978) – but also explore the allocative and cost efficiencies of the airlines. In the first stage, a traditional DEA analysis is conducted to evaluate airline efficiency. The DEA model is structured as input-oriented, and the authors pursue both *constant returns to scale* (CRS) and *variable returns to scale* (VRS) estimations. After the initial analysis stage, the authors then perform a regression analysis of the first-stage DEA efficiency scores. In this follow-on analysis stage, the first-stage efficiency scores are the dependent variable, which are regressed against exploratory (independent) variables.

In this research study, Merkert and Hensher (2011) present that a *bootstrapping* (bias-correction) treatment of the data is required to prevent unintended inflation of the efficiency scores when utilized in a serial correlation model. Review of the data after the analysis confirmed expectations that uncorrected efficiency scores would be inflated – i.e. overestimate the efficiency of the DMUs (airlines) relative to the corrected scores. However, after reviewing some of the results of the second-stage analysis, the authors conclude that bootstrapping did not have a significant effect on the results and hypothesize that for the given sample (commercial aviation industry), bootstrapping may not be as important.

The study by Merkert and Hensher (2011) demonstrates how DEA can be an effective method to consume operating data to make market- or industry-level deductions. Their research analyzes efficiencies of different airlines which can be affected by fleet size, age of aircraft, aircraft capacity, and specific flight distances for the data points. Through the evaluation of decision-making efficiency, the authors were able to confirm some expected trends, while showing numerical statistically significant results that contradict the current knowledge base. For example, the analysis did show that as airlines increased in business size – i.e. increased total market exposure through additional aircraft, larger aircraft, etc. – they enjoyed marginally improved efficiencies. However, the data contradicted expectations that longer stage lengths induce greater cost efficiencies. The lack of significant relationship suggests that while the aircraft may enjoy a cost savings in fuel burn, longer flying aircraft have greater crew and/or maintenance requirements (e.g. needing to have maintenance capabilities at non-hub destinations) which counter any fuel savings.

Multi-staged DEA applications in airline efficiency. The previously reviewed Merkert and Hensher (2011) study presented a research approach where the results of the DEA analysis are interim values which are processed in a consecutive research phase. In the last several years, DEA models have been expanded to facilitate multiple analysis stages. The outputs of the first stage are interim values; the following analysis is also a DEA optimization which consumes these interim values as inputs. Each analysis phase can be defined by its own equations and optimization focus – e.g. they can be input-oriented, output-oriented, CRS, VRS, etc.). The results of the combined multi-stage model represent the combined choices made by a DMU.

The multi-stage approach has been used with success in airline efficiency research. The different stages allow focus on different facets of firm performance. Zhu (2011) utilized a two-stage DEA analysis to review 21 airlines operating in the United States. The first stage evaluated an airline's operational efficiency – i.e. it measured an airline's ability to convert material and labor resources into capacity to serve passengers. Specifically, the inputs of this stage included fuel costs, the cost of benefits to passengers or employees, operating cost per seat mile, as well as salaries and wages. In this phase, the DEA analysis was used to determine the optimal load factor and fleet size that could be generated with these inputs. While the first stage yielded awareness to the optimal capacity that the airline can offer, it does not reflect the market share or revenue actually gained.

The second stage of Zhu's analysis was utilized to evaluate how well the airline was developing revenue. This is a measure of how attractive the airline's product is to the consumer and how effective the airline is at making this product available to its consumer base. The load factor and fleet size generated in the first-stage serve as the inputs, and the outputs of this phase are passenger revenue and revenue passenger miles. Zhu (2011) depicts his two-stage model and variables in Figure 1.

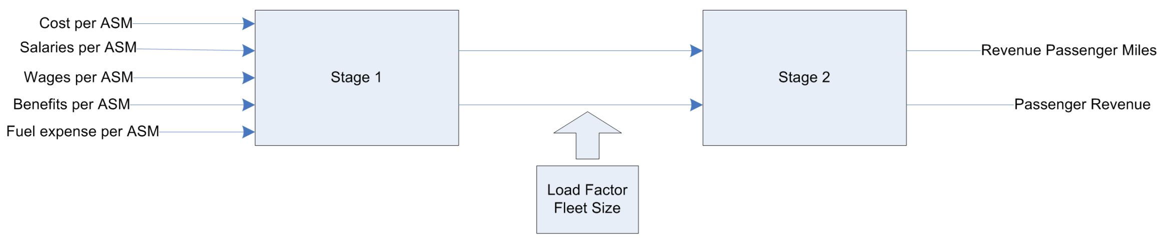

Figure 1. Representation of two-stage airline efficiency model from Zhu (2011).

Examining the effectiveness of revenue generation provides greater understanding of the total performance of an airline. For one of the years of study, while seven of the airlines had achieved optimal fleet utilization (load factor and fleet size) given their available resources, only three of the airlines were operating optimally for revenue generation. It should be noted that there were no airlines that operated at optimal efficiency for both stages.

The number of stages in a multi-stage DEA analysis can be tailored to match the researchers' desires in modeling the choices for a DMU. Mallikarjun (2015) expands on two-stage models – like the Zhu (2011) airline analysis – by adding a stage, segregating the generation of revenue passenger miles from the recognition of pure revenue. This model's first-stage also evaluates the airline's ability to consume labor and material resources to generate product capacity – available seat miles. The inputs include crew and employee wages, fuel and maintenance supplies, and other costs directly related to airline operations (e.g. insurance expenses). Mallikarjun (2015) describes the airline's performance in this phase to be cost efficiency.

The analysis then utilizes a second stage to evaluate an airline's ability to transform these available seat miles into revenue passenger miles. In this second stage – which Mallikarjun (2015) labels *service effectiveness* – the airlines ability to transform ASMs to RPMs is evaluated, framed within the environmental influences of the airline's fleet size and destinations offered. Mallikarjun highlights that the combined evaluation of the cost efficiency (first stage) and service effectiveness (second stage) yields an airline's cost effectiveness. The third stage of the Mallikarjun (2015) model measures the airline's ability to market its revenue passenger miles and recognize revenue. Labeled the "Sales" stage, this segment of the analysis is said to evaluate the "revenue generation" capabilities of the airline. The comparison and optimization of the inputs and final outputs of the three-stage model define the overall operating efficiency of the airline. This model is presented in Figure 2.

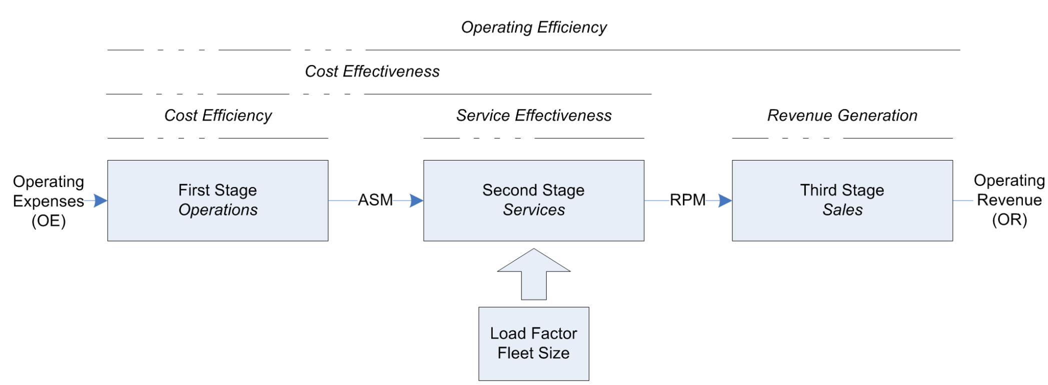

Figure 2. Representation of U.S. domestic airline operating efficiency measurement model from Mallikarjun (2015).

Philosophically, Mallikarjun’s model design is more representative of real-world airline operations than the previously reviewed Zhu (2011) two-stage model. The expenses consumed in both models translate to products and services (available seat miles) that can be utilized by passengers. However, the airline must allocate this capacity via aircraft and routes for them to be consumed by customers. A portion of the ASMs are also not revenue generating; the airline may use them to reposition flight crews to operate aircraft starting in a different location. These ASMs could also be utilized as award travel for passengers in airline loyalty programs. The third stage measures an aspect of airline performance that Zhu’s model does not. The previously reviewed two-stage model by Zhu (2011) converts the cost inputs directly to revenue. Conversely, the Mallikarjun (2015) three-stage model specifically reviews airline decision making to understand if the revenue generated reflects the maximum possible.

The three-stage model developed by Mallikarjun (2015) has served as a strong example for DEA-based measurement of airline efficiency. Li, Wang, and Cui (2015) used this model as their basis to evaluate 22 international airlines over a period from 2008 to 2012. The researchers argue that while the original model is sound, the application of a slacks-based measure (SBM) methodology in the three-stage model will help differentiate between DMUs that are considered efficient – i.e. help provide a greater understanding of which of several efficient airlines is more or less efficient. In the 2015 study, Li et al. review different SBM approaches available in exigent literature. *Super SBM*, a common SBM technique, supports the comparison of different efficient DMUs by extracting the evaluated DMU from the reference DMUs utilized for comparison. The validity threat of this method, however, is that every DMU under evaluation is being compared to a different reference set.

Li et al. (2015) choose to promote the Virtual Frontier Network SBM model. In this approach, the reference DMU set is independent of the evaluation DMU set – i.e. all the DMUs are evaluated against the same reference set, but none of the evaluated DMUs are in that reference set. The research study utilizes a traditional network SBM method, as well as the Virtual Frontier Network SBM model to assess the same airline. The authors highlight that the traditional network denotes a number of airlines as efficient for performance in the first phase (cost efficient operations). However, when the Virtual Frontier Network SBM model is applied, the first-stage bias is removed.

The reviewed literature highlights DEA's recent applications to the measurement of efficiency in airline operations. Multi-stage models allow effective operations research to be conducted as the different aspects of firm decision-making can be combined in a large analytical model.

Environmental Impacts in Aviation

In line with the growing societal focus of protecting the environment, increased efforts are being leveraged to understand and mitigate the impacts of aviation to our surroundings. As the volume of air transportation demand and capacity grows, a strategy for sustainable development of the aviation industry is critical (Lu & Morrell, 2006). Therefore, resources are being committed to address expectations to reduce and abate the pollutants associated with aircraft operations.

Environmental motivations in aviation. The focus of airlines on their environmental footprint can be attributed to philosophies of business ethics and corporate responsibility. Lynes and Andrachuk (2008) review the goal of corporate and social environmental responsibility (CSER) as an artifact defined by influences of the social acceptance, the culture of the firm's constituents, and at times by industry-specific expectations. The authors review several reasons for investment in CSER goals identified in exigent literature, including long-term cost management (investing in technology that is more efficient), realizing savings through waste reduction, improving branding, acquiescing to stakeholder pressure, and avoiding / delaying regulatory action. Through their research, SAS (Sweden's flag carrier airline) is reviewed; a case study is performed to evaluate SAS's reasons for adopting CSER practices.

In line with current research focused on CSER, influencing forces on SAS were reviewed. The political and social systems of Sweden (and Scandinavia as a whole) point to more democratic, consensus-based societies where a greater importance is placed on efficiency (in all processes) and specifically on environment and conservation. Though this is specific to that geographic and cultural sample, the review of the market system highlighted that CO2 trading permits for emissions quota tracking and airport landing charges targeted at high-polluting aircraft were both market-based influences for SAS firm decisions to embrace CSER objectives (Lynes & Andrachuk, 2008). Interviews with senior management of SAS revealed that the financial benefits of CSER goals were not only tied to regulatory or national expectations.

In addition to embracing the cost-savings associated with more efficient consumption, SAS believed that its corporate earnings would be improved by gaining and maintaining corporate customers who expected corporate responsibility. A specific example was the customer expecting their suppliers or partners to maintain standard certification demonstrating environmental responsibility, such as ISO 14000. A quote by SAS's CEO established that investing in CSER goals added value to the company – not only in cost-reduction translated to increased revenues, but that a better environmental footprint translated to a better and stronger company image that could be transformed into financial value through a superior negotiating position, especially with the government and industry regulatory agencies (Lynes & Andrachuk, 2008).

Environmental studies on aircraft operations. The primary environmental impacts of aircraft operations lie in particulate and acoustic emissions. Both sources of pollution are primarily created by the combustion process of aircraft engines. In the interests of promoting understand of the influence of aviation operations on our world, Lu and Morrell (2006) developed methods to calculate these impacts utilizing a social cost estimation method.

Quantifying environmental impacts of aviation. The noise-specific impacts of aviation have the largest impact on the communities surrounding airports (Lu & Morrell, 2006). These impacts can be a nuisance, but also can have detrimental health effects via disruptions to daily life – e.g. by causing sleep deprivation. Due to the negative impact aircraft operations can have on communities, governments have imposed additional rules and penalties to promote reasonable noise management. Most airports near communities are driven to restrict night flights through restrictions, curfews, or quotas. In some cases, charges are levied for violation of requirements or just for operations after a certain time at night. As the negative impacts are experienced by the inhabitants of communities surrounding airports, Lu and Morrell (2006) present a method for calculating the noise social cost based on population density of these communities. The formula utilizes the hedonic price method to relate noise depreciation index (NDI) and the annual average house rent near the airport to the difference in noise the aircraft noise contours create over the ambient noise. The density of the community is incorporated into the calculation by recognition of the number of residences impacted by the noise contour.

Lu and Morrell (2006) also worked to quantify the particulate pollutant impacts of engine operations. From a noise perspective, the aircraft provides the majority of its impact during taxi, take-off, and landing (TT&L) segments of a flight. During taxi, the aircraft is operating with running engines and in close proximity to nearby communities. During take-off and landing, the engines are operated at their greatest thrust settings, generating the acoustic and particulate emissions relative to all phases of flight. However, this phase is also one of the shortest, with respect to the other segments of a flight; it would be unfair to consider emissions during TT&L as representative of the average flight engine performance. To recognize the different modes of operation, Lu and Morrell (2006) developed a summation equation which combined the particulate generation for each phase of flight – recognizing both the time in that mode of flight and the particulates created at that power setting (information which is collected as part of the certification activities of any aircraft propulsion system).

Pollution abatement via fleet planning. Reducing the impacts of aircraft on the environment has become a focus for many airlines. Rosskopf et al. (2014) identify three primary motivations for airlines to invest in environmental goals: (a) to avoid penalties and / or restrictions associated with emission-intensive aircraft; (b) to demonstrate environmental commitment and invest to avoid further regulatory action; and (c) to develop a brand that is environmentally-conscious, with the interest of attracting or retaining customers.

An obvious strategy for reducing the emissions impact is to leverage aircraft with efficient engines that yield fewer and less concentrated emissions. In the research study by Rosskopf et al. (2014), the researchers leverage a fleet planning optimization model originally designed to help an airline minimize costs while building an aircraft fleet. The model utilizes cost data, airline network requirements (e.g. destinations served, flight schedules), and business financial capabilities (preferences and abilities to buy vs. lease) to determine the optimal fleet composition over a multi-year period. The authors augmented this previously developed optimization model with an additional variable that characterized an aircraft's nitrogen oxide emissions (NOx) per unit distance traveled. Similar to the previously discussed research by Lu and Morrell (2006), these authors also focused on the fidelity of differentiating the particulate emission of every flight phase. The authors identified a typical airline flight profile from exigent research and developed an effective expression to obtain a total emissions per kilometer of distance flown, while preserving the relationship between the climb and cruise portions of a flight leg to other engine operating conditions (e.g. taxi, take-off, or landing). Utilizing engine operating data retained by regulatory agencies, the researchers calculated an appropriate particulate emission relationship to flight segment length specific to each aircraft type.

The augmented model was utilized to maximize fleet asset value at the end of the multi-year period, while minimizing a cumulative of the NOx emissions over that period of time (Rosskopf et al., 2014). Utilizing a baseline optimal fleet strategy, the researchers set NOx reduction goals of 5%, 10%, and 15% to evaluate effects on net assets. As part of the exploratory study, the researchers varied fuel prices to gauge the effect on the fleet optimization model. The authors concluded that increasing fuel costs and more stringent environmental goals were complimenting requirements; both goals necessitated earlier retirement of aging, less-efficient aircraft (whose older technology also made them more emissions-intensive) by newer and more efficient aircraft. Even though the optimization model rewarded staying within common aircraft types, the optimal solutions drove airlines to incur the reduced commonality penalties (e.g. increased maintenance costs due to lower component commonality and increased training for technicians) due to the far greater operating efficiency of new families of aircraft – i.e. the Airbus A350, Boeing B787, and Boeing B737 MAX aircraft.

The aircraft fleet optimization research by Rosskopf et al. (2014) provides substantiated literature demonstrating effective and viable means by which airlines can reduce their environmental impacts while supporting increased volumes of customer demand. However, this research study establishes that this improved environmental performance comes at a cost, e.g. the investment in aircraft associated with achieving a 6% improvement in the emissions reduction goal had a net impact of a 3% reduction in economic performance.

Environmental impact abatement today. Though investing in new aircraft to reduce particulate emissions and improve fuel efficiency are an obvious target for airlines to demonstrate CSER-focused philosophy, the financial investment in fleet composition changes are significant. Lynes and Andrachuk (2008) highlight that airlines now record their actions in support of CSER goals through publicly distributed corporate responsibility reports. The content of these reports presents several different paths by which airlines are trying to improve their environmental footprint.

Spills and waste management. Delta's (2017) Corporate Responsibility Report highlights that they measure their environmental impact not only through aircraft operations (air quality compliance), but it includes the entirety of the company's operations, including material disposal and spills and waste handling. Delta tracks spills for several different industrial fluids including diesel / gasoline (ground equipment), glycol, hydraulic fluid, aviation fuel (Jet A), and aircraft lavatory fluids and waste. In their 2015 report, the company recognized a slight increase in spills relative to 2014 but recognized that over the period, Delta had started including "Delta Connection Carriers" (affiliated regional airline operations supporting small destination traffic to Delta hubs) in their sphere of responsibility. In their sustainability report, Lufthansa (2017) publicly reported on the quantity of fuel dumped as well. It should be noted that the maximum take-off weight for aircraft exceeds the maximum landing weight – in case of an in-flight emergency or immediate need to land, the aircraft must burn excess fuel or release it through fuel ejection ports. Lufthansa's report not only disclosed the volumes of fuel and the reasoning for fuel dumping (e.g. medical need, technical need, etc.), but also tracked the change versus the previous year as a commitment to improving their environmental impact.

Reducing waste via recycling. Airlines have recognized that their operations produce significant waste, and as part of their CSER goals, have implemented changes to increase recycling and reduce the total waste that cannot be recovered. In work environments, KLM and Air France (Air France-KLM, 2017) have implemented computer printer restrictions – known as Follow Print – which require an employee to confirm a print job at the physical printer. This measure led to an 8% reduction of paper printing at Air France in 2015 (compared to 2014 requirements).

Air France-KLM (2017) suggest that in-flight catering produces 70% of all non-hazardous waste generated by aircraft operations. Today, a significant number of airlines are instituting measures to recover the waste through recycling. In 2007, Delta instituted an in-flight “single stream” recycling program (Delta, 2017). This program enabled flight attendants to quickly collect plastic, aluminum, and paper materials, maintaining the efficiency of cabin operations. Upon arrival, the recyclable waste was processed by a single-stream service contracted by Delta to segregate the different materials for their individual recycling streams. KLM improved recycling operations by investing in design improvements in catering trolleys. Modifications to the trolley designs included facilities to stack plastic cups (keeping them segregated for recycling) as well as different container sections to segregate glass, cans, and PET bottles from regular waste (Air France-KLM, 2017).

Minimizing fuel burn in ground operations. Fossil fuel combustion during ground operations poses an opportunity for reducing particulate emissions. Ground support equipment (GSE) is typically comprised of commercial-grade, gasoline- or diesel-powered machines. Some vehicles are used for on-ramp operations, transporting fuel, cargo / luggage, flight supplies (e.g. food); other vehicles are used to provide electrical power or pre-conditioned air supply to parked aircraft (Air France-KLM, 2017). In the latter example, GSE vehicles are preferable to running aircraft auxiliary power units (APUs) but still contribute to particulate emissions. In 2015, Air France recognized an 11% reduction in annual GSE fuel consumption through reduced reliance on aircraft APUs versus alternative GSE. At the end of 2015, over 70% of KLM's pre-conditioned air supply carts were electric – not fossil fuel-based. Air France and KLM state that per their long-term strategic goals, their GSE vehicles at Paris's Charles De Gaulle and Amsterdam's Schipol airports are almost 50% and should increase in the future. All airlines track the fuel expenditures and general utilization of GSE vehicles in the interests of CSER goals. By the end of 2015, Delta (2017) noted a transformation of over one-third of the off-road diesel vehicle fleet into electrical vehicles in support of their California operating locations to help reduce particulate emissions, over and above the 2016 emissions mandate.

A significant contribution of particulate emissions during airline ground operations is the aircraft taxi phase (Ganev et al., 2016). An aircraft can spend up to an hour on the ground with an engine running. Typically, the aircraft is spending the majority of its time sitting, or rolling with no power; when it does require acceleration, it uses a fractional power setting (and typically only one engine). However, to ensure the power is available for the aircraft to move in queue, it has to leave the engine running up until it starts the remaining engines for preparation to take-off.

A number of companies have performed significant research into opportunities to reduce the fuel consumption and emissions generated by this wasteful phase of airline operations. Honeywell Aerospace and Safran developed an electric taxiing system, eTaxi (Ganev et al., 2016). This system relies on electrically driven motors to be connected to wheels on the aircraft main landing gear, allowing the aircraft to perform ground operations without the thrust of the engines. The electrical requirements of the eTaxi system are low enough that it can be run by the aircraft's APU. On a different path, Lufthansa Technik (an engineering and technology subsidiary of the Lufthansa aviation group) has developed and certified TaxiBot, a robotic, diesel-electric aircraft tug (Lufthansa, 2017). TaxiBot looks like a regular aircraft tug, but it can be controlled remotely by the pilot inside the aircraft cockpit. Utilizing TaxiBot, the aircraft can be relocated to a position close to take-off without running engines, at which point the tug can disengage and return to the airport ramp while the crew starts the engines in preparation for departure. Now certified by the European Aviation Safety Agency (EASA), multiple TaxiBot vehicles are in operation at airports in Europe.

Minimizing fuel burn in air. It is widely accepted that any investment to reduce fuel consumption will translate to reduced emissions generation. Delta (2017) claimed an emissions reduction of 115,000 metric tons through fuel-savings initiatives that resulted in 12 million fewer gallons of fuel consumed in 2015. The fuel savings measures deployed by the airlines can be both flight- or passenger-related. While fleet modernization and aircraft replacements can provide a step-change in fuel efficiency and emissions output, airlines have recognized significant savings through weight reduction of the aircraft.

Lufthansa (2017) performed studies recognizing that they could reduce magazines and newspapers carried onboard by tailoring their offerings to the flight regions. Similarly, a study of waste accumulation and volume available on the larger A380 aircraft demonstrated that it was more efficient to have two lightweight waste trolleys in lieu of a compacting machine that was used for plastic waste. KLM focused time to study the packaging utilized for their inflight catering. A redesign of the packaging for sandwiches led to a 50,000 kg reduction in the annual usage of cardboard (Air France-KLM, 2017). After evaluating how their passengers utilized their time airborne and shopping services, Delta eliminated their Skymall magazine (located at every seat), as well as any Duty Free service.

More extensive vehicle-related weight-savings initiatives have been employed by both airlines and aircraft manufacturers while aircraft are in-service. Significant modifications can include lighter weight brake materials, addition / augmentation of aerodynamic devices such as winglets, or replacement of large systems (even engines). Major aircraft changes require substantial non-recurring cost due to the design and certification requirements associated with ensuring the aircraft's airworthiness after changing flight-critical components. Airlines are more likely to pursue strategies that do not affect the flight-critical systems of the aircraft to avoid cost and achieve a quicker implementation. An example of pursuing a reduction in weight without impacting the aircraft was demonstrated by Air France (Air France-KLM, 2017) and Delta (Delta, 2017) who both identified weight savings opportunities by replacing mandatory pilot manuals with electronic flight bags (tablet computers certified as pilot aids in lieu of a printed manual).

Environmental offsets. A final aspect of investments which airlines are making to minimize their environmental impact includes investing directly in conservation organizations which are working to improve the environment (Delta, 2017). SAS (2017) allows passengers to donate directly to Carbon Neutral, a certification agency run by Nature Capital Partners. While the organization helps evaluate and designate corporations as having neutral greenhouse gas emissions, it also directs corporations to environmental projects that can benefit from funding and support (About: CarbonNeutral, 2017). These projects can include development of renewable energy sources, reforestation initiatives, or special projects which may reduce the consumption of water – e.g. the Sustainable Sugarcane Initiative in India (Nature Capital Partners, 2017).

Delta (2017) provides an additional path for customers to contribute to carbon offset programs. Delta has partnered with The Nature Conservancy, a non-profit organization focused on reforestation and forest management. In addition to directing their customers to The Nature Conservancy, Delta allows its loyalty program members to donate “Skymiles” – Delta’s currency unit for rewards tickets – to charities of their choice, including environmental organizations such as The Nature Conservancy.

Current research and industry data present that airlines are trying to fulfill CSER goals utilizing a number of strategies. While capital investment into new aircraft can provide the greatest impact, the financial requirements of such investments require less cost-intensive solutions. The literature highlights that airlines are focusing heavily on the variable costs associated with airline operations as an area of opportunity for reducing environmental impacts. Airlines are also enabling direct funding of environment-focused improvement initiatives to counter adverse impacts of their operations for a net *green* footprint.

Research of airline efficiency inclusive of environmental impacts. The review of previous literature on analytical methods supports DEA as an appropriate choice for the decision-management aspect of operations research, as well as assessing airline efficiency. In very recent literature, researchers have begun to apply the DEA methodology to evaluate airline performance with respect to the environment.

Arjomandi and Seufert (2014) work to extend the body of knowledge through airline performance analysis utilizing CO_x as an undesirable output of a DEA model. The analysis models focus on airline decisions to pursue *technical efficiency* – i.e. effective consumption of inputs to generate ASMs and revenue – and the reduction of fuel-consumption and emissions. The research models were structured as single-stage DEA, utilizing a VRS frontier. Similar to Mallikarjun (2015), VRS was deemed appropriate for modeling airlines as the industry is such that airlines often operate at non-optimal scales due to internal inefficiencies, imperfect competition, and financial constraints. The authors sampled a large group of air carriers, wanting to observe trends in carriers supporting different regions of the world, as well as encompassing both full-service carriers (FSCs) and airlines executing a low-cost carrier (LCC) business model. In total, 35 FSCs and 13 LCCs comprised the analysis dataset. The geographic breakdown of the airlines were: 13 were from Europe (and Russia); 13 from North Asia and China; 11 from North America & Canada; 6 from the Asia Pacific; 4 from Africa and the Middle East; and 1 from Latin America.

The review of literature on DEA has presented that the analysis technique precludes the need for finding variables with common units; the nature of DEA allows measures on dissimilar scales to be recognized in the efficiency measurement. However, Arjomandi and Seufert (2014) wished to remove any bias related to the business aspects of the airline operation, focusing specifically on the efficiency of the airline's flight activities. Therefore, the inputs and outputs are all non-monetary measures. The inputs reflect the labor and capital resources of the airline. Labor is defined by the flight crews only – pilots and flight attendants – preventing maintenance overhead from impacting the efficiency measurement of flight activities. The capital resources are defined by aircraft flying capacity; this is calculated by taking the product of the maximum available take-off weights of all aircraft and operating days in the year – operating days were defined as the total flight hours divided by average daily revenue hours. Similarly, the outputs of the airline DMUs in this model were the available ton kilometers (a non-passenger specific capacity measure similar to ASMs) and CO_2 emissions.

Arjomandi and Seufert (2014) also employ a bootstrapping method to help resolve validity threats due to results biasing caused by the sampling variation. As previously reviewed, bootstrapping can resolve the sensitivity of efficiency scores to bias by leveraging a progressive resampling stage within the analysis – i.e. repeating the data generation process. The authors review of the non-bootstrapped (biased) and bootstrapped (*bias-corrected*) results highlight the importance of comparing the two results as the *bias-corrected* results can confirm the original results or highlight a concern if the results possess different efficiency behaviors. As part of the results interpretation, the authors presented whether the efficiency score for a particular airline suggested it was experiencing increasing or decreasing returns to scale.

The results of the study highlight that airlines executing the FSC business model typically have greater technical efficiencies. However, the top environmental efficiency airlines include both FSC and LCC airlines. A prevalent dichotomy is that airlines typically excel at one of the two efficiencies but rarely both. It was noted that over the period of study, the environmental efficiencies of the FSC airlines had an increasing trend that suggested investment toward fuel-burn reduction, resulting in lower net emissions (Arjomandi & Seufert, 2014).

A recent extension of DEA research in airline environmental efficiency was published by Cui and Li (2016) last year. In their study, the authors developed a two-stage DEA model to evaluate 22 international airlines to assess an *airline energy efficiency* measure, from 2008 to 2012. The first stage of the DEA model is very similar to the first stage of other multi-stage DEA models reviewed: the first stage inputs include wages and benefits for the employees and the operating expenses associated with fuel and aircraft assets. The outputs of this first stage are the airline marketable capacity – revenue passenger kilometers (RPKs) and revenue tonne kilometers (RTKs) – but also include an estimated carbon dioxide emissions quantity associated with that flying capacity. In the following "abatement stage", the only carry-through variable is the estimated CO_2; in addition, the airline consumes an abatement expense (funds invested to reduce energy consumption or produce carbon emissions). The overall efficiency accounts for how much capacity is produced in the first stages as well as the net CO_2 emissions generated in the second stage of the analysis.

This recent study by Cui and Li (2016) highlights a current and future trend of airlines as they invest to promote CSER goals, as previously discussed by Lynes and Andrachuk (2008). In their airline energy efficiency measure, the researchers are assessing the airline's efficiency in executing CSER goals with respect to their investments. The results of the research highlighted that between the two stages, airlines were much stronger in operational efficiency than environmental efficiency, reinforcing the more recent focus on CSER goals. Similar to previous literature reviewed, all of the airlines in this sample improved in environmental efficiency over the period of study.

Data Envelopment Analysis (DEA)

Origins of DEA. Data envelopment analysis (DEA) was developed and first applied in scholarly literature by Charnes et al. (1978). DEA is a nonparametric analysis technique that assesses multiple decision-making units (DMUs), each with multiple inputs and outputs. One of the key attributes of DEA is that the technique does not require valuation of the inputs and outputs under study. The units of measure of the inputs and outputs can be determined by the researcher, irrespective of an actual market value. The analysis technique then leverages linear programming models to estimate relationships based on these inputs and outputs. In actuality, this technique develops an optimal DMU, based on the DMUs under analysis, and then assesses and presents relative efficiencies of the decision-making units to this optimal DMU and each other.

DEA is considered to be a new data-oriented approach for evaluating peer entities. DEA can be applied to a variety of applications due to its ability to define the individual DMUs in a generic and flexible fashion – the analysis technique can easily process decision-making relationships with multiple input and outputs that have different scales or units. In academic and professional studies, it has become a focused tool in the operations research arena to evaluate business performance in applications including hospitals, military organizations, municipalities, and courts (Zhu, 2014).

Charnes et al.'s DEA formulations – an input-oriented model. The original developers applied this technique to study public programs (Charnes et al., 1978). The method begins with a measure of efficiency through a ratio of weighted outputs of a DMU to the weighted inputs. Charnes et al.'s original efficiency expression is presented in Equation 1.

$$max\ h_0 = \frac{\sum_{r=1}^{s} u_r\, y_{r0}}{\sum_{i=1}^{m} v_i\, x_{i0}} \qquad (1)$$

subject to:

$$\frac{\sum_{r=1}^{s} u_r\, y_{r0}}{\sum_{i=1}^{m} v_i\, x_{i0}} \leq 1\ ; \qquad\qquad j = 1, \dots, n,$$

$$u_r, v_i\ \geq 0\ ; \quad r = 1, \dots, s\ ; \qquad i = 1, \dots, m$$

where:

- y_{rj} is the known output of the j^{th} DMU
- x_{ij} is the known input of the j^{th} DMU
- u_r and v_i are the variable weights which the linear programming will solve for

Charnes et al. (1978) proceeded to transform the efficiency expression into a linear programming set of equations for further use. The authors start with the reciprocal of Equation 1, in order to present an inefficiency measure, presented in Equation 2.

$$min\ f_0 = \frac{\sum_{i=1}^{m} v_i\, x_{i0}}{\sum_{r=1}^{s} u_r\, y_{r0}} \qquad (2)$$

subject to:

$$\frac{\sum_{i=1}^{m} v_i\, x_{i0}}{\sum_{r=1}^{s} u_r\, y_{r0}} \geq 1\ ; \qquad j = 1, \dots, n,$$

$$v_i\ ,\ u_r\ \geq 0\ ;$$

Charnes et al. (1978) proceed to convert this inefficiency measure, which is in nonconvex, nonlinear form to an ordinary linear programming system. The first step lays out the desired linear programming system and maximization goal, as presented in Equation 3.

$$max\ z_0 \tag{3}$$

subject to:

$$-\sum_{j=1}^{n} y_{rj}\,\lambda_j \,+\, y_{r0}\,z_0 \,\leq 0\,; \qquad r = 1, \ldots, s$$

$$\sum_{j=1}^{n} x_{ij}\,\lambda_j \,\leq x_{i0}\,; \qquad i = 1, \ldots, m$$

$$\lambda_j \,\geq 0\,; \qquad j = 1, \ldots, n,$$

Every ordinary linear programming problem can be rewritten with a dual problem. The solution of a dual problem presents an upper bound of the original problem (referred to as the primal problem in duality scenarios). Charnes et al. (1978) use the duality theory to present the corresponding dual problem of Equation 3, presented in Equation 4.

$$min\ g_0 = \textstyle\sum_{j=1}^{m} \omega_i x_{i0} \tag{4}$$

subject to:

$$-\sum_{r=1}^{s} \mu_r\, y_{rj} \,+\, \sum_{i=1}^{m} \omega_i\, x_{ij} \,\geq 0\,,$$

$$\sum_{r=1}^{s} \mu_r\, y_{r0} \,= 1\,,$$

$$\mu_r, \omega_i \geq 0 .$$

Charnes et al. (1978) utilize the theory of linear fractional programming and the transformation defined in Equation 5 to create Equation 6 – the linear fractional programming equivalent of Equation 4.

$$\omega_i = t\, v_i ; \qquad i = 1, \dots, m , \tag{5}$$

$$\mu_r = t\, u_r ; \qquad r = 1, \dots, s ,$$

$$t^{-1} = \sum_r u_r y_{r0},$$

$$\text{For } t > 0 \tag{6}$$

$$min\ f_0 = \frac{\sum_{i=1}^{s} v_i\, x_{i0}}{\sum_{r=1}^{s} u_r\, y_{r0}}$$

subject to:

$$\sum_{i=1}^{m} v_i\, x_{ij} - \sum_{r=1}^{s} \mu_r\, y_{rj} \geq 0 , \qquad j = 1, \dots, n ,$$

$$v_i\, ,\ u_r \geq 0 .$$

Charnes et al. (1978) note that Equation 6 is in fact the same as Equation 2. Therefore, using substitutions and mathematical manipulation, Equations 1 and 2 can be solved utilizing the Equation 4 form. Equation 7 reduces Equation 4 when the most efficient weights, v_i^*, u_r^*, are utilized. This in turn establishes Equation 8 to calculate efficiency, which equates to 1 only for the optimal DMU values.

$$f_0^* = g_0^* = z_0^* \tag{7}$$

$$h_0^* = {}^{1}\!/_{z_0^*} \tag{8}$$

Charnes et al. (1978) introduced the basis for DEA with the formulations derived above. As DEA has been applied to different systems and entities, different techniques and strategies have presented themselves, providing researchers with various manners by which to employ the analytical method. This model may be referred to as the “CCR model”, in reference to the original authors, Charnes, Cooper, and Rhodes (1978).

Constant returns to scale (CRS) versus variable returns to scale (VRS). An important facet of DEA to understand when developing an analytical model is the expectations surrounding the relationships between input and output. Defining the relationship of the inputs to outputs framed as a linear frontier was first proposed by Farrell (1957). Farrell’s approach separated the total relationship of input to output into pieces, allowing linear mathematical expressions to define the input-output relationship. Charnes et al. (1978) took this approach in their original paper, coining the term *data envelopment analysis*.

When creating a DEA model, the DMUs are driven to make the most efficient decisions based on rules the formulations are based on. Economic theory presents alternate scenarios where the output varies with the variable cost – i.e. increasing and diminishing returns. Similarly, when the variation of inputs will result in a corresponding proportional variance in the outputs, the inputs and outputs have a constant relationship. Framed in a functional or operational sense, the outputs reflect a constant rate of return for the function based on the input (Coelli et al., 2005), described as constant returns to scale (CRS). Conversely, if the proportion of output to input is not always the same, the DMU operates with variable returns to scale (VRS). Zhu (2014) presents the difference in CRS and VRS utilizing a single depiction similar to the chart presented in Figure 3.

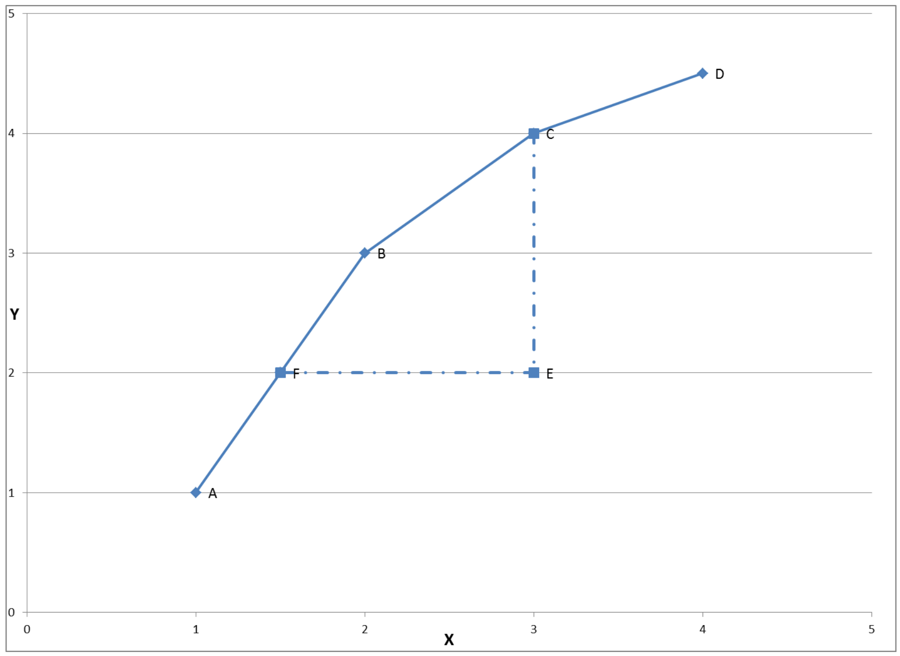

Figure 3. Example DEA production frontier demonstrating VRS.

The figure presents a graphical depiction of the relationship between the output (***y***) and the input (***x***). Segment AB exhibits increasing returns-to-scale (IRS), segment BC exhibits constant returns-to-scale (CRS), and segment CD exhibits decreasing returns-to-scale (Zhu, 2014). If any of those segments represented the entirety of the frontier, then the output would be constants proportional to the input, suggesting a CRS frontier. As the frontier in Figure 1 has varying relationships between the input and output, it is a VRS frontier.

The DEA model developer must choose how the DMU will operate; a CRS or VRS operational characteristic defines the formulations that are used to simulate DMU behaviors. Applying CRS behavior to a DMU models a scenario when the DMUs are operating at an optimal scale. This model design may be useful to help explore optimal decision-making and productivity ceilings. However, real firms are influenced by factors which prevent operating at their optimum scale – e.g. regulatory constraints, economic limitations, or industry characteristics that prevent perfect competition (such as high capital / resource requirements for market entry). If the goal is to effectively model and compare efficiencies for real-world applications, the VRS frontier is more appropriate (Coelli et al., 2005).

Banker et al.'s DEA formulations – an output-oriented model. Banker, Charnes, and Cooper (1984) extended the original CCR model to incorporate the aforementioned concept of returns-to-scale. The model laid out below also incorporates the concept of output orientation. In the input-oriented model previously reviewed (CCR), an inefficient DMU is recognized as improving efficiency by proportionally consuming fewer inputs to realize the same output. Output-oriented DEA recognizes efficiency improvement when an inefficient DMU has a proportional increase in output without any change to the inputs.

Banker et al. (1984) started their output-oriented model development considering three different DMUs related to the production frontier presented in Figure 4.

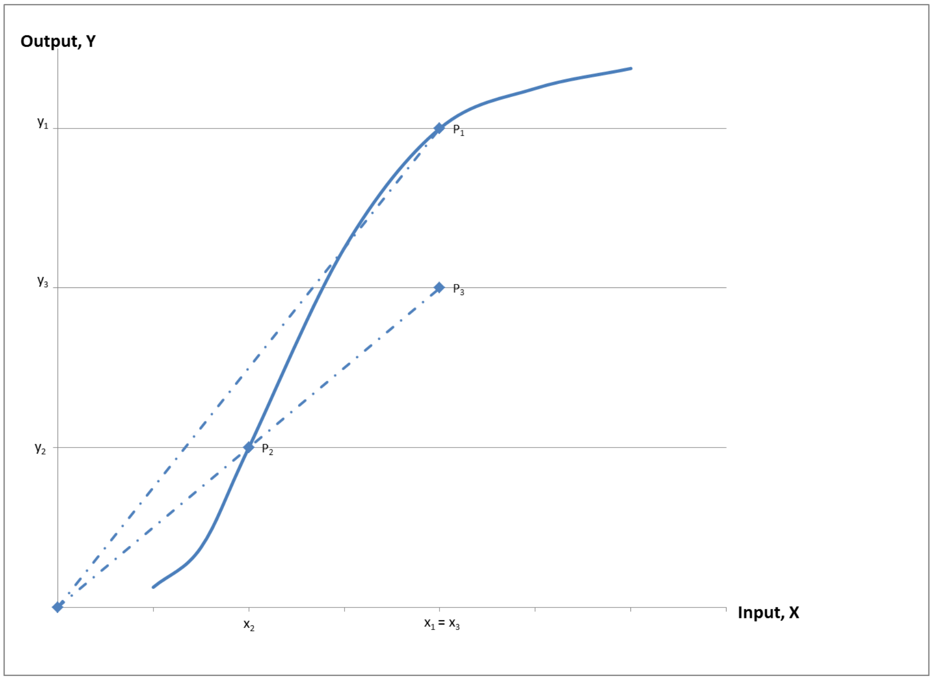

Figure 4. Example production function denoting three different DMU operating points.

In this scenario, the authors present three different DMUs, P_i, operating relative to the production frontier. P_1 and P_2 are operating on the boundary of the production frontier, while P_3 is operating within the production scope. The DMUs operating positions are defined by the following parameters – where x_i and y_i represent the DMU's input and output coordinates, respectively – presented in Equation 9.

$$P_1 : y = \frac{y_1}{x_1} x \tag{9}$$

$$P_2 : y = \frac{y_2}{x_2} x$$

$$P_3 : y = \frac{y_3}{x_3} x$$

Where

$$y = \frac{y_2}{x_2} x = \frac{y_3}{x_3} x$$

The formulation of the output-oriented model commences with the CCR ratio definition of efficiency presented in Equation 10.

$$\text{For } t > 0 \tag{10}$$

$$max\ h_0 = \frac{\sum_{r=1}^{s} u_r\, y_{r0}}{\sum_{i=1}^{m} v_i\, x_{i0}}$$

subject to:

$$1 \geq \frac{\sum_{r=1}^{s} u_r\, y_{rj}}{\sum_{i=1}^{m} v_i\, x_{ij}}\ , \qquad j = 1, \dots, n\ ,$$

with

$$u_r, v_i \ \geq 0,\ \ j = 1, \dots, n\ ; r = 1, \dots, s\ .$$

The original ratio expression is then rewritten to ratio a single output to a single input, for the DMU, P_i, as presented in Equation 11. In this formulation,

$$max\ h_0 = \frac{u y_1}{v\, x_1} \tag{11}$$

subject to:

$$1 \geq \frac{u y_1}{v\, x_1}, \qquad 1 \geq \frac{u y_2}{v\, x_2}, \qquad 1 \geq \frac{u y_3}{v\, x_3}, \qquad u\ \ , v \quad \geq 0\ .$$

Reviewing the different DMU positions in Figure 3 presents that P_1 operates at a point where the tangential to the production function is aligned with a ray from the origin. P_2, while on the production function, is operating below the ray from the origin to P_1. Similarly, P_3 operates below the ray from the origin to P_1 and also is not on the boundary of the production function. The relative positioning presents that P_1 is relatively efficient while P_2 and P_3 are not. As P_2 and P_3 lie on the same ray from the origin, they are deemed to possess equal levels of efficiency (or in this case, equally inefficient).

Similar to the development of the CCR model, Banker et al. (1984) proceed through a mathematical analysis to develop a model which relates inputs to outputs for a decision-making unit, creating an assessment or measure of efficiency. The authors apply four property postulates to a normal production set: (1) Convexity; (2) Inefficiency – i.e. inefficiency is always possible through greater input consumption, lower output production, or both; (3) Ray Unboundedness – any constant greater than zero can be applied to both input and output coordinates on the production function and identify a real operating possibility; and (4) Minimum Extrapolation. The last postulate surmises that the subject production possibility set in the mathematical theory satisfies the previous three postulates.

Having defined the production possibility set of focus, the authors apply Shepard's distance function to relate the set to the CCR efficiency model. Shepard (1970) defines the "distance function", *g(X, Y)* for an input set *L(Y)* in Equation 12.

$$g(X, Y) = \frac{1}{h(X,Y)} \tag{12}$$

where:

$$h(X, Y)1 = \min\{h : h\mathrm{X} \in L(Y), h \geq 0\} .$$

Substituting the production possibility set into Equation 11 allows the authors to construct a linear programming problem which resolves itself into the CCR efficiency model with one exception: rather than the components having to be positive, they now only require non-negative values (zero is within the bounds of the model). The authors use this derivation to assert validation by demonstrating an equivalent result to the original CCR model (utilizing the same sample simple production frontier).

Having validated the model, the authors move to constrain their expression to only identify the efficient production surface. This segregation within the expression is accomplished by removing the third postulate ("Ray Unboundedness"). The revised definition of the production possibility set coordinates are expressed in Equation 13.

$$(X_j, Y_j) \text{ is in set } T\text{, if} \tag{13}$$

$$X \geq \sum_{j=1}^{n} \lambda_j X_j \;, Y \geq \sum_{j=1}^{n} \lambda_j Y_j$$

The authors now substitute this revised production possibility set definition in Shepard's distance function to yield Equation 14. Equation 14 is translated into a linear programming optimization function, presented in Equation 15.

$$g(X, Y) = \frac{1}{h(X,Y)} \tag{14}$$

where:

$$h(X, Y)1 = \min\{h \mid h\mathrm{X} \in L(Y), h \geq 0\} \,.$$

$$min\, h = h(X_0, Y_0) \tag{15}$$

subject to:

$$hX_0 - \sum_{j=1}^{n} \lambda_j X_j \geq 0 \,, \sum_{j=1}^{n} \lambda_j Y_j \geq Y_0 \,, \sum_{i=1}^{n} \lambda_j = 1$$

$$\lambda_j \geq 0 \,,\ j = 1, \dots, n \,, .$$

The linear programming problem presented in Equation 15 is considered for all nonnegative values of X_j and Y_j and reformatted as a fractional programming problem, presented in Equation 16.

$$Max \qquad (15)$$

$$\sum_{r=1}^{s} u_r y_{r0} - u_0$$

subject to:

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} - u_0 \leq 0 \,, \qquad j = 1, \dots, n,$$

$$\sum_{i=1}^{m} v_i x_{i0} \,, \qquad u_r, v_i \geq 0$$

$$Max \qquad (16)$$

$$\frac{\sum_{r=1}^{s} u_r y_{r0} - u_0}{\sum_{i=1}^{m} v_i x_{i0}}$$

subject to:

$$\frac{\sum_{r=1}^{s} u_r y_{r\mathrm{j}} - u_0}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1 \,, \qquad \forall j, \qquad u_r, v_i \geq 0$$

The relationships in Equation 16 reflect efficiency assessed from input possibility sets. When the distance function for output possibility sets are utilized, the fractional programming resolves to Equation 17.

$$Max \tag{17}$$

$$h'(X,Y) = \frac{\sum_{r=1}^{s} u_r y_{r0}}{\sum_{i=1}^{m} v_i x_{i0} + v_0}$$

subject to:

$$\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij} + v_0} \leq 1\,, \qquad j = 1, \ldots, n\,, \qquad u_r, v_i \geq 0$$

Banker, Charnes, and Cooper continued their research exploring the impacts of differing returns-to-scale (increasing, constant, and decreasing). The incorporation of changing returns-to-scale and the manipulation of their programming model to focus on output possibility sets promoted a significant opportunity to the application of DEA – i.e. efficiency assessment recognizing relative efficiency with respect to output maximization (freezing input consumption), as opposed to reducing inputs. This model may be referred to as the "BCC model", in reference to the original authors, Banker, Charnes, and Cooper (1984).

Number of DMUs and influencing variables. Two key facets of a DMU analysis include the number of inputs and outputs, and the total number of DMUs. Zhu (2014) reviews previous literature where researchers presented that the number of DMUs should be two to three times that of the combined number of inputs and outputs, in order to avoid diminishment of the model's discrimination between the DMUs. While not an imperative requirement of DEA, it is suggested to maintain this relationship to avoid concern of diminishing effects.

Zhu (2014) also reflects on previous literature focused on DEA sample size and number of variables. Previous works reflect that adequate sample size is required to avoid a DEA model that does not sufficiently discriminate to a discrete few "efficient" DMUs. Zhu concludes that the purpose of the DEA method is to benchmark a group of DMUs, in order to assess and explore the individual efficiencies; the purpose is not meant to serve as a regression analysis. Zhu recommends that a DEA analysis that is pursuing higher levels of discrimination should consider the weighting utilized to help narrow the requirements associated with the optimal operating frontier.

Multi-stage DEA. The literature review has referenced exigent research utilizing DEA in successive stages. DEA models possessing more than one stage represent tiered decision-making efforts by the firm. A multi-stage DEA model will leverage formulas to simultaneously optimize all stages of the model by using the outputs of an upstream stage as the inputs of the successive stage. The model will then converge to a combined set of decisions (i.e. variable values) which represents the best aggregate firm decision-making for the combined model.

VRS two-stage model. Chen & Zhu (2004) present a VRS two-stage model developed to help assess the impact of the information technology division and associated investment on a firm business performance. The model is defined in Equation 18.

$$min\, \omega_1 \alpha \quad - \omega_2 \beta \tag{18}$$

subject to:

{Stage 1}

$$\sum_{j=1}^{n} \lambda_j x_{ij} \leq \alpha x_{ij0} \qquad i = 1, \dots, \mathrm{m}$$

$$\sum_{j=1}^{n} \lambda_j z_{dj} \geq \check{z}_{dj0} \qquad d = 1, \dots, \mathrm{D}$$

$$\sum_{j=1}^{n} \lambda_j = 1$$

$$\lambda_j \geq 0 \qquad j = 1, \dots, n$$

$$\alpha \leq 0$$

{Stage 2}

$$\sum_{j=1}^{n} \mu_j z_{ij} \leq \check{z}_{dj0} \qquad d = 1, \dots, \mathrm{D}$$

$$\sum_{j=1}^{n} \mu_j y_{rj} \geq \beta y_{rj0} \qquad r = 1, \dots, \mathrm{s}$$

$$\sum_{j=1}^{n} \mu_j = 1$$

$$\mu_j \geq 0 \qquad j = 1, \dots, n$$

$$\beta \geq 0$$

where:

x_i : First stage inputs

z_d : First stage intermediate outputs / second stage intermediate inputs

y_r : Second stage outputs

w_1/w_2 : User-defined weights of the two stages

This model reaches optimal efficiency when $\alpha* = \beta* = 1$, signifying optimal performance in both stages. If the optimum $\alpha*$ or $\beta*$ is equal to one while the other is a value other than unity, the optimal production frontier can only exist for a single stage and only if the intermediate measures reach an optimal measure (Zhu, 2014).

Variants of two-stage DEA relationships. Halkos et al (2015) present four categories of two-stage DEA models, including: (a) independent two-stage, (b) connected two-stage (where both stages must be efficient), (c) relational two-stage models, and (d) two-stage models based on game theory. The previous example by Zhu (2014) was constructed for usage as a connected two-stage model. Relational two-stage models execute a structure where the overall efficiency of a firm is a function of the operations of internal stages – be it additive, multiplicative, or derived by another relationship.

Kao and Hwang (2008) establish a multiplicative relational two-stage model for a production system with related sub-processes to assess efficiencies in the Taiwanese non-life insurance industry. The authors present a production process where two sub-processes constitute the overall process, as presented in Figure 5.

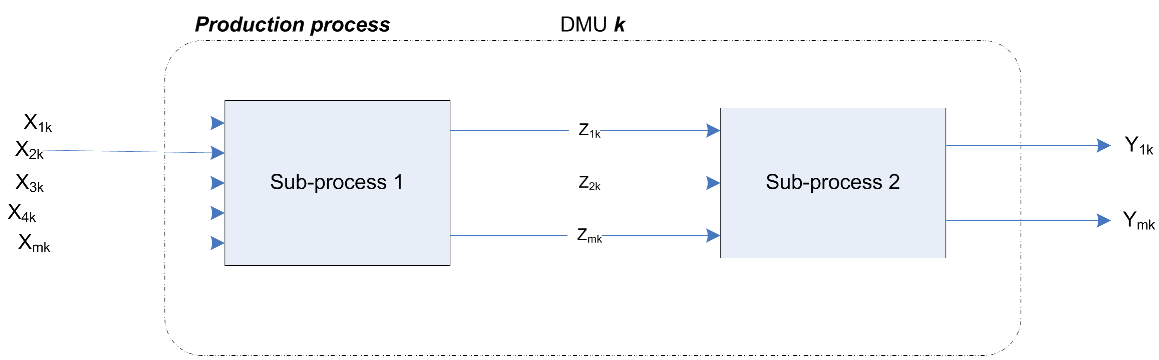

Figure 5. Representation of a tandem system with inputs *X*, outputs *Y*, and intermediate products *Z* from Kao and Hwang (2008).

The authors start with a system of equations that are used to independently measure efficiency in each of two sub-systems, presented in Equation 19.

$$E_k^1 = \max \tag{19}$$

$$\sum_{p=1}^{q} w_p Z_{pk} \Bigg/ \sum_{i=1}^{m} v_i X_{ik}$$

s.t.

$$\sum_{p=1}^{q} w_p Z_{pj} \Bigg/ \sum_{i=1}^{m} v_i X_{ij} \leq 1 \;, \qquad j = 1, \dots, n$$

$$w_p, v_i \geq \varepsilon \;, \qquad p = 1, \dots, q \;, \qquad i = l, \dots, m$$

$$E_k^2 = \max$$

$$\sum_{r=1}^{s} u_r Y_{rk} \Bigg/ \sum_{p=1}^{q} w_p Z_{pk}$$

s.t.

$$\sum_{r=1}^{s} u_r Y_{rj} \Bigg/ \sum_{p=1}^{q} w_p Z_{pj} \leq 1 \;, \qquad j = 1, \dots, n$$

$$u_r, w_p \geq \varepsilon \;, \qquad r = 1, \dots, s \;, \qquad p = l, \dots, q$$

In order to present a total efficiency co-dependent of both sub-processes, the authors modify the system of equations to the formulas presented in Equation 20.

$$For \text{ DMU } k \tag{20}$$

$$E_k = \sum_{r=1}^{s} u_r^* Y_{rk} \Bigg/ \sum_{i=1}^{m} v_i^* X_{ik} \leq 1$$

$$E_k^1 = \sum_{p=1}^{q} w_p^* Z_{pk} \Bigg/ \sum_{i=1}^{m} v_i^* X_{ik} \leq 1$$

$$E_k^2 = \sum_{r=1}^{s} u_r^* Y_{rk} \Bigg/ \sum_{p=1}^{q} w_p^* Z_{pk} \leq 1$$

where

u_r^*, v_i^*, w_p^* ≡ multipliers the DMU has selected

E_k, E_k^1, E_k^2 ≡ total and sub-process efficiencies

These equations reduce to demonstrate that the total efficiency is the cross product of the two sub-process efficiencies, presented in Equation 21.

$$E_k = E_k^1 \times E_k^2 \tag{21}$$

The multiplicative relationship simply combines two efficiencies to define a total efficiency. However, the production process in Figure 5 presents a pair of sub-processes in series sharing intermediate variables. Kao and Hwang (2008) incorporate the ratio constraints of the two sub-processes to account for the series relationship, yielding the system of equations presented in Equation 22.

$$E_k = \max \tag{22}$$

$$\sum_{r=1}^{s} u_r Y_{rk} \Bigg/ \sum_{i=1}^{m} v_i X_{ik}$$

s.t.

$$\sum_{r=1}^{s} u_r Y_{rj} \Bigg/ \sum_{i=1}^{m} v_i X_{ij} \leq 1 \ , \qquad j = 1, \dots, n$$

$$\sum_{p=1}^{q} w_p Z_{pj} \Bigg/ \sum_{i=1}^{m} v_i X_{ij} \leq 1 \ , \qquad j = 1, \dots, n$$

$$\sum_{r=1}^{s} u_r Y_{rj} \Bigg/ \sum_{p=1}^{q} w_p Z_{pj} \leq 1 \ , \qquad j = 1, \dots, n$$

$$u_r,\ v_i,\ w_p \geq \varepsilon\ , \qquad r = 1, \dots, s\ , \qquad i = l, \dots, m\ , \qquad p = 1, \dots, q$$

Converting the previous system of equations to a linear program results in Equation 23.

$$E_k = \max \tag{23}$$

$$\sum_{r=1}^{s} u_r Y_{rk}$$

s.t.

$$\sum_{i=1}^{m} v_i X_{ik} = 1$$

$$\sum_{r=1}^{s} u_r Y_{rk} - \sum_{i=1}^{m} v_i X_{ij} \leq 0 \ , \qquad j = 1, \dots, n$$

$$\sum_{p=1}^{q} w_p Z_{pj} - \sum_{i=1}^{m} v_i X_{ij} \leq 0 \ , \qquad j = 1, \dots, n$$

$$\sum_{r=1}^{s} u_r Y_{rj} - \sum_{p=1}^{q} w_p Z_{pj} \leq 0 \ , \qquad j = 1, \dots, n$$

$$u_r,\ v_i,\ w_p \geq \varepsilon\ , \qquad r = 1, \dots, s\ , \qquad i = l, \dots, m\ , \qquad p = 1, \dots, q$$

Kao and Hwang (2008) further evolve their model to define systems of equations which specifically seek maximization of either of the two sub-process efficiencies. The models constructed were then applied to the revenue generation pursuits of firms offering non-life insurance products in Taiwan. A key result of this research is usage of multiplicative relational two-stage DEA, where the overall efficiency will be the product of the individual stage efficiencies of the two sub-processes.

Gaps in Exigent Literature

The previous sections reveal that research into airline efficiency has evolved to utilize several different methodologies and has focused on varying parts of the airline operations. Post airline deregulation research focused on the airlines ability to maximize load factors on their routes. As competition increased, focus began to concentrate on specific facets of the business operations within industry. Since airlines could fill seats with pilot / crew repositioning or delayed passengers, the effective revenue generation of flights gained focus. Airline fleets and routes grew, leading to focus in fleet aging, maintenance cost management, and aircraft availability. Fuel efficiency was initially a research focus as it composes a significant percentage of direct operating costs; however, as awareness to social responsibility and environmental impacts has increased, fuel efficiency and particulate emissions have become the most recent focus of airline efficiency research.

The review of the DEA analytical method reveals that it is well suited to perform assessments of the efficiency of a business entity. As usage of the method has evolved, researchers have found ways to replicate complex sequences of business decisions by creating optimization models that manage decisions surrounding intermediate outputs (created within the DMU's internal functions) by creating stages in the decision-making process. In multiple examples, this method has been successfully used to add fidelity to the decision-making simulation.

However, exigent literature does not contain a complex DEA model that includes high-fidelity representations of decisions concerning both fiduciary and environmental responsibilities. A gap in the body of knowledge exists here, where airline efficiency modeling can be extended to create high-fidelity models that incorporate the concepts of operational efficiency (load factor maximization), revenue-generation effectiveness, and environmental impact abatement.

Summary

The review of exigent literature presents a progressive history of study in airline efficiency, presenting the DEA analytical method. The theory and application of several extensions of DEA were presented, including multi-stage models that can model tiered decision-making required in complex business units. While several analysis methods have been pursued over the last several decades, DEA has developed an established purpose for academic research in efficiency measures, not limited only to the aviation industry. Several applications of DEA to evaluate different facets of airline operations were presented.

This literature review also introduces recent trends promoting social environmental responsibiilty in commercial aviation. Studies and industry data sources highlight that the participants of the commercial aviation industry are recognizing value and deploying strategies with respect to environmental responsibility and mitigating their operational impact. Different areas of study regarding environmental considerations in aviation were revealed, including the evaluation of airlines around an environmental performance index. The literature search revealed that the focus in CSER goals has only now culminated in DEA applications to understand airline efficiencies with respect to environmental impacts and pollutant / emissions abatement.

CHAPTER III

METHODOLOGY

Research Approach

This research study defines a study of existing data submitted by commercial air carriers to the Department of Transportation as part of their quarterly operating requriements. The study utilizes a two-phase, two-stage DEA model to assess and compare the efficiencies of the subject airlines with respect to cost efficiency, carbon abatement effectiveness, and operating efficiency.

The following sub-sections explain the derivation of the analytical model utilized for the study. The theoretical model was originally conceived as a variant to a three-stage airline efficiency model defined by Mallikarjun (2015). This model was modified to incorpoate measures to evaluate efficiencies related to carbon dioxide emissions abatement. As further evolution to the model, the three-stage architecture was converted to a two-phase, two-stage model utilizing princples established by Kao and Hwang (2008). This multiplicative two-stage relational DEA model architecture was then utilized to deploy several analysis models on the study sample.

First conceptual model – theoretical three-stage model design. The first version of the DEA model conceived for this study possesses a three-stage structure similar to those utilized by Mallikarjun (2015) and Li et al. (2015) in the reviewed literature. In these studies, the three stages separate the activities of the DMUs to better model the transformation of varying inputs into operating revenues. In Mallikarjun (2015), the first stage transforms operating expenses (fixed and variable costs) into the airline's total capacity – i.e. available seat miles (ASMs). The subsequent stage focuses on the airlines' services offered and transforms the ASMs into revenue passenger miles (RPMs), utilizing additional inputs for the number of flights and destinations available. In the final stage, the operating efficiency of the airline is assessed as the RPMs are transformed into operating revenue. For this study, the three-stage airline efficiency model has been tailored to incorporate an evaluation for environmental efficiency, depicted in Figure 6.

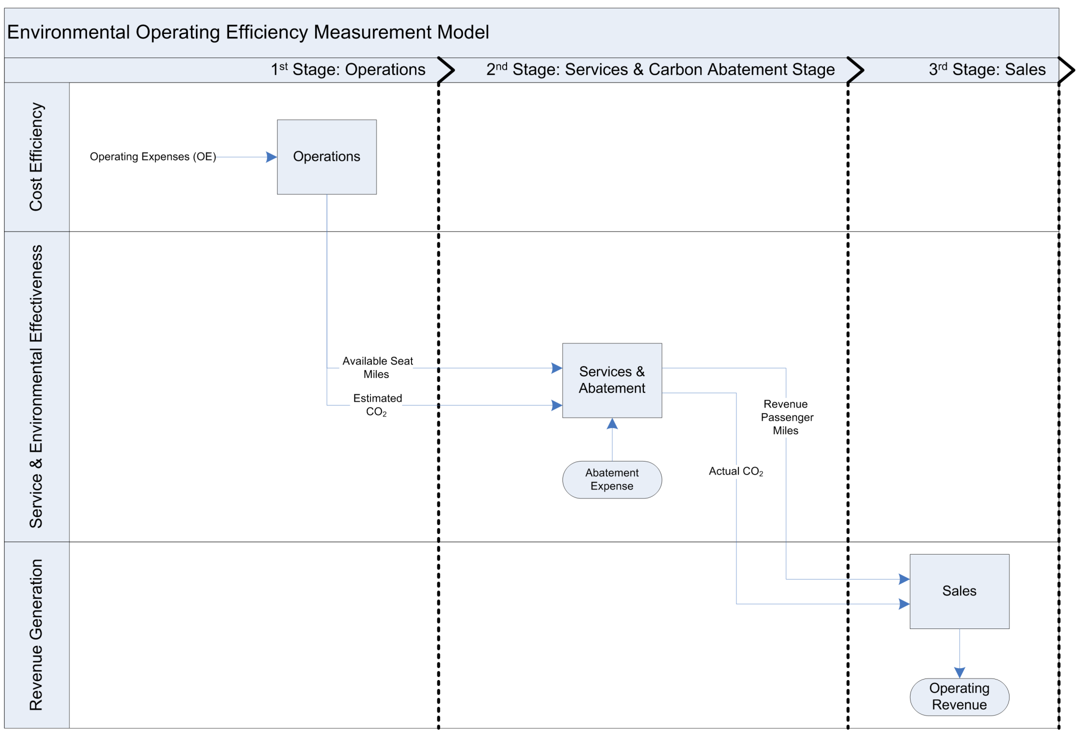

Figure 6. Proposed Three-stage environmental operating efficiency measurement model.

Stage 1: operations. The first stage evaluates the airline DMU with respect to cost efficiency (Mallikarjun, 2015). In this stage, the operating expenses – i.e. the costs the airline incurs in relation to the business operations – are consumed to generate an intermediate output: ASMs. The operating expenses consumed include the wages /

salaries for all operational employees (pilots, flight attendants, maintenance staff, etc.), the operating material costs (e.g. fuel), and other miscellaneous operating expenses. From a philosophical perspective, the first stage consumes labor and material resources (specifically excluding capital) to generate a supply of product; the ASMs represent the capacity that the business can choose to price and distribute. A detailed depiction of the nodes in this stage is presented in Figure 7.

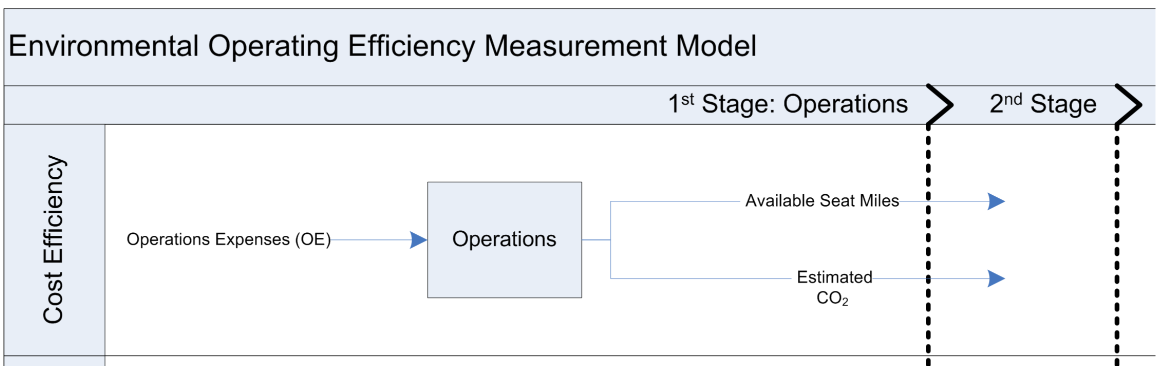

Figure 7. Environmental operating efficiency measurement model – Stage 1: operations.

Stage 2: services & carbon abatement. The second stage is similar to the "Service" stage from Mallikarjun's (2015) three-stage model, but also adopts input and output variables to incorporate decision-making aspects associated with reducing net environmental impact. With respect to the service effectiveness aspect of airline operations, this stage consumes as an input the ASMs that were generated by the first stage and transforms them into an intermediate output, RPMs, which depicts the service demand of the airline (Mallikarjun, 2015). RPMs specifically help us understand what number of revenue-generating passengers were on a trip between two destinations, as a function of the ASMs available. Mallikarjun (2015) defines this phase as indicating the service effectiveness of the airline. However, when combined with the first stage, he notes that it helps demonstrate the cost effectiveness.

The environmental-impact related variables in the second stage facilitates an environmental efficiency measure into the analysis model. Following the application by Cui and Li (2016) of a two-stage DEA which includes carbon abatement in the evaluation of a production process, the abatement process is incorporated in the second stage following the operations phase. The intermediate output of the preceding operations stage – which feeds this segment as an input – is the estimated carbon dioxide emissions (ECO_2) associated with aircraft fuel consumption. The ECO_2 is defined by Carbonfund.org, utilizing data standards established by the Environmental Protection Agency (EPA). This calculation is presented in Equation 18, where ASM represents the available seat mile capacity for that specific airline, and λ is the emissions coefficient defined by the EPA (Carbonfund.org, 2017). In the latest publication of the EPA's emissions factors for greenhouse gas inventories, the coefficient is equal to 0.143 kg CO_2 emissions per available seat mile (Environmental Protection Agency, 2015).

$$ECO_2 = ASM * \lambda \tag{18}$$

In addition to the estimated carbon dioxide emissions, this stage also consumes abatement expense, the financial expenditures of the airline to alleviate the environmental impacts of business operations. As discussed in the literature review, airlines invest resources to reduce and abate the environmental impacts of their flight and ground operations. These contributions include recurring abatement activities, as well as non-recurring investment into emissions reduction technology or capabilities. Recurring costs for environmental impact abatement include expenses associated with activities such as recycling program operations or alternative energy sources. Non-recurring investment is typically reflected in the design and development costs to deploy capabilities such as the electrical aircraft taxi systems and lighter onboard galley carts.

The abatement-related intermediate output of this stage is actual CO_2 emissions. The actual CO_2 emissions reflect the net carbon impact to the environment; this value recognizes the avoidance in environmental impact (the value of abatement) subtracted from the estimated total carbon emissions.

A detailed depiction of the nodes in this stage is presented in Figure 8.

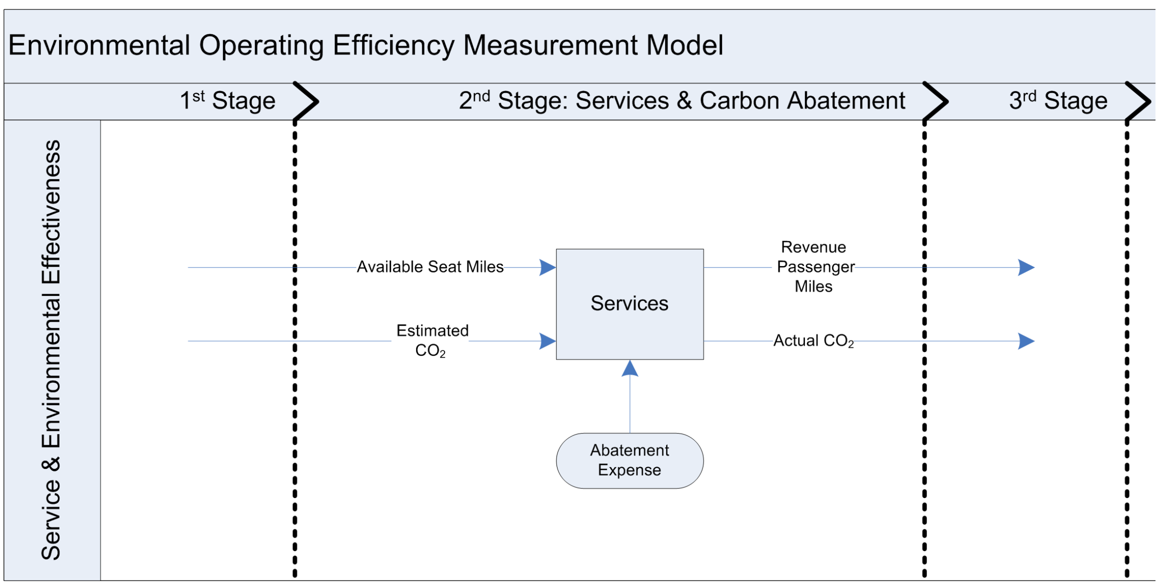

Figure 8. Environmental operating efficiency measurement model – Stage 2: services and carbon abatement

Stage 3: sales. The third and final stage of this efficiency measurement model incorporates the intermediate outputs of Stage 2 to produce total recognized revenue. In this stage, the DMU markets the RPMs and transforms this intermediate service into revenue. However, the operating revenue is impacted by the efforts the airline makes to abate operating impact to the environment. Therefore, this stage also consumes the CO_2 output from the abatement segment of Stage 2.

The values for the final outputs of this stage (operating revenues) are obtained from data extracted from air carrier filings, made available through the Bureau of Transportation Statistics online databases (BTS, 2017). A detailed depiction of the nodes in this stage is presented in Figure 9.

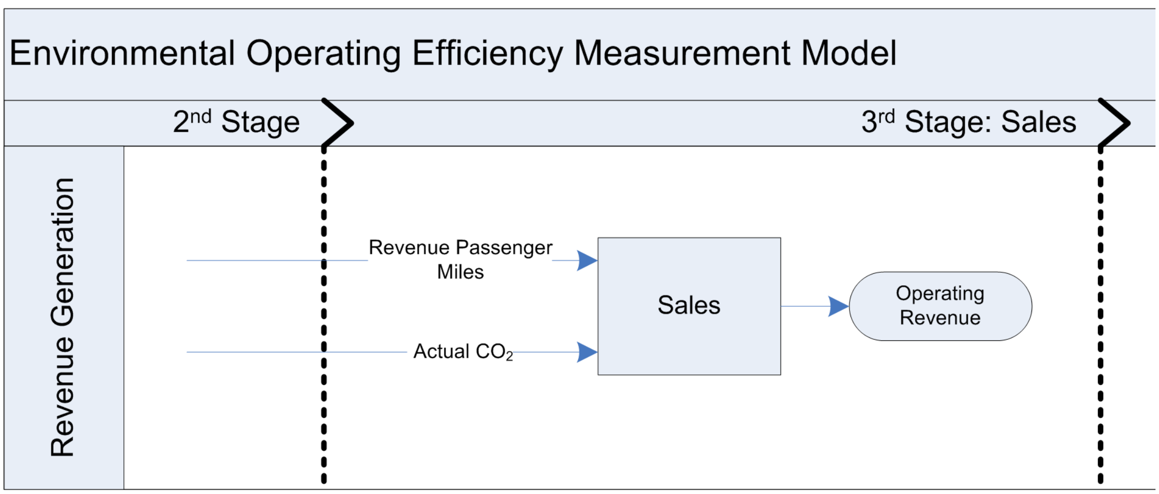

Figure 9. Environmental operating efficiency measurement model – Stage 3: sales.

First conceptual model – three-stage DEA model formulation. The previous section describes the theory behind the development of a proposed three-stage model. The following paragraphs layout the DEA model formulas specific to each stage. The DMU orientation strategy follows the base-oriented DEA principle; it is structured to maximize efficiency by both reducing input consumption and increasing output production. This study is focused on reducing the environmental impacts of air carrier operations and also incorporating an environmental abatement intermediate input into the model – it is therefore important to simultaneously improve both aspects of the DMU operations.

With respect to the airline industry as a whole, the base-oriented approach accurately reflects an airline's business model. While every for-profit business attempts to minimize costs and input consumption, the capital costs of aircraft are very high and not easily liquidated – the cost requirements therefore drive a long-term investment and procurement strategy. With high financial requirements associated with the aircraft capital, air carrier operations must focus on direct operating efficiency. From an operational standpoint, the DMUs focus on both minimizing all the other (non-aircraft) variable costs (inputs), while also maximizing the outputs. This base-oriented theoretical model would require an iterative algorithm that alternates between an input-oriented step and an output-oriented step (Mallikarjun, 2015).

Stage 1: operations. The first stage utilizes a VRS model to simultaneously decrease input levels while increasing the intermediate outputs. In this stage, the objective function drives to either minimize the efficiency of the first stage for airline *k* or maximize its approximate inverse efficiency. The first two constraints are used to ensure the optimal production frontier airline is increasing in efficiency through the iterations. The first constraint ensures there are no increases in consumption of operating expense inputs for successive iterations (it can only decrease). In parallel, the second constraint ensures that an optimal airline is increasing airline capacity generation for each successive iteration. The final constraint is utilized to ensure variable returns-to-scale is modeled. The first stage formulas are presented in Equation 24.

$$min\, E_{1kt} \text{ or } max\ \theta_{1kt} \tag{24}$$

subject to:

$$\sum_{j=1}^{n} \lambda_{jt}\ (OE)_{j0} \leq \begin{cases} E_{1kt}\ (OE)_{k0}, & t = 1 \\ E_{1kt} \sum_{j=1}^{n} \lambda_{jt-1}^{*}\ (OE)_{j0}\,, & t > 1 \end{cases}$$

$$\sum_{j=1}^{n} \lambda_{jt}\ (ASM)_{j0} \geq \begin{cases} E_{1kt}\ (ASM)_{k0}, & t = 1 \\ E_{1kt} \sum_{j=1}^{n} \omega_{j(t-1)b}^{*}\ (ASM)_{j0}\,, & t > 1 \end{cases}$$

$$\sum_{j=1}^{n} \lambda_{jt} = 1$$

$$E_{1kt} + \theta_{1kt} = 2$$

$$\lambda_{jt} \geq 0; \qquad \forall j$$

$$E_{1kt},\ \theta_{1kt} \geq 0$$

where:

E_{1kt} : Efficiency of 1st stage for airline k during iteration t

θ_{1kt} : Approximate inverse efficiency of 1st stage for airline k (iteration t)

n : Total number of airlines

OE_{j0} : Total operating expenses consumed by airline j

ASM_{j0} : Available seat miles of airline j

λ_{jt} : Weight placed on airline j by airline k when solving Stage 1 (iteration t)

ECO_{2kt} : Estimated CO_2 generated by airline k (iteration t)

Stage 2: services & carbon abatement. The second stage defines the services and carbon abatement stage of the airline operations. In the first (forward) pass through this stage, the objective function minimizes the efficiency of airline *k* during iteration *t* or maximizes the approximate inverse efficiency. Similar to the first stage, the first constraint drives improvement in operations through the iterations: the first constraint prevents increased consumption of ASM input in consecutive iterations, and the second constraint does not allow reduction of RPM output in consecutive iterations. The formulas defining this stage are defined in Equation 25.

$$min\, E_{2ktf} \text{ or } max\, \theta_{2ktf} \tag{25}$$

subject to:

$$\sum_{j=1}^{n} \omega_{jtf}\, (ASM)_{j0} \leq E_{2ktf} \sum_{j=1}^{n} \lambda_{jt}^{*}\, (ASM)_{j0}$$

$$\sum_{j=1}^{n} \omega_{jtf}\, (RPM)_{j0} \geq \begin{cases} \theta_{2ktf}(RPM)_{k0}, & t = 1 \\ \theta_{2ktf} \sum_{j=1}^{n} \omega_{j(t-1)\mathrm{b}}^{*}\, (RPM)_{j0}\,, & t > 1 \end{cases}$$

$$\sum_{j=1}^{n} \omega_{jtf} = 1$$

$$E_{2ktf} + \theta_{2ktf} = 2$$

$$\omega_{jtf} \geq 0\,; \qquad \forall j$$

$$E_{2ktf},\, \theta_{2ktf} \geq 0$$

where:

E_{2ktf} / E_{2ktb} : Efficiencies of airline *k* when solving the 2nd stage during forward and reverse iterations (iterations *t*)

θ_{2ktf} / θ_{2ktb} : Approximate inverse efficiencies of airline *k* when solving the 2nd stage during forward and reverse iterations (iterations *t*)

ω_{jtf} / ω_{jtb} : Weight placed on airline *j* by airline *k* when solving the 2nd stage during forward and reverse iterations (iterations *t*)

$(RPM)_{j0}$: Revenue passenger miles of airline *j*

As previously stated, this DEA model is base-oriented, and so employs input- and output-oriented steps in the model defining the second stage DMU. To generate this phenomenon, the model algorithms deploy "forward" and "backward" passes through the second stage DMU. The objective function for the backward pass of Stage 2 minimizes the relative efficiency of the second stage of airline *k* during iteration *t* or maximizes its approximate inverse efficiency by the equivalent amount. The primary constraints ensure: (a) the optimal production frontier airline consumes no more intermediate input (ASM) as from the forward pass and (b) produces at least as much intermediate output (RPM) as during the forward pass. The formulas defining the backward pass of Stage 2a are defined in Equation 26.

$$min\, E_{2ktb} \text{ or } max\, \theta_{2ktb} \tag{26}$$

subject to:

$$\sum_{j=1}^{n} \omega_{jtb}\, (ASM)_{j0} \leq E_{2ktb} \sum_{j=1}^{n} \omega_{jtf}^{*}\, (ASM)_{j0}$$

$$\sum_{j=1}^{n} \omega_{jtb}\, (RPM)_{j0} \geq \theta_{2ktb} \sum_{j=1}^{n} \mu_{jt\mathrm{b}}^{*}\, (RPM)_{j0}$$

$$\sum_{j=1}^{n} \omega_{jtb} = 1$$

$$E_{2ktb} + \theta_{2ktb} = 2$$

$$\omega_{jtb} \geq 0 ; \quad \forall j$$

$$E_{2ktb}, \theta_{2ktb} \geq 0$$

In parallel, this stage models the airline activities to offset a portion of carbon emissions produced through investment and expenditures to particulate emission generation. The objective function for this stage minimizes the relative abatement efficiency associated with airline *k* during iteration *t* or maximizes the approximate inverse abatement efficiency by the same quantity. The first constraint of this stage ensures that in consecutive iterations, the abatement expense pursued by the frontier airline does not increase. The second constraint ensures that the CO_2 reduction – defined by the difference between estimated CO_2 generated due to fuel consumption in operations and the total net emission impacts after abatement adjustment – does not reduce in quantity over consecutive iterations. The remaining constraints define a variable returns-to-scale system and prevent the model from driving to inefficient behavior. The formulas defining abatement are defined in Equation 27.

$$min\, E_{2ENV} \text{ or } max\, \theta_{2ENV} \tag{27}$$

subject to:

$$\sum_{j=1}^{n} \eta_{jt}(AE)_{j0} \leq \begin{cases} E_{2kENV}\,(AE)_{k0}, & t = 1 \\ E_{2kENV} \sum_{j=1}^{n} \eta^{*}_{j(t-1)}\,(AE)_{k0}\,, & t > 1 \end{cases}$$

$$(ECO_2)_{jt} = (TF)_{jt}\psi_{AK}$$

$$\sum_{j=1}^{n} \eta_{jt}\left[(CO_2)_{j0} - (ECO_2)_{j0}\right]$$

$$\geq \begin{cases} E_{2kENV}\left[(CO_2)_{k0} - (ECO_2)_{k0}\right] \;, & t = 1 \\ \theta_{2kENV} \sum_{j=1}^{n} \eta^{*}_{j(t-1)}\left[(CO_2)_{k0} - (ECO_2)_{k0}\right] \;, & t > 1 \end{cases}$$

$$\sum_{j=1}^{n} \eta_{jt} = 1$$

$$E_{2kENV} + \theta_{2kENV} = 2$$

$$\eta_{jt} \geq 0 \,; \qquad \forall j$$

$$E_{2kENV}, \theta_{2kENV} \geq 0$$

where:

E_{2ENV} : Environmental efficiency of airline k when solving the 2nd stage for iteration t

θ_{2ENV} : Approximate inverse environmental efficiency

${ECO_2}_{jt}$: Estimated carbon dioxide emissions of airline j when solving the 2nd stage for iteration t

$(TF)_{jt}$: Total fuel consumed by airline j in iteration t

ψ_{AK}: CO_2 emissions per gallon coefficient for aviation kerosene

AE_k : Abatement expense of airline k

CO_{2k} : Net carbon dioxide emissions of airline k

Stage 3: sales. The third and final stage of this multi-stage DEA model also utilizes a VRS model to decrease input levels while simultaneously increasing the intermediate outputs. The objective function minimizes the relative efficiency of the third stage for airline *k* during iteration *t* or maximizes the approximate inverse efficiency for the same value. The constraints of this stage are used to ensure the optimal airline is not consuming more intermediate input (RPM) and not generating less output (OR) for each iteration *t*. The third stage formulas are presented in Equation 28.

$$min\, E_{3kt} \text{ or } max\, \theta_{3ktf} \tag{28}$$

subject to:

$$\sum_{j=1}^{n} \mu_{jt}\,(RPM)_{j0} \leq E_{2ktf} \sum_{j=1}^{n} \omega_{jtf}^{*}\,(RPM)_{j0}$$

$$\sum_{j=1}^{n} \mu_{jt}\,(OR)_{j0} \geq \begin{cases} \theta_{3kt}(OR)_{k0}, & t = 1 \\ \theta_{3kt} \sum_{j=1}^{n} \mu_{j(t-1)}^{*}\,(RPM)_{j0}\,, & t > 1 \end{cases}$$

$$\sum_{j=1}^{n} \mu_{jt} = 1$$

$$E_{3kt} + \theta_{3kt} = 2$$

$$\mu_{jt} \geq 0\,; \quad \forall j$$

$$E_{3kt},\, \theta_{3kt} \geq 0$$

where:

E_{3kt} : Efficiency of airline *k* when solving the 3rd stage during iteration *t*)

θ_{3kt} : Approximate inverse efficiency of airline *k* when solving the 3rd stage during iteration *t*

μ_{jt} : Weight placed on airline *j* by airline *k* when solving the 3rd stage during iteration *t*

OR_{j0} : Actual total operating revenue generated by airline j

Final model – theoretical multiplicative relational two-stage model design. The three-stage structure similar to those utilized by Mallikarjun (2015) and Li et al. (2015) in the reviewed literature requires a forward-backward recursive iteration to facilitate the second stage. The review of exigent literature establishes an appropriate application of the multiplicative relational two-stage model presented by Kao and Hwang (2008). Leveraging two-stage analysis while retaining the better representation of the airline business through the three stages – conceived by Mallikarjun – is desirable for an airline analysis model; these characteristics would provide a model that is easily deployable and scalable for larger datasets.

The proposed analysis model architecture leverages (a) the multiplicative two-stage relationship – where the total efficiency is the cross product of two sub-process efficiencies, and (b) the relationship two-stage efficiency model developed by Kao and Hwang (2008) for two sub-processes conducted in series. The two-phase, two-stage model is presented in Figure 10, where each of two phases is a two-stage DEA model, and the efficiency of each phase is combined to produce the total environmental operating efficiency measurement model.

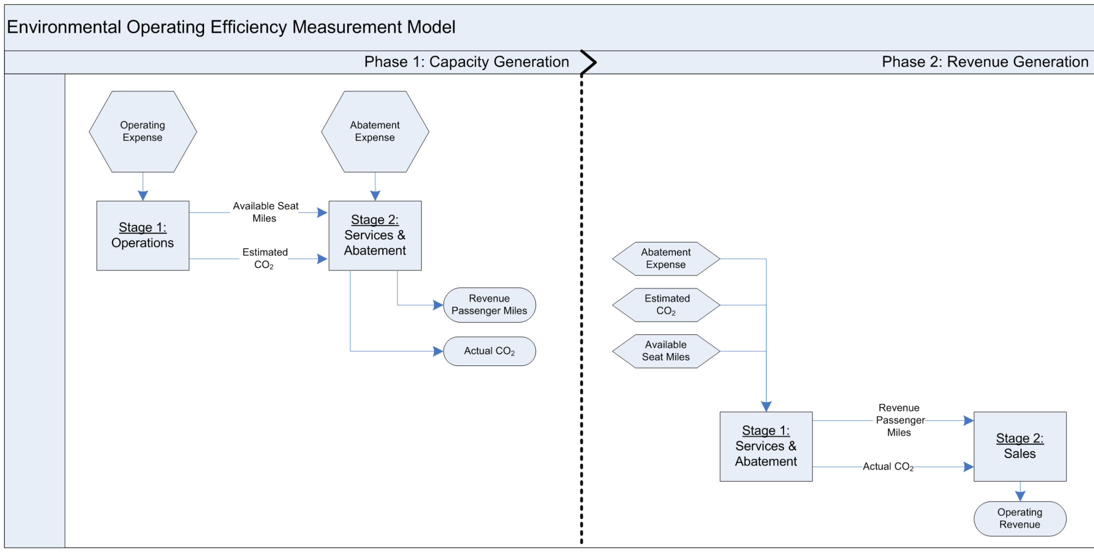

Figure 10. Environmental operating efficiency measurement model.

Upon immediate review, it is evident that the second stage of Phase 1 duplicates the first stage of the Phase 2. The purpose of this model construction limits the model to only two-stage DEA while simultaneously ensuring the fidelity of the Mallikarjun (2015) philosophical construct of the airline business model is preserved. The evaluation of capacity considers both (a) the transformation of material and labor resources to produce ASMs and (b) the scheduling and route optimization required to effectively transform that basic aircraft capacity to RPMs – marketable capacity. Similarly, the revenue recognition phase does not only account for RPM conversation to revenue, but includes the optimization analysis for DMUs to convert ASMs to RPMs. In both phases, the impact of environmental abatement is included to influence the efficiency evaluation of the airline through that phase.

Phase 1: capacity generation. In Phase 1, the two stages combine to define an efficiency that reflects capacity generation from material and labor resources. As in the previously derived three-stage model, the first stage consumes the operating expenses –

i.e. the costs the airline incurs in relation to the business operations – to generate an intermediate output of capacity: i.e. ASMs.

The second stage parallels the second stage from the previously developed three-stage model which combines both the service effectiveness evaluation from Mallikarjun's (2015) airline efficiency model and an evaluation of environmental efficiency with respect to the abatement of carbon dioxide emissions. For the service effectiveness aspect of airline operations, this stage consumes as an input the ASMs that were generated by the first stage and transforms them into an intermediate output, RPMs, to depict the service demand of the airline. As in the three-stage model, the combination of this evaluation with the operations evaluation in the first stage helps analyze the cost effectiveness of the airline.

The environmental-impact related variables in the second stage also parallels the three-stage model by applying Cui and Li (2016) two-stage DEA carbon abatement evaluation. The ECO_2 variable is defined by Carbonfund.org, utilizing data standards established by the Environmental Protection Agency (EPA). This calculation is previously presented in Equation 18. In addition to the estimated carbon dioxide emissions, this stage also consumes abatement expense, the financial expenditures of the airline to alleviate the environmental impacts of business operations.

The abatement-related intermediate output of this stage is actual CO_2 emissions. The actual CO_2 emissions reflect the net carbon impact to the environment; this value recognizes the avoidance in environmental impact (the value of abatement) subtracted from the estimated total carbon emissions.

The abatement expense and actual CO_2 emissions data are obtained from the sustainability, environment, and corporate social responsibility reports of the airlines included in this study. All other inputs and the intermediate outputs are defined by data extracted from air carrier public filings, either those made available through the Bureau of Transportation Statistics online databases (BTS, 2017), or those publicly disclosed by the airlines through their websites or other media vehicles.

A detailed depiction of the nodes in this stage is presented in Figure 11.

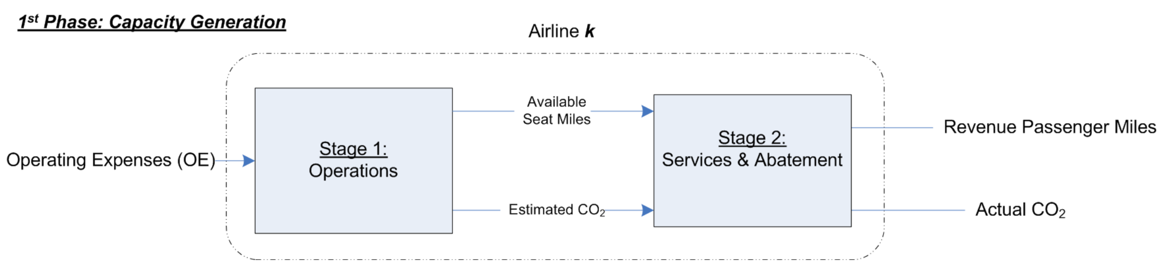

Figure 11. Environmental operating efficiency measurement model – Phase 1.

Phase 2: revenue generation. In the second phase, the two stages of the DEA model combine to define an efficiency measure of revenue generation. The first stage replicates the second stage of Phase 1 in evaluating both (1) RPM generation from ASMs, and (2) the effectiveness of the airline's carbon dioxide emissions abatement. The second stage of this phase incorporates the intermediate outputs of the first stage to produce total recognized revenue. In this stage, the DMU markets the RPMs and transforms this intermediate service into revenue. However, the operating revenue is impacted by the efforts the airline makes to abate operating impact to the environment. Therefore, this stage also consumes the CO_2 output from the abatement segment of the first stage.

A detailed depiction of the nodes in this stage is presented in Figure 12.

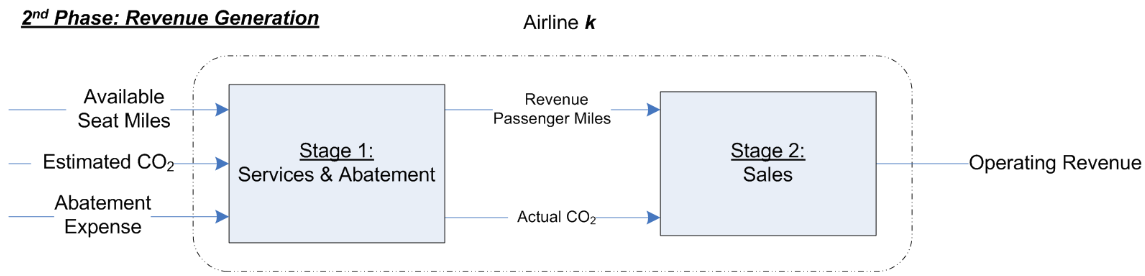

Figure 12. Environmental operating efficiency measurement model – Phase 2.

Final model – multiplicative relational two-stage model formulation. The previous section describes the theory behind the development of a proposed two-phase research model that incorporates two different two-stage DEA models. The following paragraphs lay out the DEA model formulas specific to each stage. The two-stage DEA models both follow the multiplicative two-stage relational model structure similar to that developed by Kao and Hwang (2008).

Phase 1: capacity generation. The first phase utilizes a two-stage VRS DEA model to decrease input levels while simultaneously increasing the outputs. In this phase, the objective function drives to either maximize the efficiency of the first stage for airline *k*, or minimize the approximate inverse efficiency of the second stage. The first two constraints are used to ensure the optimal production frontier airline is increasing in efficiency through the iterations. The first constraint ensures there are no increases in consumption of operating expense inputs for successive iterations (it can only decrease). In parallel, the second constraint ensures that an optimal airline is increasing airline capacity generation for each successive iteration. Kao and Hwang's original two-stage multiplicative VRS model equations (first presented in Chapter II) are presented in Equation 29.

$$E_k = \max \tag{29}$$

$$\sum_{r=1}^{s} u_r Y_{rk}$$

s.t.

$$\sum_{i=1}^{m} v_i X_{ik} = 1$$

$$\sum_{r=1}^{s} u_r Y_{rk} - \sum_{i=1}^{m} v_i X_{ij} \leq 0 \ , \qquad j = 1, \ldots, n$$

$$\sum_{p=1}^{q} w_p Z_{pj} - \sum_{i=1}^{m} v_i X_{ij} \leq 0 \ , \qquad j = 1, \ldots, n$$

$$\sum_{r=1}^{s} u_r Y_{rj} - \sum_{p=1}^{q} w_p Z_{pj} \leq 0 \ , \qquad j = 1, \ldots, n$$

$$u_r,\ v_i,\ w_p \geq \varepsilon \ , \qquad r = 1, \ldots, s \ , \qquad i = l, \ldots, m \ , \qquad p = 1, \ldots, q$$

Substituting the specific variables of our airline operating model construct – including both revenue generation and carbon emissions abatement – yields the Phase 1 equations of the environmental operating efficiency measurement model, presented in Equation 30.

$$E_{1j} = \max \tag{30}$$

$$\sum_{r=1}^{s} u_r\{(Y_{rRPM})(Y_{rCO2})\}$$

s.t.

$$\sum_{i=1}^{m} v_i\{(X_{iOE})\} = 1$$

$$\sum_{r=1}^{s} u_r\{(Y_{rRPM})(Y_{rCO2})\} - \sum_{i=1}^{m} v_i\{(X_{iOE})\}_j \leq 0 \ , \qquad j = 1, \dots, n$$

$$\sum_{p=1}^{q} w_p\{(Z_{pASM})(Z_{pECO2})\}_j - \sum_{i=1}^{m} v_i\{(X_{iOE})\}_j \leq 0 \ , \qquad j = 1, \dots, n$$

$$\sum_{r=1}^{s} u_r\{(Y_{rRPM})(Y_{rCO2})\}_j - \sum_{p=1}^{q} w_p\{(Z_{pASM})(Z_{pECO2})\}_j \leq 0 \ , \qquad j = 1, \dots, n$$

$$u_r,\ v_i,\ w_p \geq \varepsilon\ , \qquad r = 1, \dots, s\ , \qquad i = l, \dots, m\ , \qquad p = 1, \dots, q$$

where:

E_{1j} : Phase 1 efficiency of airline j

X_{iOE} : Operating expenses input for every iteration i for airline j

Y_{rRPM} : Revenue passenger mile output for every iteration r for airline j

Y_{rCO2} : Actual CO_2 output for every iteration r for airline j

Z_{pASM}: Available seat mile intermediate output for every iteration p for airline j

Z_{pECO2}: Estimated CO_2 intermediate output for every iteration p for airline j

u_r, v_i, w_p : All equal 0.5 for equivalence in weighting across input and output variables for both stages of the phase

Phase 2: revenue generation. The second phase also utilizes a two-stage VRS DEA model to decrease input levels while simultaneously increasing the outputs. Just like the first phase, Phase 2 leverages Kao and Hwang's original two-stage multiplicative VRS model. Applying the revenue generation constructs of the theoretical environmental operating efficiency measurement model yields the formulas for Phase 2, presented in Equation 31.

$$E_{2j} = \max \tag{31}$$

$$\sum_{r=1}^{s} u_r\{(Y_{rOR})\}$$

s.t.

$$\sum_{i=1}^{m} v_i\{(X_{iASM})(X_{iECO2})\} = 1$$

$$\sum_{r=1}^{s} u_r\{(Y_{rOR})\} - \sum_{i=1}^{m} v_i\{(X_{iASM})(X_{iECO2})\}_j \leq 0 \ , \qquad j = 1, \dots, n$$

$$\sum_{p=1}^{q} w_p\{(Z_{pRPM})(Z_{pCO2})\}_j - \sum_{i=1}^{m} v_i\{(X_{iASM})(X_{iECO2})\}_j \leq 0 \ , \qquad j = 1, \dots, n$$

$$\sum_{r=1}^{s} u_r\{(Y_{rRPM})(Y_{rCO2})\}_j - \sum_{p=1}^{q} w_p\{(Z_{pRPM})(Z_{pCO2})\}_j \leq 0 \ , \qquad j = 1, \dots, n$$

$$u_r,\ v_i,\ w_p \geq \varepsilon\ , \qquad r = 1, \dots, s\ , \qquad i = l, \dots, m\ , \qquad p = 1, \dots, q$$

where:

E_{2j} : Phase 2 efficiency of airline j

X_{iASM} : Available seat miles input for every iteration i for airline j

X_{iECO2} : Estimated CO_2 input for every iteration i for airline j

Y_{rOR} : Operating revenue output for every iteration r for airline j

Z_{pRPM}: Revenue passenger mile intermediate output for iteration *p,* for airline *j*

Z_{pCO2}: Actual CO_2 intermediate output for iteration *p,* for airline *j*

u_r, v_i, w_p : All equal 0.5 for equivalence in weighting across input and output variables for both stages of the phase

To determine the total efficiency of each airline, the multiplicative efficiency property is applied, and the cross product of the two-phase efficiencies yields the total model efficiency, presented in Equation 32.

$$E_k = E_k^1 \times E_k^2 \tag{32}$$

Apparatus and materials. This proposed study obtains all input data from a publicly available database maintained by the Department of Transportation (BTS, 2017) or from airline public disclosures (various sources); no survey instrument is required. The study utilizes the DEA methodology; computational analysis is performed via Frontier Analyst. This software is utilized for data preparation as well as the DEA calculations.

Population/Sample

The sample selected for this study includes operations by specific air carriers operating through the United States from 2013 through 2015, with their operations reported to the U.S. Department of Transportation. The air carrier population is defined based upon public availability of data, specifically the availability of corporate sustainability / responsibility reports that present airline expenditures in the pursuit of satisfying CSER goals. In addition, the airlines in the study will have served a minimum of 5,000,000 passengers (in 2015).

The study sample size includes 15 total carriers, which includes both U.S. carriers as well as international flag carriers. These carriers will be employing both the FSC and LCC airline business models, operating on both domestic and international segments. As discussed in the literature review, Zhu (2011) recommends that the number of DMUs in the sample is at least twice the number of variables. For the proposed study, the number of airlines included was limited by the requirements of having a mixed passenger transportation profile (domestic and international), and having publicly distrusted sustainability data for the study period. With eight variables utilized in the three-stage analysis, the sample size of 15 carriers is deemed to be close to the recommendation by Zhu (2011).

Airline performance data is collected (reported) quarterly, while the airline-specific emissions data is collected annually. Inputs for the analysis will reflect summary data used to trend and assess performance in each year, as well as over the period of study.

The airlines comprising the study population include:

- Air Canada
- Alaska Airlines
- Air France – KLM
- All Nippon Airways
- American Airlines
- British Airways

- Delta Air Lines
- Emirates
- Etihad Airways
- Japan Airlines
- JetBlue Airways
- Lufthansa German Airlines
- Southwest Airlines
- United Air Lines
- Virgin America

Sources of the Data

Airline data to be used for investigating operating costs and aircraft usage trends was obtained from TranStats – airline operating data collected by the Bureau of Transportation Statistics (BTS) (BTS, 2017) – or from airline public disclosures that are stored on the internet.

Financial data. For U.S. air carriers, the analysis consumes quarterly air carrier financial reports collected under Title 14 Part 41 requirements and made available through TranStats (BTS, 2017). The data collected consists of airline-specific datasets including (but not limited to):

Air carrier financials: schedule P-5.2 expenses

- Total aircraft operating expense (direct operating expense)
- Aircraft configuration, group, and type
- Carrier identification
- Year

- Quarter

For international carriers, all financial data were extracted from public disclosures made available through the airline websites.

Air carrier operational data. The air carrier operations data for both U.S. and international carriers were obtained through TranStats (BTS, 2017). The following variables were extracted from the T100 segment table:

T100 segment – all carriers

- Payload
- Available seats
- Passengers transported
- Freight transported
- Mail transported
- *Load factor
- Carrier identification
- Aircraft group
- Aircraft configuration
- Aircraft type
- Year
- Quarter

Emissions data. In addition to the aforementioned data tabulated from BTS (2017), the carbon oxide (CO_x) particulate generation from aircraft operations were obtained from the individual airline corporate sustainability reports or annual reports (depending on the airline's reporting format).

Ethical issues. The proposed study does not contain any ethical issues or concerns. The data used in this study does not require collection from human subjects, therefore approval by the Institutional Review Board is not required. Additionally, all data used in the study is publicly available data. Operational data for all airlines in the study is obtained from BTS's online database. Financial data for U.S. airlines is also obtained from BTS. Financial data for non-U.S. airlines, and all emissions data is obtained from airline public disclosures. In all cases, private and sensitive information has been removed by the data provider to facilitate public consumption and availability.

Treatment of the Data

Data preparation. Prior to data analysis, the data was acquired from public databases and then cleaned. The model variables for each analysis stage are calculated from the collected data and then segregated into groups for each analysis model. After the data is prepared, the analysis model was executed.

Data acquisition. The airline operational data was downloaded from the BTS website. From the data tables referenced in the "Sources of Data" section, the specific variables were extracted and recorded in a database for further processing. The data is available in a comma-delimited (.csv) format and were imported into Microsoft Excel for cleaning.

The airline-specific emissions data was collected from the annual corporate sustainability reports – depending on the airline, these are sometimes referred to as social responsibility or environmental responsibility reports. The emissions-specific data was extracted from each report and input into the Excel database.

Data cleaning. The acquired data was parsed to identify sets within the sample that are missing data points; these sets were extracted from the data. With the sample containing only full sets, any data sets not applicable to *large air carriers* (carriers serving a minimum of 5,000,000 passengers within a year – for the study period) were removed. The remaining datasets should contain sample data representative of the population under study and contain characteristics allowing segregation by airline, quarter, and year.

Variable preparation. Utilizing the collected data, the input and output variables of each stage are prepared by: (a) direct extraction from the data source, or (b) calculation of the variable from data points within the collected data. The definition of each variable is outlined in the following subsections and tabulated in Table 1.

Stage 1: operations. The input for the first stage – total operating expenses – is defined by the "Total Operating Expense" variable from the "Air Carrier Financial: Schedule P-1.2" database (BTS, 2017).

The two intermediate outputs for the first stage are: (a) Available Seat Miles (ASMs) and (b) Estimated Carbon Dioxide emissions (ECO2). ASMs are defined by the "Available Seats" variable from the "T100 Segment – All Carriers" database (BTS, 2017) for U.S. airlines and by company annual reports for the international airlines.

ECO2 for an airline is the previously reviewed calculation defined by Carbonfund.org, utilizing data standards established by the Environmental Protection Agency (EPA). This calculation is presented in Equation 18, where ASM represents the available seat mile capacity for that specific airline, and λ is the emissions coefficient defined by the EPA (Carbonfund.org, 2017). In the latest publication of the EPA's emissions factors for greenhouse gas inventories, the coefficient is equal to 0.143 kg CO_2 emissions per available seat mile (Environmental Protection Agency, 2015).

$$ECO_2 = ASM * \lambda \tag{18}$$

Stage 2: services and carbon abatement. The two intermediate inputs for the second stage – ASM and ECO2 – were previously defined. An additional input to this phase is abatement expense (AE). AE is defined as the expenditures by airlines to mitigate their carbon emissions as a result of airline operations. This variable is defined by data presented in the airline social and corporate responsibility reports.

The two intermediate outputs for the second stage are: (a) Revenue Passenger Miles (RPMs) and (b) Actual CO2 Emissions Cost (CO2). RPMs are defined by the "Revenue Passenger Miles" variable from the "T100 Segment – All Carriers" database (BTS, 2017) for U.S. carriers and is obtained from corporate annual reports for the international carriers.

CO2 for an airline is a reported quantity that is available in every airline's annual social responsibility report or another reporting vehicle to meet the requirements of the Global Reporting Initiative (GRI). The reported CO2 value in the public reports is an annual value and therefore requires no further transformation, except for units standardization (if any airlines within the sample report a different value to metric tonnes of CO_2).

Stage 3: sales. The two intermediate inputs for the third stage – RPM and CO2 – were previously defined. The two outputs of the third stage are: (a) the Net Income realized by the airline in the time period under analysis and (b) Total Operating Revenues. The data for both of these variables are defined by variables from the "Air Carrier Financial: Schedule P-1.2" database (BTS, 2017) for the U.S. airlines and in corporate annual reports for the international carriers.

Table 1

Summary of DMU Input & Output Variables

Variable	Stage	Type	Definition
OE	1	Input	Total Operating Costs
ASM	1/2	Output/Input	Available Seat Miles
ECO2	1/2	Output/Input	Estimated CO_2 Emissions
AE	2	Input	Abatement Expense
RPM	2/3	Output/Input	Revenue Passenger Miles
CO2	2/3	Output/Input	Actual CO_2 Emissions
NINC	3	Output	Net Income, Profit, or Loss
OR	3	Output	Total Operating Revenues

Demographics. The demographics of the sample data were qualitatively reviewed. This analysis includes airline operating characteristics including (but not limited to):

- Carrier flag status – U.S. or non-U.S. carrier
- Carrier business model – FSC, LCC, or point-to-point (P2P)

Review of the sample demographics allows discovery of unexpected trends or variances in the data that would suggest a validity threat due to data collection / sampling.

In addition, the sample demographics were compared to the population demographics to help ensure the sample is representative.

Descriptive statistics. Descriptive statistics are presented for the analysis constituents. This presentation includes: count, mean, standard deviation, and variance of the input and output variables.

DEA model execution. The analysis phase executed several DEA models to review the airline DMU efficiency from several different perspectives. The models were defined by the same mathematical formulas as presented earlier in this section; however, the DMU data processed in each model varied to allow the model to focus on specific categories within the sample.

Efficiency differences over time. From a temporal perspective, models were created to examine the airline efficiency for each year of the study individually, as well as for the duration of the study period. Reviewing the total airline performance annually (in addition to the study aggregate) enables understanding of trending in each airline's efficiency performance – e.g., in a specific year the airline may not perform well relative to the benchmark, while it still is one of the top performing airlines in the study period. To ensure the study facilitates a better understanding of the variation of performance during the data collection periods, four models were required: three annual models, and one aggregate model.

U.S. versus non-U.S. airlines. As described in the Delimitations section of Chapter I, this study includes both U.S. and non-U.S. airlines. As all airlines execute network and fleet deployment for flight legs representing regional / transcontinental and intercontinental distances, the aggregate models should provide direct comparison capability. To account for potential results bias due to the network differences, two DEA models were executed to compare more similar network types: (1) the first model includes only U.S. carrier operations for the entire study period, and (2) the second model includes only non-U.S. carrier operations for the entire study period.

Airline business model differentiation. This analysis includes airlines deploying different business models, including both the FSC and LCC business models. To best account for the differences in airline business models on airline efficiency (specifically related to flight operations), the analysis reviewed the efficiencies of the FSC and LCC airlines separately. Two DEA models were executed for the study period data in aggregate (all years of study). One model specifically only contained data entries for FSC carriers. The second model only contained LCC carriers or data sets from air carriers operating point-to-point networks.

Validity testing. External validity was addressed by a demographics review of the sample, as described in the prior Demographics sub-section. The sample demographics were reviewed and assessed in comparison to the population. Any abnormal characteristics were assessed for impacts to the study.

As the study employs linear programming models, reliability testing of the model is not required. However, the reliability of the data is ensured by the BTS through their data collection methods. As defined in their Statistical Standards Manual (BTS, 2005), the BTS deploys several different strategies for data collection repeatability and data quality assurance. These strategies were developed to conform to requirements and guidance established by the U.S. Office of Management and Budget to ensure objectivity and integrity of information generated by U.S. federal agencies.

With respect to data collection, the BTS statistical methods utilize recurrent training for participants and defined collection methods to standardize the incoming data. In addition, reports and key performance indicators measure trends in the data allowing automatic notification of potential issues with the data collection. From a quality assurance perspective, the BTS also deploys protocols for quality verification, which includes an analysis of response rates and initiates a nonresponse bias evaluation if response rates fall below 70%.

In addition to the aforementioned strategies to ensure data reliability, the proposed study utilized qualitative review between the different models to demonstrate general repeatability of the models. The repeatability was assessed by comparing the results of a specific model to airline's business execution in the timeframe included in that model – e.g., reflect on 2013 events for the airlines versus their performance in the 2013 single-year analysis model. Qualitatively reviewing the top and bottom performers in the individual models to that year's business performance and noteworthy events helped establish the repeatability of the model.

Presentation of Results

The results described in this section are presented from the data processing phase of this study. These results include substantiation for conclusions related to the research questions as well as data reviewed to support validity confirmation.

Sample review. As described above, demographics of the sample are presented to help substantiate the representativeness of the sample for use in the study. The demographics include (but are not limited to) airline passenger traffic, operating costs, revenue, emissions, and environmental abatement. In addition, descriptive statistics for the inputs, intermediate outputs, and final stage outputs are presented. The descriptive statistics include annual and aggregate models, as well as the differentiated models for operating flag (U.S. versus international carriers) and operating business model (i.e. FSC versus non-FSC).

Airline efficiency. The results of the efficiency analysis are presented for all of the airlines in the study. Presentation of the analysis results include the input-output correlations and the efficiency ratios for the three stages (inputs, intermediate outputs, and final outputs).

Efficient versus inefficient carriers. After the DEA results are presented for all airlines, a comparison of the airlines is presented, highlighting those that demonstrate statistical efficiency or inefficiency. The presentation of efficient and inefficient carriers are presented for the annual and aggregate models, as well as the differentiated models for operating flag (U.S. versus international carriers) and operating business model (i.e. FSC versus non-FSC).

Recommendations for inefficient carriers. The conclusion of this proposed study includes recommendations for the airlines deemed by the analysis to be inefficient. Potential improvement strategies are conceived and presented based on the efficiency scores of the input and output variables.

The proposed methodology and procedures for this research study are outlined in the preceding chapter. The next chapter captures the results of the analysis.

CHAPTER IV

RESULTS

This study utilized airline operating data to assess and compare the operating efficiencies of each airline. A multi-stage data envelopment analysis (DEA) model was constructed to incorporate the constructs of revenue generation and carbon dioxide emissions abatement in the evaluation of efficiency. Annual data from 15 airlines were collected for the three-year period of study – 2013-2015. The multi-stage DEA was conducted for individual years as well as the entire study period to evaluate the air carrier business efficiency with respect to revenue generation and environmental impacts. Additional DEA models were constructed and deployed to segregate and compare airlines utilizing carrier flag affiliation (i.e. U.S.-owned airlines as opposed to international carriers) and the airline business model.

This section presents the demographics and descriptive statistics of the sample, as well as efficiency results from the different DEA models conducted. As DEA is a linear programming method of analytics, the results in this chapter are presented and discussed within the context of the specific models – i.e. whether or a not an airline was efficient, and what airlines defined the optimal production execution for a specific model. The Discussion and Recommendations sections in Chapter V reflect upon the results in context of the airlines' business philosophy, and then make airline-specific assessments.

Demographics

The 15 airlines in the study sample operate different business models and conduct their activities utilizing operational and administrative headquarters in different parts of the world. Both characteristics of the airlines included in the study ensure the study explores different airline business philosophies.

The multinational facet of the airline industry was the reason for selection of an intentionally diverse sample of the industry. Airlines in the United States have a significant focus on domestic operations. The size and frequency demand of the U.S. domestic air travel industry drive significant size and revenue generation focus in the regional and transcontinental markets. Some U.S. carriers also deploy international routes, which require significant investment in larger long-range aircraft and overseas hubs. European-based airlines may similarly have a mix of short and long-range operations. Due to the relatively closer proximity of different countries, even international legs may be shorter. This has led to a significant dichotomy between LCCs and the FSCs. As most of the LCCs reviewed do not report greenhouse gas emissions, the European carriers in this study are all FSCs. Emirates – the sole Middle East carrier in the study – operates predominantly long-range operations. Finally, Air Canada and the two Japanese carriers (All Nippon Airways and Japan Air Lines) both operate both domestic and international routes. However, the competition and smaller domestic markets reduces the size and overall revenues of these airlines.

In addition to the operating location, the airlines in the sample operate different business models with respect to the level of service. The FSC model is characterized by (1) traditional levels of amenities which are included as part of the fare cost, and (2) a route and scheduling strategy which leverages a large network of destinations supported by major hubs (the hub-and-spoke network strategy). Some of the other airlines in the sample operate the LCC business model where the airlines eliminate amenities and frills from their fares to provide an absolute low-cost option. Traditionally, these airlines operate point-to-point networks to avoid the costs of a large hub presence. Jet Blue and Alaska Airlines are two unique carriers who present the pure point-to-point operating model. The airlines focus their business strategy on particular routes and regions; however, they provide full-service offerings, as opposed to minimum-frills. As their operating network philosophy matches that of an LCC, these two airlines are reviewed as part of the LCC/P2P group.

The different operating bases and business models are further explored through the model results presented in this section. A table of the airlines, their location group, and business operating philosophy is presented in Table 2.

Table 2

Airline Operational Characteristics

Airline	Location Group	Operating Model
Air Canada	Non-U.S.	FSC
Air France – KLM	Non-U.S.	FSC
Alaska Airlines	U.S.	Point-to-Point
All Nippon Airways	Non-U.S.	FSC
American Airlines	U.S.	FSC
British Airways	Non-U.S.	FSC
Delta Air Lines	U.S.	FSC
Emirates	Non-U.S.	FSC
Japan Airlines	Non-U.S.	FSC
JetBlue Airways	U.S.	Point-to-Point
Lufthansa Airlines	Non-U.S.	FSC
Southwest Airlines	U.S.	LCC
United Airlines	U.S.	FSC

Descriptive Statistics

Descriptive statistics for each variable are presented in Table 3. From the original study sample, two airlines have been eliminated from the study (Etihad Airways and Virgin America); the exclusions are addressed in the following Missing Data & Outliers section. With those airlines eliminated, most variables have 100% of the data set values present for the study period. The specific omissions are for British Airways in 2015 when the airline did not publicly report in accordance with the expectations of the Global Report Initiative (GRI).

Table 3

Descriptive Statistics – All Airlines

Variable (units)	N	Minimum	Maximum	Mean	SD
OpExpenses ($1000s)	39	4,293,788	42,751,965	19,758,671	11,056,135
ASM (1000000s seat-mi.)	39	16,033	220,437	119,237	69,531
ECO2 (metrics tons CO_2)	39	2,292,719	31,522,487	17,050,836	9,942,884
AE ($)	38	0	21,324,498	1,464,402	4,795,230
RPM (1000000s pax–mi.)	39	12,883	188,375	97,201	58,682
CO2 (metrics tons CO_2)	38	4,337,568	42,300,000	20,656,127	12,204,412
NetIncome ($1000s)	39	(2,637,620)	10,549,234	1,158,784	2,180,254
OpRevenues ($1000s)	39	5,150,814	43,349,652	22,343,522	12,037,311

Note. N = Available data points; SD = Standard Deviation; OpExpenses = Total Operating Expenses; ASM = Available Seat Miles; ECO2 = Estimated CO_2 Emissions; AE = Abatement Expenses; RPM = Revenue Passenger Miles; CO2 = Net CO_2 Emissions; NetIncome = Net Income; OpRevenues = Passenger-based Operating Revenues.

The data gathered demonstrates that the airlines in the study represent a variety of operating models and states of success with respect to their business operations. The wide variation between the minimum and maximum operating expenses, available seat miles, revenue passenger miles, and revenues highlight the presence of both large FSCs as well as smaller carriers operating LCC or P2P business models. The data also shows a negative value for the lowest annual net income – both Air France and American Airlines reported negative net income in 2013; this breadth of income generation highlights that the study has captured airlines operating profitably as well as those struggling with profitability.

Missing Data

Due to missing data or data inconsistencies, three airlines had data removed from the study: British Airways, Etihad Airlines, and Virgin America. The quantity of missing data points for each variable is identified in Table 3 – only two data points are missing (one each for AE and CO2) which constitutes 2.6% missing data for those variables. Both missing values are part of the 2015 British Airways dataset detailed below. All other airlines in the study had complete data sets of observations for the three-year period. As the sample effectively is the population under study – airlines meeting the criteria of domestic or international traffic inclusive of the U.S. national air system, which also publicly report on environmental programs – the missing data does not impact the results of the study; instead the impacts are as noted below.

British Airways. As previously mentioned, British Airways did not report environmental data in 2015. As such, it was omitted from the 2015-specific analysis for all airlines. The flight and revenue data were included in the three-year cumulative studies, so the business operations (seat capacity and revenue generation) are included in all multi-year analyses that included international or full-service carriers. The expected effect is that British Airways performs relatively worse with regards to environmental efficiency (and therefore total efficiency) for the three-year studies. In a report by the

International Council on Clean Transportation (ICCT), it was identified that through a study period ending in 2014, British Airways had the worst fuel efficiency for any airline facilitating transatlantic flights (ICCT, 2015). As such, it is expected that a different airline would have been identified as the benchmark by the DEA analysis, even if British Airways' 2015 environmental numbers had been included.

Etihad Airlines. During the data gathering process, an international claim against Etihad Airlines was identified for part of the study period (Mouawad, 2015). The claim highlighted that Etihad intentionally does not disclose all the normal financial data that most U.S. and international carriers report – the allegations state that the omission is intentional to prevent discovery of excessive and unpublished financial benefits provided to the airline by the United Arab Emirates government. The claim goes on to highlight in specific business quarters, the airline might be operating with negative revenue generation (which is not identified in the public data made available). In light of the public discussions on the accuracy of Etihad Airlines published commercial data, Etihad was completely removed from this study.

Virgin America. In April 2016 (during the development of this dissertation's proposal and its subsequent approval), Virgin America was bought by the Alaska Air Group. Subsequent integration plans led to legal merger in January 2018 with discontinuation of the Virgin America brand (i.e. rebranding all aircraft, employees, and assets as Alaska Air) by April 2018. While the revenue generation and aircraft operations data is still available through the Bureau of Transportation Statistics' online archives, any environmental data found in corporate responsibility reports was to be merged with Alaska Airline moving forward. During the data collection phase, the

Virgin America corporate responsibility website was closed (with links to Alaska Air) and previous annual reports were no longer available. Therefore, Virgin America was omitted completely from this study.

To maintain the same number of total DMUs, Virgin Atlantic was considered as a replacement airline for utilization in this study. After review, Delta Air Line's 49% ownership of Virgin Atlantic suggested that a significant share of its business may be sustained through Delta code-sharing. To preclude any validity threats, Virgin Atlantic was not included in the sample data.

Reliability and Validity of Data

Reliability. As the study employs linear programming models, reliability testing of the model is not required. However, the reliability of the data is ensured by the Bureau of Transportation Statistics (BTS) through their data collection methods. As defined in their Statistical Standards Manual (BTS, 2005), the BTS deploys several different strategies for data collection repeatability and data quality assurance. These strategies were developed to conform to requirements and guidance established by the U.S. Office of Management and Budget to ensure objectivity and integrity of information generated by U.S. federal agencies.

The first component of strategies employed by BTS focuses on its rules and practices for data collection. The BTS statistical methods utilize recurrent training for participants and collection methods which are documented, reviewed, and internally approved to standardize the incoming data. These methods also prescribe specific requirements to the design of the different instruments used for data collection – which includes electronic instruments such as algorithms which may download data from an available database. Prior to deployment, any instrument must be verified through a pilot deployment in a representative environment of the population with known data to ensure the data points are collected accurately. In addition to the scrutiny around the data collection instruments and participants, reports and key performance indicators measure trends in the data allowing automatic notification of potential issues with the data collection once the methods are implemented.

A second component of the BTS strategy to ensure data reliability is the quality assurance component of BTS's data collection, cleaning, and preparation procedures. BTS's methods require vehicles by which the data is reviewed for omissions, duplicates, or contradicting data points within a dataset. Across the sample, BTS also identifies and removes data that may be biased due to response quantity. For this quality verification method, BTS conducts an analysis of response rates and initiates a nonresponse bias evaluation if unit response rates fall below 80%, or if specific item response rates fall below 70%. In addition to addressing whether or not the missing data is significantly changing the sample demographics, BTS also verifies that the unit or item nonresponses are random and are not induced by a failure in the data collection protocols.

Validity. The validity of the analysis is conducted by review of the sample demographics. The standard deviations and variation between minimum and maximum values presented in Table 3 signify very different values among the different airlines. For these variables, more variation is expected, as these variables denote the effectiveness of the business operation execution: abatement expense, actual emissions, and net profit. A greater level of variation signifies differences between the airlines in their business operations and results. The results are corroborated by the study sample definition and airline annual reports which present varying levels of operating success for airlines executing the hub-and-spoke, point-to-point, and LCC business models.

For the other variables, similar competitors in an established market should present similar operating performance indicators. The variety of operating networks and business models deployed by the airlines in the sample explains large standard of deviation values for the different variables.

To verify the validity of the sample, descriptive statistics were calculated for subsets of the sample to ensure there was less deviation between airlines operating similar models in similar regions as opposed to the statistical differences between philosophically different airlines. The first subset explored is the U.S.-based FSCs: American Airlines, Delta Air Lines, and United Airlines. Table 4 presents the descriptive statistics for datasets only associated with these airlines.

Table 4

Descriptive Statistics – U.S. Full-Service Carriers

Variable (units)	N	Minimum	Maximum	Mean	SD
OpExpenses ($1000s)	9	24,271,912	37,928,055	32,136,307	4,881,970
ASM (1000000s seat-mi.)	9	154,497	220,437	199,594	24,075
ECO2 (metrics tons CO_2)	9	22,093,023	31,522,487	28,541,919	3,442,766
AE ($)	9	0	21,324,498	3,746,128	7,278,304
RPM (1000000s pax–mi.)	9	128,410	188,375	167,610	178,561
CO2 (metrics tons CO_2)	9	31,548,428	42,300,000	37,566,660	4,389,108
NetIncome ($1000s)	9	(1,525,707)	10,549,234	2,736,953	1,113,817
OpRevenues ($1000s)	9	25,760,245	40,815,767	35,621,520	37,864,132

Note. OpExpenses = N = Available data points; SD = Standard Deviation; Total Operating Expenses; ASM = Available Seat Miles; ECO2 = Estimated CO_2 Emissions; AE = Abatement Expenses; RPM = Revenue Passenger Miles; CO2 = Net CO_2 Emissions; NetIncome = Net Income; OpRevenues = Passenger-based Operating Revenues.

Review of the descriptive statistics from the total sample (presented in Table 3) shows that the standard deviation is typically 51%-60% the value of the mean for all variables except Abatement Expense and Net Income. Reviewing the descriptive statistics of the same variables in Table 4 establishes that the data points for U.S-airlines operating FSC business models correlate very well – the standard deviations for the same variables are 10-15% of the mean.

Table 5 presents descriptive statistics for a subset of the sample only including non-U.S. airlines deploying the FSC business model. Table 6 presents descriptive statistics for the two U.S. airlines deploying a P2P business strategy – Alaska Airlines and JetBlue.

Table 5

Descriptive Statistics – Non-U.S. Full-Service Carriers

Variable (units)	N	Minimum	Maximum	Mean	SD
OpExpenses ($1000s)	21	9,355,684	42,751,965	19,252,405	9,202,855
ASM (1000000s seat-mi.)	21	16,033	207,244	109,242	61,703
ECO2 (metrics tons CO_2)	21	2,292,719	29,635,870	15,510,040	3,442,766
AE ($)	21	0	18,710,148	1,129,525	7,278,304
RPM (1000000s pax–mi.)	21	12,883	158,464	86,567	51,308
CO2 (metrics tons CO_2)	19	8,200,000	32,245,141	17,897,039	4,389,108
NetIncome ($1000s)	21	-2,637,620	3,897,931	600,546	1,173,023
OpRevenues ($1000s)	21	10,486,956	43,349,652	21,947,426	9,978,473

Note. OpExpenses = Total Operating Expenses; N = Available data points; SD = Standard Deviation; ASM = Available Seat Miles; ECO2 = Estimated CO_2 Emissions; AE = Abatement Expenses; RPM = Revenue Passenger Miles; CO2 = Net CO_2 Emissions; NetIncome = Net Income; OpRevenues = Passenger-based Operating Revenues.

Table 6

Descriptive Statistics – U.S. P2P Carriers

Variable (units)	N	Minimum	Maximum	Mean	SD
OpExpenses ($1000s)	21	4,293,788	5,308,982	4,759,378	434,802
ASM (1000000s seat-mi.)	21	30,417	49,347	39,333	6,878
ECO2 (metrics tons CO_2)	21	2,292,719	29,635,870	15,510,040	3,442,766
AE ($)	21	0	18,710,148	1,129,525	7,278,304
RPM (1000000s pax–mi.)	21	26,176	41,751	33,291	5,604
CO2 (metrics tons CO_2)	19	8,200,000	32,245,141	17,897,039	4,389,108
NetIncome ($1000s)	21	167,967	1,309,738	646,046	362,430
OpRevenues ($1000s)	21	5,150,814	6,416,127	5,630,514	406,271

Note. OpExpenses = Total Operating Expenses; N = Available data points; SD = Standard Deviation; ASM = Available Seat Miles; ECO2 = Estimated CO_2 Emissions; AE = Abatement Expenses; RPM = Revenue Passenger Miles; CO2 = Net CO_2 Emissions; NetIncome = Net Income; OpRevenues = Passenger-based Operating Revenues.

Reviewing the descriptive statistics of the non-U.S. FSC airlines also demonstrates a statistically closer grouping than the total sample. Using a similar method of comparison as before, the standard deviation as a fraction of the mean for all variables except Abatement Expense and Net Income is 22%-25%. While this is greater than the U.S.-carrier measure, the non-U.S. FSC airlines have greater variance in airline size. Air France-KLM and Lufthansa generate more than $35B in operating revenue in a single year. Air Canada, All Nippon Airways, and Japan Air Lines did not generate over $16B in the same period of study.

The descriptive statistics of Alaska Airlines and JetBlue also substantiate the validity assessment through strong correlation of key performance indicators. The ratio of standard deviation to mean for the previously mentioned variables (all except Abatement Expense and Net Income) ranged from 7%-17%. Specifically, this ratio was 7%-9% for the operating revenue and total operating expenses. When examining the capacity variables (ASMs and RPMs), the ratio of standard deviation to mean was approximately 17%. The net profit standard deviation is significantly higher, suggesting that while the two airlines are operating similar sized operations, one airline is far more successful at profit realization.

The quantitative review of the descriptive statistics of the sample and specific subsets establish that the sample data for airlines with similar business models and route networks presents similar key performance indicators for business operations, with exception to variables that would suggest greater efficiency or profitability: actual CO_2 emissions or net profits. This review validates the sample is representative of the population intended for study.

Data Envelopment Analysis

The following section presents DEA results utilizing the methodology described in Chapter III. DEA was conducted utilizing a multi-stage model. The model was bifurcated into two parts, each run as a two-stage analysis. The efficiencies of each analysis were combined to define the overall operating efficiency of the airline for the time period in analysis.

Interpretation of results. Review of DEA methodology in Chapter II establishes that a DMU can only be confirmed as operating on the efficient production frontier when its efficiency score is unity. Although an efficiency score below unity may still represent an efficient DMU, the analysis model is not corroborating the state of efficiency of that DMU. In addition to the results values, the VRS methodology used in this analysis follows the DEA principle of creating an efficient (i.e. benchmark) production frontier.

As presented in Chapter II, the frontier is a set with different combinations of variable values. As previously mentioned, the total operational efficiency score calculated in this study uses the multiplicative property (i.e. cross product) applied to the efficiency scores from two different multi-stage DEA calculations. The aforementioned aspects of the model construction and DEA methodology yield three key aspects for reviewing the results of this analysis: the different levels of efficient performance, the multiple definitions (i.e. values) of the efficient production frontier, and the interpretation of non-unity efficiency scores.

First, the airline DMUs in this study can demonstrate efficiency at three distinct levels. In each individual stage, a unity score will demonstrate that the firm is efficient for that specific stage. However, if the airline is not efficient in the other stage of that phase, it is not demonstrating efficient performance in the phase. Within the construct of the methodology established in the study, the airline can be described as demonstrating partially efficient behavior compared to the sample. If an airline possesses a unity score in both stages of a phase, the airline was operating efficiently. The total efficiency score for the airline may not have a total operating efficiency of unity through the model due to the cross-product with the efficiency of the other phase (where it was not efficient through that phase). For the methodology of this study, efficiency in a single phase does demonstrate a level of efficient performance, but only for specific aspects of the airline operating model. Finally, a firm may operate with a unity efficiency score in both phases (all four stages). A unity efficiency score would show efficient performance for the entire model.

Another aspect of the results requiring comprehension relates to the nature of a production frontier having multiple sets of values. Due to the number of variables and stages included in the model, different sets of values can demonstrate efficient production – i.e. there are multiple efficient frontier possibilities. From a model results perspective, the different contents of the production frontier provide different "closest benchmark" points for each of the different airlines in this study. This variety of available benchmarks will manifest in different benchmark references provided in the results for each stage for each inefficient airline.

The last aspect of interpreting the results of this study is the treatment of the scalar stage and total efficiency values (excluding the unity values demonstrating efficiency). When comparing the airline DMUs, the differences in non-unity efficiency scores within a stage are used to assess that an airline is closer to efficient production based upon its efficiency score. However, at the phase or full-model level, a comparison of non-unity scores requires careful review of each stage within the phase or model. As the phase and total scores are products of stage scores, a poor performance in one stage may mask the strong performance in other phases. Without understanding the individual stage scores, the wrong conclusion of relative distance to the efficient frontier is possible. This phenomenon is explored further with discussion on Alaska Airlines' results.

The results of this study show strong performance by Alaska Airlines in three of four stages; however, in some models, Alaska Airlines shows poor performance compared to the model-specific sample with respect to revenue generation. The results discussion and analysis presents that it may not be appropriate to conclude Alaska

Airlines underperformed another airline based on the operating efficiency score for the entire model.

Efficiency differences over time. An analysis of total operational efficiency inclusive of environmental abatement was conducted for all airlines for each individual year of the study period – 2013 through 2015. The airline efficiency scores for these models are presented in Table 7 (2013 results), Table 8 (2014 results), and Table 9 (2015 results). The stage-specific scores and benchmarks are tabulated in Tables A1-A12.

Table 7

2013 Operating Efficiency Results

Airline	1st Phase 1st Stage	1st Phase 2nd Stage	2nd Phase 1st Stage	2nd Phase 2nd Stage	Total Efficiency
Air Canada	1.00000	0.37664	1.00000	1.00000	0.37664
Air France – KLM	0.96758	1.00000	0.90797	0.84990	0.74666
Alaska Airlines	1.00000	1.00000	1.00000	0.33143	0.33143
All Nippon Airways	1.00000	0.42117	0.52991	1.00000	0.22318
American Airlines	0.84710	1.00000	0.99421	0.59424	0.50046
British Airways	1.00000	0.68627	1.00000	0.62725	0.43046
Delta Air Lines	1.00000	1.00000	0.75218	0.87240	0.65620
Emirates	1.00000	0.93740	0.91227	0.53433	0.45694
Japan Airlines	1.00000	0.47938	0.39998	1.00000	0.19174
JetBlue Airways	1.00000	0.97762	1.00000	0.29617	0.28954
Lufthansa Airlines	0.52609	0.91257	0.94162	1.00000	0.45206
Southwest Airlines	1.00000	0.85297	1.00000	0.51761	0.44151
United Airlines	1.00000	1.00000	0.72121	0.88321	0.63699

Table 8

2014 Operating Efficiency Results

Airline	1st Phase 1st Stage	1st Phase 2nd Stage	2nd Phase 1st Stage	2nd Phase 2nd Stage	Total Efficiency
Air Canada	1.00000	0.38800	1.00000	1.00000	0.38800
Air France – KLM	1.00000	0.99190	0.72334	1.00000	0.71748
Alaska Airlines	1.00000	1.00000	1.00000	0.36244	0.36244
All Nippon Airways	1.00000	0.45880	0.48085	1.00000	0.22061
American Airlines	0.76157	1.00000	0.99045	0.70825	0.53423
British Airways	1.00000	0.69287	1.00000	0.65765	0.45566
Delta Air Lines	0.95294	1.00000	1.00000	1.00000	0.95294
Emirates	0.88910	1.00000	0.84993	0.63898	0.48285
Japan Airlines	1.00000	0.51641	0.33361	0.97822	0.16853
JetBlue Airways	1.00000	0.98210	1.00000	0.33803	0.33198
Lufthansa Airlines	0.61330	0.85003	0.93753	1.00000	0.48875
Southwest Airlines	1.00000	0.47410	0.87228	1.00000	0.41355
United Airlines	0.94792	1.00000	0.80145	1.00000	0.75971

Table 9

2015 Operating Efficiency Results

Airline	1st Phase 1st Stage	1st Phase 2nd Stage	2nd Phase 1st Stage	2nd Phase 2nd Stage	Total Efficiency
Air Canada	1.00000	0.49755	1.00000	1.00000	0.49756
Air France – KLM	1.00000	0.99678	0.93221	0.81323	0.75566
Alaska Airlines	1.00000	1.00000	1.00000	0.41158	0.41158
All Nippon Airways	1.00000	0.42168	0.63568	1.00000	0.26805
American Airlines	0.73109	1.00000	0.79999	0.92818	0.54286
Delta Air Lines	1.00000	1.00000	1.00000	1.00000	1.00000
Emirates	1.00000	0.89504	0.79046	0.65101	0.46059
Japan Airlines	1.00000	0.49273	0.45512	1.00000	0.22425
JetBlue Airways	1.00000	1.00000	1.00000	0.40008	0.40008
Lufthansa Airlines	0.60252	0.77293	0.94216	1.00000	0.43877
Southwest Airlines	1.00000	0.96481	1.00000	0.57415	0.55395
United Airlines	1.00000	0.97621	0.82812	1.00000	0.80842

Note. British Airways is omitted from analysis due to lack of environmental data.

2013 results. In 2013, no airline's performance signifies obvious efficient operation in all stages of the model. Every airline shows efficient second stage performance in both phases. Air Canada and Alaska Airlines both demonstrate efficient performance in three of the four model stages; however, Air France-KLM holds the highest total efficiency score. Delta Air Lines and United Airlines are the only two airlines besides Air France-KLM with total efficiency scores significantly over 50%.

Review of the stage-specific scores and benchmarks in Tables A1-A4 present an additional layer of information in the results. While all but three of the airlines scored unity efficiency in the first stage of Phase 1, all of the FSCs utilized Emirates as a benchmark – suggesting that it was a better performing airline – with the exceptions of Delta Air Lines and United Airlines (the analysis presented that these airlines were defining their own efficient frontier values). Both Alaska Airlines and JetBlue also define their efficient frontier operating points. With the exception of the aforementioned airlines defining their own efficient frontiers, all of the remaining airlines used JetBlue's performance (in conjunction with Emirates) to define the efficient production frontier.

The first stage benchmarks specifically highlight that several airlines were operating at the efficient production frontier defined by the two-stage model. However, certain airlines performed so strongly in the first stage that their performance partially defined the efficient frontier for another efficient airline – i.e., an airline could execute the first stage more similarly to another airline and would remain on the efficient production frontier while increasing one of the intermediate outputs for the phase. It is noteworthy that Emirates served as a benchmark for all of the airlines – with the exception of the individual airlines that defined their own efficient frontiers. With a business strategy focusing on long-haul international routes, it makes sense that Emirates excels at maximizing seat generation per input costs (the key intermediate output of the phase).

Review of the second stage benchmarks in Table A2 shows a number of airlines obtaining a unity efficiency score within the stage. Each of these airlines defines its own production frontier, with the exception of Air France-KLM (who uses Alaska Airlines and Delta Air Lines to define its benchmark). Looking across the stage results, all of the remaining airlines either used a combination of Air Canada, Alaska Airlines, and Delta Air Lines to define the closest point on the efficient frontier. The use of multiple airlines for the efficient frontier is reasonable for the analysis model utilized in this study. All of the stages have either multiple inputs or outputs through the stage. The second stage of Phase 1 specifically evaluates efficiency in ASM conversion to RPMs, as well as carbon dioxide abatement. As the two processes are significantly different and independent, an improved performance level – i.e. performance on the efficient production frontier – will require performance improvements in multiple directions (or multiple variables) in order to approach benchmark-setting performance.

As previously discussed, the first stage of Phase 2 mimics the focus area (ASM conversion to RPMs and carbon dioxide abatement) of the previously discussed stage. Inclusion of this stage in a separate two-stage DEA model with the revenue realization stage helps differentiate which airlines are presenting high efficiency scores due to ASM conversion. The 2013 results presented in Table A3 show that the airlines with multi-airline benchmarks for every airline in the stage had the largest proportion (weighting) of the improvement defined by the performance of Air Canada or Alaska Airlines; Delta Air Lines supplied the other defining benchmark.

Reviewing the efficiency and efficient frontier definition data tabulated in Table A4 helps explain the benchmarks and efficiency scores in both the first and second stages of Phase 2. While four airlines obtain a unity efficiency score, only Air Canada defines its own point on the efficient production frontier. All Nippon Airways and Japan Airlines show Air Canada and Alaska Airlines as potential for efficient production improvements; Lufthansa shows Alaska Airlines and Delta Air Lines as potential improvements to efficient production. The results present that the Japanese airlines are optimized in their emissions abatement but need greater revenue generation. Lufthansa presents an optimized execution in revenue generation but has opportunities to further improve carbon dioxide emissions abatement.

2014 results. In 2014, no airline demonstrated efficient performance through the entire model (all four phases). Delta Air Lines obtained the highest score in total efficiency and demonstrated efficient performance in three of the four stages. However, Delta is one of five airlines not to post a perfect efficiency score in the first stage of Phase 1. The only two other airlines to demonstrate efficient performance in three of the stages are Alaska Airlines and Lufthansa Airlines. However, neither of those airlines demonstrated one of the top three total efficiency scores for this year; United Airlines and Air France-KLM possessed the second and third highest total efficiencies, respectively.

The first stage results and benchmarks presented in Table A5 show that most airlines demonstrated efficient performance through the first stage of Phase 1. The four airlines not demonstrating efficient performance were American Airlines, Delta Air

Lines, Emirates, and Lufthansa Airlines. These results depict that in 2014, these four carriers – all full-service carriers – struggled with conversion of input resources to ASMs compared to the other sample constituents. While full-service carriers typically lag behind low-cost carriers and point-to-point operators due to investment in more passenger services, the results of the first stage presents four full-service carriers operating efficiently in the model: Air Canada, Air France-KLM, All Nippon Airways, and Japan Airlines.

Air France-KLM and JetBlue defined the efficient frontier for most of the airlines in this phase. A notable observation in this model is that Emirates serves as a benchmark for both Delta Air Lines and United Airlines. This result is interesting as none of the three airlines presented efficient operations in this phase; however, Emirates underperformed the two airlines (of which it set a benchmark). Review of the analytical model design reveals that the operating expense inputs consumed in the first stage generate two intermediate outputs: available seat miles (ASMs) and estimated carbon dioxide emissions (ECO2). Review of business information of each of these three airlines presents that Delta Air Lines and United Airlines operate similar large FSC operations combining regional, transcontinental, and international routes, while Emirates operates a focused long-haul international FSC operation. Considering the seemingly anomalous results in context of the airlines' operating philosophies presents a possibility that Delta Air Lines and United Airlines may have been efficient in creating one of the two intermediate outputs but underperformed in creation of the other – in this case, to such a large extent that it shows the airline as not performing efficiently.

Review of the results for the second stage of Phase 1 (presented in Table A6) shows that only four of the airlines demonstrate efficient performance – Alaska Airlines, American Airlines, Delta Air Lines, and Emirates. Three of these four airlines define their own efficient frontier, while Emirates utilizes Alaska Airlines and Delta Air Lines as benchmarks. For the remaining airlines, three distinctive sets of efficient frontiers are defined as performance opportunities for a group of airlines. The first pair, Air Canada and Southwest Airlines, is benchmarked by the performance of Air Canada and American Airlines – with the benchmark weightings more heavily focused on American Airlines' performance. Combining these results with review of American Airline's annual reports (which highlight strong ASM to RPM conversion) suggests that Air Canada and Southwest Airlines both operated with relatively strong emissions abatement while they had opportunities to maximize RPM creation from their supply of ASMs.

The second group of inefficient airlines includes All Nippon Airways, British Airways, and Japan Airlines. Air Canada, Alaska Airlines, and Delta Airlines define the efficient frontier for these airlines' performance. With the efficient frontier definition coming from three efficiently-performing airlines, the results present that the rest of the sample has outperformed the inefficient airlines in this second group. The deficiencies in performance are for both RPM creation from ASMs and carbon dioxide emission abatement – i.e. there are multiple facets on which these airlines can improve performance to move toward the efficient production frontier.

The third group of inefficient airlines includes Air France-KLM, JetBlue, Lufthansa Airlines, Southwest Airlines, and United Airlines. The performance of each airline in this last group is benchmarked by Alaska Airlines and Delta Air Lines. In most cases, the closest points on the efficient frontier are defined by a much higher weighting toward Delta Air Lines, signifying that the airlines are operating closer to Delta Air Lines' position on the benchmark frontier, as opposed to Alaska Airlines. Reviewing these results suggests that each of the airlines with a strong Delta Air Lines benchmark factor is operating at or close to efficient operations with respect to RPM creation from ASMs (and has greater improvements to make with respect to carbon dioxide emissions abatement). JetBlue has the opposite ratio, with the closest point on the efficient frontier defined by an Alaska Airlines factor of 0.930. The interpretation of this result is inconclusive as JetBlue executes a similar business philosophy to Alaska Airlines – it is possible that Delta Air Lines serving as the other benchmark indicates that JetBlue would need more efficient creation of RPMs in order to reach the efficient frontier. Air Canada's almost equal weighting between the Alaska Airlines and Delta Air Lines benchmarks suggests that Air Canada is equidistant from the efficient production frontier, whether it pursues greater emissions abatement or improved RPM creation.

The efficiency scores and benchmarks for the first stage of Phase 2 tabulated in Table A7 present five airlines with efficient performance: Air Canada, Alaska Airlines, British Airways, Delta Air Lines, and JetBlue. Air Canada and Delta Air Lines are the only DMUs to define their optimal efficient frontier operations using their own individual performance. British Airways' efficient stage score uses Alaska Airlines and Delta Air Lines as benchmarks. Alaska Airlines and all of the inefficiently performing airlines had benchmark opportunities set through a combination of Air Canada, Alaska Airlines, and Delta Air Lines.

The efficiency scores and benchmarks for the second stage of Phase 2 tabulated in Table A8 present that half of the model sample demonstrates efficient performance. Air Canada, Delta Air Lines, and Lufthansa each individually define their own efficient frontier positions. Four of the remaining efficient airlines (Air France-KLM, All Nippon Airways, Southwest Airlines, and United Airlines) have efficient frontier improvement opportunities defined by Air Canada and Lufthansa Airlines. The last efficient airline, United Airlines, has improvement opportunities defined by Delta Air Lines and Lufthansa Airlines.

Though no single airline demonstrates efficiency throughout the 2014 single-year model, Alaska Airlines and Delta Air Lines both stood out as performers who defined the closest efficient frontier positions for other airlines in most stages, as well as most often individually defining their own efficient frontier position.

2015 results. In the 2015 single-year model, Delta Air Lines again scores the highest overall total efficiency ranking. Different from the 2014 single-year model, Delta demonstrates efficient production performance in all stages of the model. Alaska Airlines and JetBlue are the only other airlines to demonstrate efficiency in at least three out of the four model stages. United Airlines and Air France-KLM demonstrate the second and third highest total efficiency scores, respectively.

The efficiency scores and benchmarks for the first stage of Phase 1 tabulated in Table A9 present that all but two airlines demonstrate efficient performance relative to the model (American Airlines and Lufthansa are the only two inefficient airlines). Air France-KLM, Alaska Airlines, Delta Air Lines, Emirates, and JetBlue each individually define their positions on the efficient production frontier. Air Canada, All Nippon

Airways, Japan Airlines, and Southwest Airlines all present efficient performance, though the model results identify improvement opportunities for these four airlines defined by the performance of Air France-KLM and JetBlue. The final efficient airline, United Airlines, uniquely has a performance improvement opportunity defined using the performance of Delta Air Lines and Emirates.

The efficiency scores and benchmarks for the second stage of Phase 1 identify four airlines operating efficiently: Alaska Airlines, American Airlines, Delta Air Lines, and JetBlue. Each of the efficient airlines individually defines its own position on the efficient production frontier. The remaining airlines have mostly dissimilar benchmarks, which are tabulated along with the individual efficiency scores in Table A10. An interesting note from the results is that Air Canada's performance (in conjunction with the performance of a few other airlines) is used to define performance improvement opportunities for itself and four other airlines, even though Air Canada alone does not demonstrate efficient performance. As discussed for this stage in previous models, the different objectives of the ASM to RPM conversion and carbon dioxide abatement allow the airlines to use different strategies to pursue operating improvement toward the efficient production frontier. The presence of Air Canada in defining production opportunities suggests that those airlines may approach the efficient frontier from their current operational location by improving their carbon emissions abatement.

The results from the first stage of Phase 2 provide some corroboration to observations made in the previous stage. The results in Table A11 present efficient performance from Air Canada, Alaska Airlines, Delta Air Lines, JetBlue, and Southwest Airlines. Air Canada and Delta Air Lines individually define their own positions on the efficient frontier. Air France-KLM and Southwest Airlines have performance improvement opportunities defined by Alaska Airlines and Delta Air Lines. Finally, Alaska Airlines has opportunities defined by Air Canada, Delta Air Lines, and itself. The inefficient airlines all have reference benchmarks defined by the aforementioned Alaska Airlines / Delta Air Lines or Air Canada / Alaska Airlines / Delta Air Lines combinations.

The 2015 single-year model results tabulated in Table A12 present six efficiently performing airlines in the second stage of Phase 2. Air Canada, Delta Air Lines, and Lufthansa Airlines each individually define their own positions on the efficient frontier. All Nippon Airways and Japan Airlines demonstrate efficient performance, while possessing performance improvement opportunities defined by Air Canada and Lufthansa Airlines. Finally, United Airlines demonstrates efficient performance while having improvement opportunities defined by Delta Air Lines and Lufthansa Airlines. Three of the inefficient airlines (Alaska Airlines, JetBlue, and Southwest Airlines) have reference efficient frontier positions defined by Air Canada and Lufthansa Airlines. Alaska Airlines and JetBlue both have high weights associated with the Air Canada benchmark factor, suggesting that they have strong revenue generation relative to the emissions abatement input (signifying strong emissions abatement). Conversely, Southwest Airlines presents a 0.935 weight to the Lufthansa Airlines efficient frontier factor, suggesting its revenue generation as related to RPMs is at or close to efficient performance. The remaining three airlines (Air France-KLM, American Airlines, and Emirates) have their closest efficient frontier position completely defined by Lufthansa's 2015 performance.

The 2015 single-year model presented the first model of this study with an airline demonstrating efficient production throughout all stages of the model. As with the 2014 single-year model results, Alaska Airlines presents itself as the primary airline defining the efficient production frontier with respect to carbon dioxide abatement.

2013-2015 combined three-year study. The analysis for the combined study period was conducted separately – not calculated as a combination of individual year efficiencies. The efficiency results for each stage of this analysis are presented in Table 10.

Table 10

Total Efficiency Results – 3 Year Study Period (2013-2015)

Airline	1st Phase 1st Stage	1st Phase 2nd Stage	2nd Phase 1st Stage	2nd Phase 2nd Stage	Total Efficiency
Air Canada	1.00000	0.42263	1.00000	1.00000	0.42264
Air France – KLM	0.99233	1.00000	0.92276	0.83220	0.76203
Alaska Airlines	1.00000	1.00000	1.00000	0.36631	0.36631
All Nippon Airways	1.00000	0.43871	0.54746	1.00000	0.24018
American Airlines	0.79069	1.00000	0.91702	0.73383	0.53209
British Airways	1.00000	0.69325	1.00000	0.64631	0.44805
Delta Air Lines	0.98210	1.00000	1.00000	1.00000	0.98210
Emirates	0.91302	1.00000	0.84028	0.60418	0.46352
Japan Airlines	1.00000	0.49746	0.38924	1.00000	0.19363
JetBlue Airways	1.00000	0.98628	1.00000	0.34205	0.33736
Lufthansa Airlines	0.57807	0.84035	0.94035	1.00000	0.45681
Southwest Airlines	1.00000	0.76289	0.95937	1.00000	0.73190
United Airlines	0.95086	1.00000	0.72635	0.97626	0.67426

Note. British Airways data includes flight capacity (seat miles) and revenue generation from 2015, but no environmental data.

Similar to the 2014 single-year study results, no airline demonstrates efficient performance through every stage of this analysis model. Delta Air Lines obtains the highest total efficiency score (over 98%). Air France-KLM and Southwest Airlines are the only other airlines with total efficiency scores over 70%. Air Canada and Alaska Airlines are the only carriers besides the benchmark (i.e. Delta Air Lines) to demonstrate efficient operations in three of four of the stages.

Table A13 presents the first stage efficiency scores and performance benchmarks of each airline in the combined three-year model, identifying five efficient airlines (British Airways' efficient performance is not recognized due to the unavailability of environmental data). Alaska Airlines and JetBlue are the only two efficient airlines who each individually define their own positions on the efficient frontier. The remaining efficient airlines had performance improvement opportunities defined by Air France-KLM and JetBlue.

The results for the second stage of Phase 1 are presented in Table A14, identifying six airlines demonstrating efficient performance. Alaska Airlines, American Airlines, and Delta Air Lines each individually define their own positions on the efficient production frontier. The remaining efficient airlines use Alaska Airlines and Delta Air Lines to define performance improvement opportunities. The two Japanese carriers perform inefficiently and have performance benchmarks defined by Air Canada, Alaska Airlines, and Delta Air Lines. The remaining inefficient airlines identified in this stage have the closest operating positions defined by Alaska Airlines and Delta Air Lines, with the exception of Air Canada. Air Canada's improvement opportunity is defined by American Airlines and itself – though it demonstrates inefficient performance in the stage. When the Air Canada performance is framed against all the other inefficient airlines utilizing Alaska Airlines and Delta as benchmarks, the comparison suggests that

Alaska Airlines and Delta Air Lines defined the greatest extremes in frontier boundaries for emissions abatement and ASM conversion to RPMs, respectively. Air Canada did not perform on the efficient frontier, but its own benchmark definition suggests that it executed strong emissions abatement (relative to the other DMUs in the model), and its path to the efficient frontier requires improvements in ASM to RPM conversion. American Airlines' identification as Air Canada's other benchmark suggests that American Airlines position on the efficient frontier has greater ASM to RPM conversion efficiency than Delta Air Lines, but a lower emissions abatement efficiency.

Table A15 presents the three-year combined model efficiency scores and benchmarks for the first stage of Phase 2. The stage results identify four efficient airlines (British Airways is not considered as previously noted): Air Canada, Alaska Airlines, Delta Air Lines, and JetBlue. Only Air Canada and Delta Air Lines individually define their optimal positions on the efficient frontier – a shift from previous model results where typically only Alaska Airlines set its own benchmark in this stage. This change from previous results may be an artifact of using three years of data to define performance. In individual-year models, Alaska Airlines serves as its own benchmark because it defines the emissions abatement extreme of the efficient frontier; in a three-year sample, Air Canada and Delta Air Lines demonstrate comparable emissions abatement while also surpassing Alaska Airlines with respect to ASM conversion to RPMs.

The results of the second stage of Phase 2 are presented in Table A16, identifying six airlines performing efficiently. Air Canada, Delta Air Lines, Lufthansa Airlines, and Southwest Airlines all individually define their optimal positions on the efficient frontier.

All Nippon Airways and Japan Airlines, while performing efficient within the model, have performance opportunities defined by Air Canada and Lufthansa Airlines. All inefficient airlines have their benchmarks defined by Lufthansa alone, or a combination of Air Canada and Lufthansa Airlines' performance.

Summary of individual and three-year model results. A summary of the total efficiencies for each analysis year, the combined total efficiencies, and an efficiency average are presented in Table 11.

Table 11

Total Efficiency Summary

Airline	2013	2014	2015	3-Year Analysis	3-Year Average
Air Canada	0.37664	0.388	0.49756	0.42264	0.42073
Air France – KLM	0.74666	0.71748	0.75566	0.76203	0.73993
Alaska Airlines	0.33143	0.36244	0.41158	0.36631	0.36848
All Nippon Airways	0.22318	0.22061	0.26805	0.24018	0.23728
American Airlines	0.50046	0.53423	0.54286	0.53209	0.52585
British Airways	0.43046	0.45566	N/A	0.44805	0.44306
Delta Air Lines	0.65620	0.95294	1.00000	0.98210	0.86971
Emirates	0.45694	0.48285	0.46059	0.46352	0.46679
Japan Airlines	0.19174	0.16853	0.22425	0.19363	0.19484
JetBlue Airways	0.28954	0.33198	0.40008	0.33736	0.34053
Lufthansa Airlines	0.45206	0.48875	0.43877	0.45681	0.45986
Southwest Airlines	0.44151	0.41355	0.55395	0.73190	0.46967
United Airlines	0.63699	0.75971	0.80842	0.67426	0.73504

Note. British Airways data includes flight capacity (seat miles) and revenue generation from 2015, but no environmental data.

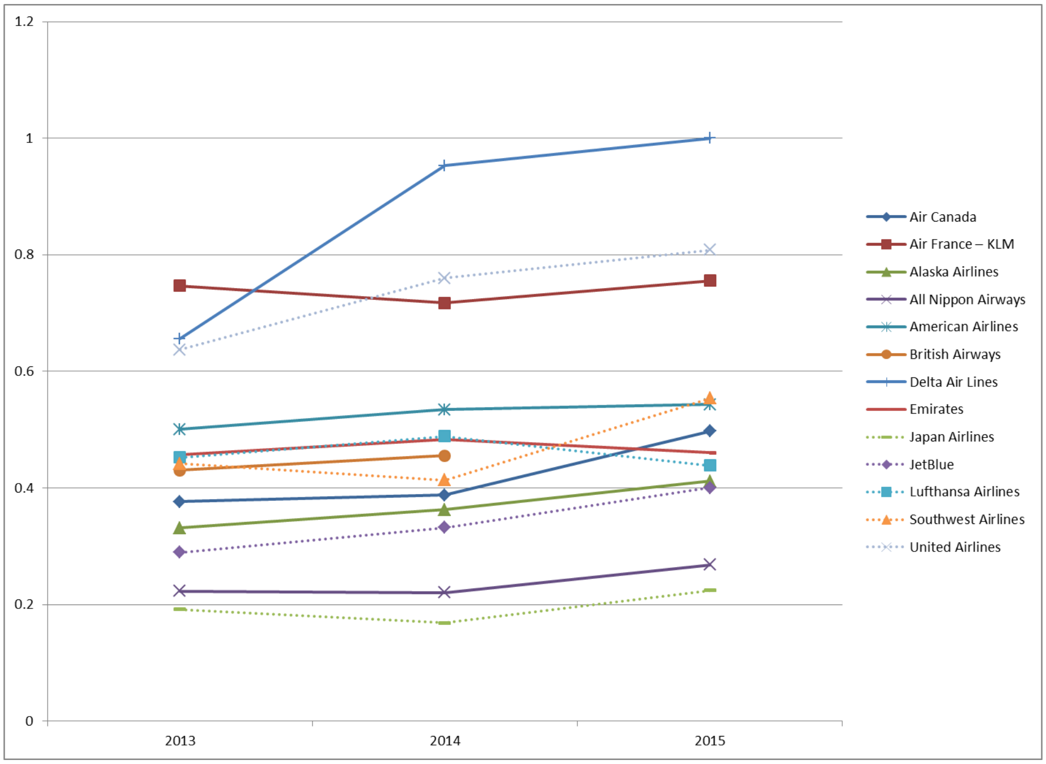

Figure 13. Airline annual efficiency performance.

Figure 13 graphically presents the annual total efficiency scores for each airline over the three years of the study period. From 2013 to 2014, Delta Air Lines and United Air Lines show discernible improvements in annual efficiency, while Air France-KLM and Southwest Airlines show reductions in total efficiency relative to the sample. From 2014 to 2015, Delta Air Lines and United Airlines continue to improve, though with less improvement relative to the 2013-to-2014 change. Southwest Airlines makes a significant improvement, surpassing its 2013 efficiency score. Both Emirates and Lufthansa Airlines demonstrate reductions in total efficiency from 2014 to 2015, after making marginal improvements from 2013 to 2014.

U.S. versus non-U.S. airlines. The study sample airlines were separated into a U.S.-based sample and a non-U.S.-based sample. The DEA methodology was applied to these two samples for the entire three-year study period.

U.S. carriers model. The overall efficiency scores are presented in Table 13. No airline presents efficient performance throughout all stages of the model; Alaska Airlines and Delta Air Lines both demonstrate efficient performance in three of four stages.

Table 12

Total Efficiency Results – U.S.-based Carriers (2013-2015)

Airline	1st Phase 1st Stage	1st Phase 2nd Stage	2nd Phase 1st Stage	2nd Phase 2nd Stage	Total Efficiency
Alaska Airlines	1.00000	1.00000	1.00000	0.37194	0.84299
American Airlines	0.74644	0.86405	0.88940	0.85779	0.83942
Delta Air Lines	0.81072	1.00000	1.00000	1.00000	0.95268
JetBlue Airways	1.00000	0.72353	0.96313	0.34852	0.75880
Southwest Airlines	1.00000	0.53671	0.92038	1.00000	0.86427
United Airlines	0.79160	0.92979	0.85647	0.95622	0.88352

The efficiency scores and benchmarks for the first stage of Phase 1 tabulated in Table A17 present that Alaska Airlines, JetBlue, and Southwest Airlines demonstrated efficient performance relative to the model. Alaska Airlines and JetBlue each individually define their efficient frontier positions. The three FSCs – American Airlines, Delta Air Lines, and United Airlines – all demonstrate inefficient performance. The results are corroborated by business practices identified in the literature review regarding FSC versus LCC cost structures. As part of their operating philosophy, the FSCs are operating short flights from smaller airports to bring passengers in to their hub airports. In the same domestic market environment, the LCC or regional airlines are operating point-to-point operations. The relative lower seat capacity of these shorter FSC flights feeding the hubs brings down their efficiency in creating ASMs from the input resources.

Table A18 presents the individual efficiency scores and benchmarks of the second stage of Phase 1. Alaska Airlines and Delta Air Lines are the only airlines identified as producing efficiently, and each individually defines its efficient frontier position. The remaining airlines have production opportunities defined by Alaska Airlines and Delta Air Lines' performance. Combining these results with review of the airline business philosophies and airline annual reports suggests that Delta Air Lines' performance is establishing the maximum performance boundary of the efficient production frontier with respect to ASM conversion to RPMs. Conversely, Alaska Airlines' performance is defining the emissions abatement performance boundary of the efficient production frontier.

The efficiency scores and benchmarks for the first stage of Phase 2 tabulated in Table A19 again define that Alaska Airlines and Delta Air Lines perform efficiently through the stage, while each individually defining its own efficient frontier position. By executing efficient performance in both the second stage of Phase 1 as well as the first stage of the second stage, the two airlines establish confidence that they are both executing efficiently to the model with respect to ASM to RPM conversion and carbon dioxide emissions abatement.

Table A20 presents the efficiency score and benchmark results for the second stage of Phase 2, identifying Delta Air Lines and Southwest Airlines as demonstrating efficient performance; both airlines each individual define their own performance benchmarks. The inefficient airlines each utilize Delta Air Lines or Southwest Airlines to define the closest position on the efficient frontier. The results of this stage align with the results observed in the other models. Alaska Airlines and JetBlue generate far less revenue due to the limited size of their operations compared with the other airlines in this model. Southwest Airlines' efficient production highlights the potential of the LCC business philosophy.

Alaska Airlines and Delta Air Lines both demonstrate efficient operations in three stages; however, Delta Air Lines presents the highest total efficiency for the U.S.-carrier group. Detailed review of the individual stage results highlight that Alaska Airlines defines the optimal performance for this model with respect to carbon dioxide emissions abatement.

Non-U.S.-carriers model. The overall efficiency scores for each stage are presented in Table 13. No airline demonstrates efficient performance throughout every stage of the model; Air Canada is the only airline to demonstrate efficient performance in three of four stages.

Table 13

Total Efficiency Results – Non-U.S.-based Carriers (2013-2015)

Airline	1st Phase 1st Stage	1st Phase 2nd Stage	2nd Phase 1st Stage	2nd Phase 2nd Stage	Total Efficiency
Air Canada	1.00000	0.72414	1.00000	1.00000	0.72415
Air France – KLM	1.00000	1.00000	0.93014	0.83220	0.77406
All Nippon Airways	1.00000	0.53671	0.55155	1.00000	0.29602
British Airways	1.00000	0.76049	1.00000	0.65139	0.49537
Emirates	1.00000	1.00000	0.84700	0.60418	0.51174
Japan Airlines	1.00000	0.86406	0.39001	1.00000	0.33699
Lufthansa Airlines	0.52171	0.92978	0.94787	1.00000	0.45979

Note. British Airways data includes flight capacity (seat miles) and revenue generation from 2015, but no environmental data.

The efficiency scores and benchmarks for the first stage of Phase 1 tabulated in Table A21 present that every airline except Lufthansa Airlines demonstrated efficient performance relative to the model. Air France-KLM, Emirates, and Japan Airlines each individually define their position on the efficient frontier. Air Canada and All Nippon Airways present efficient performance, though the model results identify improvement opportunities for these three airlines defined by Air France-KLM and Japan Airlines. Lufthansa Airlines inefficient performance has the closest opportunities to move to the efficient frontier defined by Air France-KLM’s performance.

Table A22 presents the individual efficiency scores and benchmarks of the second stage of Phase 1. Air France-KLM and Emirates are the only airlines identified as producing efficiently, and each individually defines its position on the efficient production frontier. Lufthansa Airline’s inefficient performance is again benchmarked solely by Air France-KLM’s performance. The remaining airlines have the closest improvement opportunities to move to the efficient frontier defined by Air Canada and Air France-KLM. The benchmark reference to Air Canada’s production (which does not demonstrate efficient performance) is an interesting result previously observed in another model. The three benchmark combinations established in this model stage were: Emirates (alone); Air France-KLM (alone); and a combination of Air Canada and Air France-KLM. Combining these results with review of the airline business philosophies and airline annual reports suggests that Emirates’ performance is establishing the maximum performance boundary of the benchmark frontier with respect to ASM conversion to RPMs. Conversely, Air Canada’s performance demonstrated the greatest level of emissions abatement, but its performance in converting ASMs to RPMs was not strong enough for its total stage performance to sit on the efficient production frontier. Air France-KLM defines a production point on the frontier with greater environmental abatement than Emirates, though with lower emissions abatement performance than Air Canada.

The efficiency scores and benchmarks for the first stage of Phase 2 tabulated in Table A23 present that only Air Canada performs efficiently through the stage, while individually defining its own position on the efficient production frontier. Air Canada's efficient performance here (while being identified as inefficient in the previous similar stage) highlights a scenario – established as an artifact caused by the model design – identified at the beginning of the section. Air Canada is the only efficient airline in this parallel stage, while it presented inefficient performance in the previous stage. The model design utilizes the same stage construction for the second stage of Phase 1, as well as the first stage of Phase 2. The model design evaluates the airline's performance for the same measures while paired in two different optimization partnerships – i.e. Phase 1 pairs the stage with ASM creation efficiency, while Phase 2 pairs this same stage with revenue realization from RPMs. Reviewing the results of these two stages together, Air Canada does seem to define the stage-specific efficient frontier with respect to emissions abatement. The inefficient score defined by the second stage of Phase 1 highlights that Air Canada's performance with respect to ASM and RPM generation lagged the execution of other airlines in the sample.

Table A24 presents the efficiency score and benchmark results for the second stage of Phase 2, identifying four airlines demonstrating efficient performance. Air Canada and Lufthansa Airlines each individually define their positions on the efficient frontier. All Nippon Airways and Japan Airlines present efficient performance; however, an opportunity to improve variable output on the efficient production frontier is identified using Air Canada and Lufthansa Airlines performance. Emirates inefficient performance shows that the closest opportunity to the efficient frontier is defined by Lufthansa Airlines; this result suggests that Emirates emissions abatement performance is inefficient (relative to the stage participants) enough that its best strategy to improve to the efficient frontier is through revenue generation and RPM maximization.

Air Canada is the only carrier to demonstrate efficient operations in three stages; however, Air France-KLM presents the highest total efficiency for the non-U.S.-carrier group. Detailed review of the individual stage results and benchmarks highlight that Air Canada defines optimal performance for this model with respect to carbon dioxide emissions abatement.

Airline business model differentiation. The study sample airlines were separated into two groups based upon their business models. The first group contains all carriers that operate the full-service carrier (FSC) model. The second group includes airlines operating the low-cost carrier (LCC) model and/or point-to-point (P2P) operations with flying amenities in line with the FSC offering.

Full-service carriers. The efficiency results for the FSC airlines are presented in Table 14. No airline demonstrates efficient performance through all four stages of the model; Air Canada and Delta Air Lines achieve efficient production in three of the four stages.

Table 14

Total Efficiency Results – FSC Airlines (2013-2015)

Airline	1st Phase 1st Stage	1st Phase 2nd Stage	2nd Phase 1st Stage	2nd Phase 2nd Stage	Total Efficiency
Air Canada	1.00000	0.58662	1.00000	1.00000	0.58662
Air France – KLM	1.00000	0.99371	0.92437	0.83220	0.76443
All Nippon Airways	1.00000	0.53358	0.54951	1.00000	0.29321
American Airlines	0.79069	1.00000	0.91863	0.73383	0.53302
British Airways	1.00000	0.76049	1.00000	0.64866	0.49330
Delta Air Lines	0.98210	1.00000	1.00000	1.00000	0.98210
Emirates	1.00000	0.92094	0.84175	0.60418	0.46836
Japan Airlines	1.00000	0.85998	0.38963	1.00000	0.33507
Lufthansa Airlines	0.57807	0.84093	0.94200	1.00000	0.45792
United Airlines	0.95089	1.00000	0.72762	0.97626	0.67547

Note. British Airways data includes flight capacity (seat miles) and revenue generation from 2015, but no environmental data.

The efficiency scores and benchmarks for the first stage of Phase 1 tabulated in Table A25 present five airlines producing efficiently relative to the model. Air France-KLM, Emirates, and Japan Airlines each individually define their own positions on the efficient frontier. Air Canada and All Nippon Airways present efficient performance, though the model results identify improvement opportunities for these three airlines with Air France-KLM and Japan Airlines' performance – it should be noted that this stage results are similar to those from the first stage of the non-U.S. carrier model. American Airlines, Delta Air Lines, and United Airlines all demonstrate inefficient performance; American Airlines has improvement opportunities defined by Air France-KLM and Emirates, while Delta Air Lines and United Airlines have opportunities defined by Emirates and United Airlines. The model presents that the closest position on the efficient frontier relative to Lufthansa Airlines inefficient performance is defined by Emirates' performance.

Table A26 presents the individual efficiency scores and benchmarks of the second stage of Phase 1. Opposite of the results of the first stage, American Airlines, Delta Air Lines, and United Airlines are the only carriers to demonstrate efficient production. American Airlines and Delta Air Lines each individually define their own positions on the efficient frontier; United Airlines presents efficient production but has performance improvement opportunities defined by Air Canada and Delta Air Lines. Air Canada's inefficient performance has the opportunity for the closest point on the efficiency frontier defined by its own performance and American Airlines. As discussed in previous models, this result suggests that Air Canada's emissions abatement performance has helped define the benchmark frontier; however, the airline's ASM to RPM conversion performance is low enough that it overall performs inefficiently to the model's efficient frontier definition. Air Canada and Delta Air Lines benchmark the remaining inefficient airlines.

The efficiency scores and benchmarks for the first stage of Phase 2 tabulated in Table A27 present that only Air Canada and Delta Air Lines perform efficiently through the stage, while each individually defines its position on the efficient frontier. Air Canada and Delta Air Lines benchmark the remaining inefficient airlines. This model presents the strongest confirmation between the results from the second stage of Phase 1 and the corresponding results of the first stage of Phase 2. The high level of corroboration clearly establishes efficient performance; the relative relationships of different airlines to each of these benchmarks propose that Air Canada defines the emissions abatement component of the efficient frontier, while Delta Air Lines demonstrates best-in-class ASM conversion to RPMs.

Table A28 presents the efficiency score and benchmark results for the second stage of Phase 2, identifying five airlines demonstrating efficient performance. Air Canada, Delta Air Lines, and Lufthansa Airlines each individually define their own positions on the efficient frontier. All Nippon Airways and Japan Airlines present efficient performance; however, an opportunity to improve variable output on the efficient production frontier is identified using Air Canada and Lufthansa Airlines' performance. It should be noted that the same efficient performance (with improvement opportunities defined by Air Canada and Lufthansa) was presented as the corresponding stage results in the non-U.S. carriers model. The model presents that the closest point to the efficient frontier from Emirates inefficient performance is defined by Lufthansa Airlines. Similar to the non-U.S. carrier model, this final stage result suggests that Emirates' emissions abatement performance is inefficient (relative to the stage participants) and its best strategy to improve to the efficient frontier is through revenue generation and RPM maximization.

For the full-service carrier group, Air Canada and Delta Air Lines both demonstrate efficient operations in three out of the four stages. Review of the individual stage scores and benchmarks suggests that Air Canada defines the efficient production frontier relative to emission abatement. However, Delta Air Lines' may demonstrate the most efficient performance by a full-service carrier over the three-year study period. The airline presents its only inefficient performance in the first stage of the model. The previous discussion that rationalized FSCs will have relatively lower ASM production relative to input costs – due to their higher service level – is irrelevant as this is an FSC-only model. However, Delta Air Lines' performance paralleled the other three large

U.S. FSCs, suggesting there may be a higher cost structure associated with those carriers competing in both large domestic and international markets. If the first stage inefficiency (performing at 98%) is due to a factor specific to the U.S.-market, then Delta Air Lines could be considered the most efficiently producing FSC relative to the model.

Low-cost and point-to-point carriers. The second model created to analyze airline efficiency based on business operation philosophy focused on the operational production of the LCC and P2P carriers. The efficiency results for the LCC/P2P airlines, presented in Table 15, establish Alaska Airlines as an efficient airline throughout the model.

Table 15

Total Efficiency Results – LCC/P2P Airlines (2013-2015)

Airline	1st Phase 1st Stage	1st Phase 2nd Stage	2nd Phase 1st Stage	2nd Phase 2nd Stage	Total Efficiency
Alaska Airlines	1.00000	1.00000	1.00000	1.00000	1.00000
JetBlue Airways	0.83594	1.00000	0.71975	1.00000	0.60166
Southwest Airlines	0.26806	1.00000	0.30502	1.00000	0.08177

The efficiency scores and benchmarks for the first stage of Phase 1 tabulated in Table A29 presents Alaska Airlines producing efficiently relative to the model. Alaska Airlines individually defines its own position on the efficient frontier, while also serving as the benchmark for the two inefficient airlines in the model.

Table A30 presents the individual efficiency scores and benchmarks of the second stage of Phase 1. The results of this phase present that each airline is producing efficiently. The unity efficiency scores appear to be driven by the small number of DMUs, but review of the airline annual reports corroborates the observed results of this stage. Each of the three airlines deploys a niche business strategy specifically tailored for their own success. Due to the service levels and locations of their services, all three airlines will compete often with regional airlines. Due to the lack of public published emissions data, the regional airlines are not part of this study. However, the literature review supports the conclusion that these three airlines are efficient versus their competitors, a lot of whom are not part of this study. This situation yields a stage where all three airlines demonstrate efficiency.

The efficiency scores and benchmarks for the first stage of Phase 2 tabulated in Table A31 presents that only Alaska Airlines performs efficiently through the stage, while serving as the benchmark for all airlines in the model. As discussed in review of the previous model results, the results of this stage are best reviewed while comparing to the results of the previous stage. The previous stage's results suggest that all three airlines performed efficiently with respect to emissions abatement and ASM to RPM conversion when considering their relative efficiency in producing ASMs from input resources. The results of this stage present that Alaska Airlines demonstrates the greatest efficiency in emissions abatement and ASM to RPM conversion in the context of revenue generation.

Table A32 presents the efficiency score and benchmark results for the second stage of Phase 2, identifying five airlines demonstrating efficient performance. The results of this stage present that each airline is producing efficiently, and therefore defines its own position on the efficient frontier. In alignment with the results discussion for the second stage of Phase 1, the efficient performance by all model participants may be due to the fact that each of this models' participants are successful airlines operating a niche business model, and their primary competitors are not included in the model due to data availability – or are FSCs.

The results of this model raise questions regarding Southwest Airlines' performance. Review of exigent literature suggests that Southwest Airlines' business model would show it to have greater ASM creation – and perhaps greater ASM to RPM conversion efficiency – than the other model participants. The results of previous models have established that ASM creation efficiency, ASM to RPM conversion efficiency, and revenue generation are all recognized in the generic model's architecture – and will significantly influence the total efficiency score. The results of this model suggest that the LCC business model may be less efficient in context of this model.

For the airlines deploying focused business models, Alaska Airlines clearly defined the efficient production frontier with respect to emissions abatement and revenue generation. Every airline in this group demonstrated efficient business operations in the second stages of both phases.

Summary

A multi-stage data envelopment analysis model was executed on the study sample's operating, revenue, and environmental impact data. The sample was examined using this analysis model while varying several factors, including the time period of study, the airline's domestic operations home, and the airline business model.

The methodology from Chapter III was followed, and results from the DEA are included in the present chapter. The following chapter will further discuss the results and assess the model's effectiveness in representing the airline business operations. The model's effectiveness and potential applicability of further theoretical or practical applications will also be discussed.

CHAPTER V

DISCUSSION, CONCLUSIONS, AND RECOMMENDATIONS

This section discusses the results of Chapter IV, answers the research questions posed in Chapter I, and makes final conclusions and recommendations. This chapter describes the results produced by the data envelopment analysis (DEA) models developed for this study and discusses the airline efficiency results. This section also includes the conclusions of the study, reflecting on practical and theoretical implications. Finally, recommendations are given to airlines for further research in the area of air carrier restructuring.

The purpose of the study was to construct and validate a DEA model that would assess and compare the total operating efficiency of airlines. This study focused on environmental impact abatement, by including the estimated and actual carbon dioxide emissions produced by the airlines as part of the efficiency measure.

This study constructed a two-phase, two-stage DEA model to assess and compare a sample of different airlines that included both U.S. and international carriers, as well as different business operating models – i.e. FSCs, LCCs, and non-LCC point-to-point carriers. The study combines and extends principles established by the three-stage DEA airline operating efficiency concept from Mallikarjun (2015) and the two-stage DEA airline energy efficiency measures developed by Cui and Li (2016). In addition, this study leverages multiplicative DEA relationships established by Kao and Hwang (2008) to create a model that can utilize two-stage DEA while retaining the accurate representation of the airline business model represented in Mallikarjun (2015). The DEA analysis enabled an assessment of the airlines along a variety of measures, without requiring equivalent units between the variables. This linear programming methodology utilizes all airline variable values within the model to establish a production frontier of optimum operating parameters and then compares the airlines performance to that benchmark to provide an efficiency score.

Discussion

A DEA model was constructed to comprehensively evaluate relative airline efficiencies inclusive of resource consumption, environmental impacts, and revenue generation. The study used data available through the U.S. Bureau of Transportation Statistics, airline public disclosures in airline operating reports, corporate and social responsibility reports, and reports made for the Global Reporting Index (GRI). Reviewing the structure of the model facilitates comprehension of the relative efficiency scores between the airlines.

As presented in Chapter III, this study utilized an analytical model composed of two different multiplicative two-stage DEA models: (1) the capacity generation phase (also referred to as "Phase 1"); and (2) the revenue generation phase (also referred to as "Phase 2"). Each of these two phases executes a two-stage DEA model.

The first stage of Phase 1 evaluates the "Operations" facet of the business model – i.e. the efficiency of an airline to be able to generate ASMs from the input resources (labor, materials, fuel, etc.). The second stage of Phase 1, titled "Services and Abatement", evaluates the efficiency of both: (1) the production of RPMs from ASMs (the maximization of creation profit-generating seats via the airline's route planning and flight scheduling activities); and (2) abatement (reduction) of carbon dioxide emissions.

The focus of the first stage of Phase 2 parallels the second stage focus of Phase 1 (the Services and Abatement stage). These stages both measure the “Carbon Abatement” facet of the business model (relative effectiveness of carbon abatement by an airline), as well as the “Services” facet of the airline business model (the effectiveness of creating profit-generating seats via the airline’s route planning and flight scheduling activities). However, by integrating this efficiency measurement as a different stage – paired uniquely with the “Operations” and “Sales” facets of the business model – the relative differences in efficiencies are less likely to be dominated by efficiency issues in their paired stage. The second stage of Phase 2 measures the relative efficiency of the “Sales” stage – i.e. the successful marketing and sales of seats, transforming RPMs into revenue.

Identical models were executed along three differentiating philosophies to identify and assess business model factors which may greatest influence efficiency. Based on the model validation and the results of the different DEA models, the conclusions for each of the three research questions are presented below. Following the review of the research questions, several sub-sections discuss the results of each group of models analyzed.

Research Question 1: Can airline efficiency be modeled to incorporate the cost and responsibility for abating environmental impacts in addition to traditional operating and revenue generating effectiveness?

Airline efficiency can be modeled to incorporate the cost and responsibility for environmental abatement in addition to capacity and revenue generation. The model designed in this study maintained a high-fidelity evaluation capability for business operations by ensuring the ASM creation (consumption of inputs for seat capacity), RPM creation (consumption of ASMs for route capacity), and revenue generation and recognition – i.e. effective sales of RPMs – were evaluated as separate performance functions within the operating efficiency model. In parallel, the model recognized the carbon dioxide emissions generated by flying activities, as well as the net carbon dioxide impact to the environment – a net result due to partial offsets by abatement activities.

Redefining the theoretical three-stage DEA model into the two-phase, two-stage model helped provide greater means for comparison of the airlines after the efficiencies were established. A single overall efficiency score in a three-stage model, while allowing for variable optimization across all three of the stage motifs (e.g. ASM generation, RPM generation, revenue generation) involves significant complexity in defining equations to evaluate the efficiency in a single-stage, specific to a single motif. If the equations for a single stage are assessing performance across multiple motifs, uncertainty is introduced when comparing the single-stage results of two airlines.

To avoid the aforementioned confusion in the final model design, the second stage of Phase 1 was replicated in the first stage of Phase 2. In the results of several of the models, an airline would yield an efficient score in either of these two stages (second stage of Phase 1 or first stage of Phase 2), but not demonstrate efficient production of both. Every instance of this result establishes that while such a score was efficient for one part of the analysis, a disparate efficiency value in the opposite phase signified the efficient position on the production frontier was not sustainable for business operations. Two separate two-stage models leveraging the multiplicative relational construct (Kao and Hwang, 2008) provide a means to evaluate and compare airline efficiencies utilizing a simpler model while retaining the fidelity of the three-stage model.

Research Question 2: To what extent does the cost of environmental abatement affect the efficiency of airline operations in the United States?

The implications of environmental abatement can impact the overall efficiency of airline performance in both the United States and throughout the world when emissions and carbon dioxide reduction efforts are properly accounted for. For the U.S.-based airlines in the study, only Alaska Airlines could demonstrate efficient performance in the environmental abatement component of each phase of the analytical model. When this research question is expanded to all airlines in the study, Alaska Airlines is the only airline to demonstrate efficient performance with respect to emissions abatement and RPM generation in both phases of the study for 2013 and 2014. In 2015, Alaska Airlines, Delta Air Lines, and JetBlue all show efficient performance in this regard; Alaska Airlines and Delta Air Lines also demonstrate efficient performance for emissions abatement in both phases for the three-year cumulative model. The lack of an efficient non-U.S. carrier is a topic for further research, as highlighted in the Recommendations section.

Research Question 3: What are the relative differences among airlines compared to an optimal efficiency benchmark when considering all facets of airline efficiency – i.e., inclusive of operational constraints, environmental impacts, and revenue generating effectiveness?

The response to this final research question is presented in the results discussion in the following section. These results are then used to compose airline-specific recommendations that are presented later in this chapter.

Principles of reviewing DEA output. As will be demonstrated in the following model-specific results discussion, the model's construction leveraging the multiplicative efficiency philosophy (Kao & Hwang, 2008) using two separate two-stage DEA models provides opportunities to assess efficiency, while also being able to compare multiple airlines. When reviewing DEA results, a unity efficiency rating establishes that a DMU is executing on the production frontier – one of the sets of variable values which demonstrates the theoretical benchmark for that system of equations. Non-unity scores suggest that the DMU may not be operating efficiently; however, these scores still allow relative comparison of performance as the rating establishes how far the DMU is from the efficient frontier. Applying this logic to the product of the two stage scores yields the conclusion that the total efficiency can be used to compare two airlines in relative efficiency, even if one or both stages does not demonstrate efficient operations. However, this conclusion cannot assume that the total efficiency is supplying evidence that one airline is more efficient than the other at all aspects of performance; all related deductions from the results should include a review of the individual stage scores, as well as review of which benchmarks each airline is optimizing to in each stage.

Efficiency differences over time. Execution of models for individual years presents shifts in which airlines are operating efficiently relative to each other. The differences in results between years suggest a changing environment or external influences on some of the variables utilized in the models.

2013 results discussion. In 2013, no airline presents efficient operations relative to the sample in both phases. In the first stage of Phase 1, all but three airlines demonstrate efficient performance. Lufthansa appears to have significant difficulty with efficient production of ASMs from its input resources. A review of Lufthansa's public operating data shows that their total operating expenses reduced by almost 11% between 2013 and 2014 and over 6% between 2014 and 2015, corroborating the results of the first stage. The second stage of Phase 1 has four airlines operating with a unity efficiency value, while three other airlines are demonstrating operations close to those production frontier positions. Air Canada, All Nippon Airways, British Airways, and Japan Airlines appear to be operating inefficiently relative to the efficient frontier. As previously discovered in the review of literature, British Airways was recognized during the study period for less-than-desirable operating efficiencies (which would correlate to the poor abatement facet of this stage's evaluation). Similar review of the airlines' public reports identifies 2013 and 2014 as years of focus on profitability for both Japanese airlines. The poor execution of the "Services" facet of the airline operating model is corroborated by the documented performance opportunities and subsequent improvement into 2015.

As previously discussed, the focus of the first stage of Phase 2 parallels the focus of the second stage of Phase 1. With the exception of Alaska Airlines, every airline that demonstrated efficient performance in the second stage of Phase 1 did not demonstrate benchmark efficiency in the first stage of Phase 2. This suggests that in one of the two stages, the relative efficiency of the phase is overshadowed by the ineffectiveness of the paired stage – e.g. some airlines are experiencing greater struggles to efficiently generate ASMs from input resources. Both Delta Air Lines and United Airlines demonstrated less efficient performance when evaluated as part of the second phase.

In the second stage of Phase 2, Alaska Airlines and JetBlue both show very low performance relative to the sample. As both airlines prescribe to the point-to-point business model, the low scores suggest that the airlines underperform their peers in revenue generation relative to RPMs. Reviewing Southwest Airline's performance, Southwest's revenue generation underperforms the FSC carriers while significantly outperforming Alaska Airlines and JetBlue.

Looking back at the total results, Alaska Airlines, Delta Air Lines, and United Airlines all demonstrate efficient performance through Phase 1 of the model. This is an interesting result as Delta Air Lines and United Airlines both are FSCs; similarly, while Alaska Airlines is placed in the LCC/point-to-point carrier group, it operates a service more similar to an FSC, albeit over a geographically limited network. Exigent research would suggest that Southwest Airlines should excel in Phase 1 compared to any FSC; the LCC business philosophy is based around maximizing load factor, and Southwest Airlines operates only one type of aircraft (the Boeing 737) to minimize both recurring and overhead costs.

Air Canada demonstrated efficient performance in Phase 2 of the model. The recurring efficient performance in Phase 2 (observed in Chapter IV) suggests that Air Canada is the airline closest to Alaska Airlines at effective carbon dioxide abatement, while still generating the higher levels of revenue that a larger airline can achieve. Using the multiplicative two-stage relationship with the phase scores yields Air France-KLM as the highest efficiency performer; albeit only with a 75% efficiency rating. However, as Air France-KLM did not demonstrate efficient production in either phase, it cannot be labeled as efficient through the model.

2014 results discussion. In 2014, a clearer segregation between efficient and inefficient carriers is presented. In the first stage of Phase 1, eight airlines demonstrate efficient operations, while five airlines demonstrate efficient operations in the second stage. Looking at the two-stage VRS model, only Alaska Airlines demonstrates efficient performance in Phase 1. Air France-KLM, Delta Air Lines, and Jet Blue all present efficient performance in one of the two stages, while otherwise scoring 95% or higher. Review of the collected data shows that the four carriers all had strong passenger traffic relative to their 2013 operations, as well as recurring strong performance with respect to carbon emissions abatement. The scoring for these airlines compared to the sample would corroborate that strong ASM generation coupled with carbon emissions abatement is required to demonstrate efficient performance in Phase 1.

In Phase 2, Air Canada and Delta Air Lines demonstrate performance on the efficient production frontier. Similar to 2013, while Alaska Airlines demonstrates excellent performance in Phase 1, it falls sharply in Phase 2 (specifically in the second stage). JetBlue similarly shows extremely low performance in the second stage of Phase 2, reinforcing the observation that in a combined model with large and smaller carriers, carriers with lower total revenues (irrespective of profitability) cannot demonstrate benchmark performance.

2015 results discussion. The 2015 results substantiate observations from the previous two years with respect to the methodology and results. In the first stage of Phase 1, all but two airlines (American Airlines and Lufthansa) demonstrate efficient performance. Lufthansa has more employees than any other airline in the world (which would translate to higher costs). Additionally, a number of aging aircraft in the Lufthansa fleet would increase maintenance costs and decrease aircraft availability due to downtime for scheduled maintenance, so the ratio of ASMs produced relative to input costs is not as high as the other airlines. American Airlines was the world's largest airline by revenue in 2015 but also had the largest fleet – which would suggest higher overhead costs. From examination of 2015 operating statistics, American Airlines had 10% more aircraft and 48% more employees (approximately 38,500 more) while only carrying 5% more passengers.

Three year combined results discussion. Analysis of the DEA model results suggests that this combined model accentuates where each airline struggled in efficient performance relative to the sample and the theoretical efficient production frontier. Delta Air Lines stands out with the highest total efficiency score, demonstrating efficient performance in Phase 2. The airline's efficiency in the first stage of Phase 1 is slightly off the benchmark frontier; this lack of efficiency is understandable considering that no other large carrier (except for Southwest Airlines) achieved efficient performance with respect to ASM generation. The results suggest that for the aggregate study period, the efficiency baseline for generating ASMs is defined by Southwest Airlines – the large LCC whose business model is focused on this efficiency.

In the second stage of Phase 1, the airlines further differentiate their performance with respect to RPM generation and carbon dioxide emissions abatement. One notable result is that Emirates demonstrated efficient performance – a performance level achieved in 2014, but not in 2013 or 2015. The Emirates business model executes a high quality product on long international routes with a comparatively modest domestic operating network – in reality, Emirates' "domestic market" is short-haul flying within the Middle East. This business model lends itself to fuel and emissions generation efficiency relative to each passenger-mile; the primary threat to efficiency would be the cost of the product, which would be evaluated in the first stage of Phase 1. It is possible that small differences in ASM to RPM generation negatively impacted Emirates' performance in ASM to RPM generation for 2013 and 2015; in the three-year aggregate, Emirates demonstrates efficient performance relative to the sample.

For Phase 2, British Airways' efficient performance in the first stage is voided, as no environmental data was available in 2015. Therefore, for the three-year period, British Airways would artificially show higher environmental abatement performance. Alaska Airlines, Delta Air Lines, and JetBlue demonstrate efficient performance in the first stage, but in the second stage neither of the LCC/P2P carriers generate enough revenue to demonstrate efficient performance.

In addition to Delta Air Lines, Air Canada demonstrates efficient performance in Phase 2. Further examination of all four models' results shows that Air Canada demonstrated efficient performance in the first stage of Phase 1 and through Phase 2 in every one of the four analysis models reviewed; however, the airline always performs poorly in the second stage of Phase 1.

U.S. versus non-U.S. airlines. As previously described in the demographics section, the hubs and route networks of an airline have significant implications for the manner in which the airline is operating and where it generates revenue. Execution of models for the U.S. carriers alone, and then the international carriers alone, provides an efficiency comparison more focused on the business model of those airlines.

U.S. carriers. Analysis of the results for the U.S. carriers model shows some distinct differences from the annual or aggregate models with all carriers included. In the first stage of Phase 1, the three non-FSC carriers (Alaska Airlines, JetBlue, and

Southwest Airlines) demonstrate efficient performance. This is interesting because in the annual all carrier models, some of the U.S. FSC airlines also perform efficiently for a single year (e.g. Delta Air Lines in 2015 and United Airlines in 2013). In the second stage of Phase 1, Alaska Airlines and Delta Air Lines demonstrate efficient performance. These results present that Alaska Airlines operated efficiently through the first phase of the analysis model.

In Phase 2, Delta Air Lines performs efficiently throughout the phase. Alaska Airlines is the only other airline to present efficient performance in one of the stages (in the second stage of this model). These results corroborate some of the previous results discussion focused on the all carrier models. In both the 2015 and the three-year aggregate results, Alaska Airlines performed efficiently in the first stage of Phase 2, but then performed far below benchmark in the second stage, while Delta Air Lines was at benchmark efficiency through Phase 2 in both models. This situation is best explained through review of the DEA formulation that the models are based on. With multiple input variables, two DMUs can operate at the same performance level with different variable values. In the case of the aggregate models, Air Canada had both relatively higher revenue generation than Alaska Airlines, as well as higher environmental abatement and RPM generation relative to Delta Air Lines. As such, Air Canada and Delta Air Lines, with different performing values, both were operating on the efficient production frontier.

In this model, Alaska Airlines demonstrates that it is the top U.S. carrier with respect to emissions abatement. However, Alaska Airlines' production efficiency in revenue generation (the second stage of Phase 2) reinforces the previous observation that smaller LCC and point-to-point carriers are incapable of competing with larger airlines in the last stage of the model. The results indicate that with respect to emissions abatement, RPM generation from ASMs, and revenue generation, Delta Air Lines outperforms Alaska Airlines.

Non-U.S. carriers. Similar to the U.S. carriers model, analysis of the results for the non-U.S. carrier model shows that a more segregated sample population allows certain airlines' performances to stand out among their peer group. In the first phase, both Air France-KLM and Emirates demonstrate efficient performance. For this model sample, the strong performance is corroborated by the literature review and analysis of these airlines' fleets.

Both carriers conduct some regional operations, but also operate extensive long-haul operations on large aircraft. Due to the overhead cost of long-range capable aircraft, airlines focus on scheduling and marketing techniques to ensure these aircraft are filled to capacity. In addition, Air France-KLM (who has the more significant domestic and regional operations) has launched LCC airlines (e.g. HOP!) internally owned by the company to fulfill the typically underperforming short routes that feed their larger hub airports. The strategic investment in regional airlines feeding their hubs helps improve the RPM generation efficiency by ensuring the large, long-range aircraft are filled. For the regional routes, the airline can tailor their aircraft selection to match the passenger demand on those routes. Comparably, Emirates specifically focuses on supporting long-range international routes between major hub airports. By concentrating its business operations only on routes it can be competitive on, Emirates is helping ensure its RPM generation efficiency remains high.

With the results corroborated by review of the aircraft business philosophies and annual reports, the Phase 1 efficient performance in ASM and RPM generation is appropriate. The literature review also presents that both airlines were relatively early to invest in fuel-burn and emissions reduction initiatives. The early adoption of emissions-reducing practices as well as high seat density for long-haul operations will translate to a greater emissions abatement capability, reinforcing a strong production efficiency in the second stage of Phase 1.

In Phase 2, Air Canada demonstrates efficient performance for the sample. All Nippon Airways, Japan Airlines, and Lufthansa each present efficient performance for the second stage of Phase 2. As noted in previous discussion for the aggregate model results, the larger FSC airlines (who generate more total revenue) can demonstrate high performance in the second stage due to total revenue production. In this model, these airlines can generate sufficient revenue to be on the production frontier for that stage, but only Air Canada demonstrates efficient performance through a combination of revenue generation and emission abatement.

Efficiency difference between FSCs and LCCs. As described in the demographics section, the business strategy and deployment philosophy of an airline is just as important as its geographical location and network. Execution of models that segregate the FSCs (executing a hub-and-spoke strategy), LCCs, and point-to-point airlines help reveal additional factors that may influence efficiency.

Full-service carriers. In the FSC model, no airline demonstrates efficient performance in Phase 1. Six airlines demonstrate efficient performance in the first stage, while American Airlines, Delta Air Lines, and United Airlines perform efficiently in the second stage. Analysis of the results from the previous models has presented that some FSCs have typically stood out in the total study sample with respect to ASM and RPM generation. Examination of the Phase 1 results reveal that the non-U.S. FSCs are comparatively stronger at ASM generation, while the three large U.S. FSCs are stronger at RPM generation from the ASM supply and/or emissions abatement.

Review of each airlines' operations help explain the aforementioned phenomenon (non-U.S. FSCs efficiently produce ASMs from input resources while U.S. FSCs are relatively more efficient at RPM generation from the ASM supply) as the difference in domestic operations as a function of total operations. Robust and effective domestic operations leverage regional and single-aisle aircraft to support high-demand routes. The three U.S. carriers all produce significant revenue through their domestic operations. While the other FSCs have domestic / regional operations (in Europe, short international routes utilize the same aircraft and business strategy as U.S. domestic operations), these operations are not as extensive as a function of total operations. While Emirates predominantly supports international, long-haul routes, All Nippon Airways and Japan Airlines – the market leaders in Japan – are limited by Japan's total domestic market demand. Air Canada has a similarly limited home market to Japan; an additional complication is a greater percentage of Air Canada's domestic operations require propeller aircraft or smaller regional jets based on individual city flight demand and operating constraints of some cold weather locations. Therefore, the total airline operation efficiency of the non-U.S. FSCs is more reflective of its long-haul operation, while the U.S. FSCs' operational efficiency reflects a more even split between international long-haul, domestic transcontinental, and regional/short-haul operations.

In Phase 2, Air Canada and Delta Air Lines demonstrate efficient performance throughout the phase. As previously discussed with the single year and aggregate models for the total study sample, these two airlines are both operating on the production frontier, with Air Canada leading in emissions abatement and Delta Air Lines producing more revenue. All Nippon Airways and Japan Airlines, while relatively smaller FSCs compared to other airlines in this sample, both demonstrate effective revenue generation from their RPMs. Lufthansa stands out in this model for its second stage performance; with the exception of Air Canada and Delta Air Lines, every other FSC benchmarked against Lufthansa for revenue generation in this phase.

Low-cost and point-to-point carriers. The LCC model yielded Alaska Airlines as demonstrating efficient performance through the model. The results are well substantiated as Alaska Airlines demonstrated efficient performance versus the sample with respect to emissions abatement in the other models which included FSC carriers. However, Southwest Airlines' relatively low ASM generation performance, suggests that the model would have benefited from additional DMUs.

Conclusions

This study explored airline efficiency with respect to both capacity / profit generation and emissions abatement. A two-phase, two-stage DEA model was designed to simultaneously evaluate an airline's operations for ASM generation, RPM generation, carbon dioxide emissions abatement, and revenue generation. Quarterly and annual data was collected from thirteen airlines for a three-year period. Several variants of the DEA model were executed to assess and compare the airline efficiencies over different time periods, as well as in smaller samples segregated by airline network location or business operating strategy.

Analysis of the DEA model results in conjunction with publicly disclosed airline performance data for the period of study corroborated the model's effectiveness in comparing airlines for both business operations and environmental abatement. The network and business strategy-focused models demonstrated that having analytical models including only similar airlines can help highlight the specific strengths and opportunities of those airlines. The value of the business philosophy-specific or geographical/network-specific models are demonstrated when the same airlines present average performance as part of the aggregate sample but may set a performance benchmark against more closely performing peers. Future research may consider extended models with more focused examination of airlines with similar business strategies or networks. Additionally, further studies into the model's variable weighting are recommended to more effectively deploy practical applications of the model.

Theoretical implications. This study establishes a new path of focus for airline operations, specifically in the DEA domain. The study connects previously conducted airline efficiency research that focused on: (a) different capacity and cost components of airline operations, (b) carbon dioxide emissions abatement, (c) differing airline business models associated with service levels, and (d) the implications of different routes and networks.

The study demonstrates the ability to execute a multiplicative relational DEA model (utilizing a two-phase two-stage architecture) and incorporates the construct of emissions abatement while maintaining a business operations analysis structure that allows for separate capacity and revenue generation stages. The limited existing research structures the environmental impacts or emissions abatement as an output of the total airline operations. The model construct established in this study specifically makes emissions abatement part of the firm decision-making in a phase prior to the final outputs and revenue generation. The model philosophy and design therefore make emissions abatement a decision-making variable, not a result of revenue optimization.

The DEA model in this analysis philosophically presents a combination of the three-stage philosophy for airline operating efficiency defined by Mallikarjun (2015) with the environmental operating efficiency construct developed by Cui and Li (2016). Leveraging the multiplicative two-stage property deployed by Kao and Hwang (2008), the two-phase two-stage DEA analysis model developed for this study allows the successful evaluation and comparison of relative efficiencies between the airlines included in the study. Applying a phased two-stage DEA model approach reduces the complexities associated with the forward/backward recursion required in a three-stage DEA analysis, while capturing the fidelity of the Mallikarjun approach to airline operating efficiency (2015). Although the same RPM generation and emissions abatement stage are utilized in both phases (the second stage of Phase 1 and the first stage of Phase 2), the results of the study and subsequent conclusions corroborate data found in airline public reports. This analysis model allows dissimilar decision-making units (i.e. business firms) to be compared, a useful tool considering every airline is different.

This study also provides insight into the impact of airline business model and route/network on airline efficiency comparison. As discussed earlier in this chapter, including airlines of different business models can help better understand the aspects of airline operations that a specific business model may excel – e.g. LCCs are strong at ASM generation from inputs. However, the study reinforces the perspective that DEA results are more reliable with a greater number of DMUs included in the study. By extension, the study shows that the model becomes more capable of presenting the opportunities associated with a specific business model (e.g. FSC or LCC) when a greater number of sample participants are used to represent each business model.

Practical implications. This study has contributed practical, data-driven knowledge to efforts focusing on deploying high-fidelity analytical methods to assess airline operating efficiencies. This is the first study to develop a measurement model that incorporates carbon dioxide emissions abatement as well as a high-fidelity assessment of efficiency where ASM creation, RPM generation, and revenue realization are all separately assessed as part of an airline's business operations. While DEA has been deployed to great extent as a methodology for assessing airline efficiency, any models that include carbon emissions abatement treat the environmental impact abatement as a separate stage after the operations analysis. The results of this study (as well as the model developed) provide airline industry participants, both the airlines and decision makers associated with regulatory activities, additional means by which to evaluate and compare airline efficiency.

The study reviewed the performance of thirteen airlines over a three-year period, identifying strengths and opportunities for each airline specific to ASM creation, conversion of ASMs to RPMs, carbon dioxide emissions abatement, and revenue generation. As the data used in this study is obtained from the public domain, individual airlines could utilize this analytical model construct to assess the efficiencies of their current operations, as well as prioritize strategies for future investments. As efforts are made to address specific components of operating efficiency (e.g. improving ASM creation from inputs or improving conversion of ASMs into RPMs), this model could be used by an airline to evaluate how those investments are changing the airline's total efficiency relative to its peers.

The results and related opportunities identified in this study could be used by an airline to recognize that improvements specific to their airline may be of greatest benefit if focused toward international or domestic operations. Similarly, an airline operating the FSC, LCC, or point-to-point business models could use the model to assess their own efficiency, and then determine a business improvement strategy based on the relative efficiencies of their competitors in the same marketplace – leveraging knowledge of the business model-specific operational requirements as part of their competitive strategy.

From a regulatory perspective, this model, or similar models derived from the same construct, could be leveraged by public or government entities to review the evolution of environmental abatement performance in airlines. Based upon current and expected capabilities in carbon dioxide abatement technology and processes, policy makers can use the results of these models to substantiate a strategy outlining future emissions abatement objectives and drive specific industry goals.

Methodology & data. The DEA methodology in this study provides a linear programming approach to compare different airlines among a number of different variables without requiring transformation of the variables to common units. Like most research studies, this analysis identifies several opportunities exist to further refine and evolve the model.

The two-stage DEA model requires a defined weighting between the stages; these weighting values are parameters utilized by the linear programming to define the optimization goals. In this study, a one-to-one ratio is used for all stages; however, this may not be true from an airline perspective – specific business strategies could drive a specific facet of the operating efficiency model, and therefore the corresponding DEA stage, to be weighted more. Additionally, different airlines may have different considerations of the importance of carbon dioxide abatement beyond industry requirements.

The model may be augmented by separating the emissions abatement component of the model construct from a ‘RPM creation’ or ‘revenue generation’ phase of the model. Separating this component will add additional complexity to the model, either by requiring three stages, or parallel stages in the same phase of the model.

Validity. The validity of the analysis was verified through review of the sample demographics. Descriptive statistics were calculated for the total sample, as well as subsets aligned with business operating model (e.g. only FSC carriers) and the network headquarters/location. The review of the sample participants within the framework of their operating models demonstrated high similarities with the airlines. This review validated the sample and the data collected from each airline.

The results from the models used were found to be consistent with expectations set from review of other airline models as well as airline published operating data during the period of study. Cui & Li (2016) utilized a two-stage DEA analysis to compare several different airlines while including emissions abatement in their operating efficiency model. Though the analytical models, period of study, and sample airlines were different, the analysis results for some airlines are quite similar. Specifically, in their study, Delta Air Lines and Air Canada performed efficiently when compared to other FSCs.

The generally consistent alignment of this study's results to results from other studies suggests that the model is valid. The analytical model leverages linear programming, so therefore does not require reliability testing. To protect the reliability of the model data, the study utilized data collected and managed by the BTS.

Limitations. The analysis model developed in this study utilized multiple two-stage DEA constructs. Two-stage DEA requires a weighting of the two stages for the programming to use for defining boundaries of the optimization calculations. The two-stage VRS models leveraged formulas established by Zhu (2011). In this study, the weighting between the two stages of each of the phases was one-to-one. This weighting strategy was to signify that efficiency in: (1) ASM creation from input resources, (2) carbon dioxide emissions abatement, (3) ASM conversion to RPMs, and (4) effective sales of RPMs for revenue, are all of equal importance to an airline.

This study only included Scope 1 and Scope 2 carbon dioxide emissions, as defined by the Global Reporting Initiative (GRI). Scope 1 emissions are created from direct operating activities: aircraft fuel consumption, ground support equipment fuel, HVAC refrigerants, etc. Scope 2 emissions are associated with purchased goods or utilities that the airline pays for. The Scope 2 category includes emissions from electrical power facilities supporting the airline or those associated with a leased space (e.g. airport facilities). Focusing the model to analyze the aforementioned aspects of carbon dioxide emissions ensures that the emissions identified in each year are pertinent to the business activities for that specific year (i.e. active operations) and do not reflect long-term investment projects (e.g. facilities improvements or overhaul).

A general limitation to highlight is that corporate and social responsibility, specifically the environmental focus, is still an evolving facet of airline business operations. The reporting standards for greenhouse gases changed during the period of focus in this study. While reporting per the GRI was at first voluntary, the requirements now have become more robust with ISO and GRI G4 reporting standards. As an example, American Airlines' 2013 Corporate Responsibility Report was not GRI G4 compliant, but the 2014 report was. It should be understood that the airlines in this study are in varying stages of maturity with formally reporting greenhouse gas emissions.

Recommendations

The results of this study demonstrate that the two-phase two-stage model is capable of comparing airlines with respect to operational efficiency, including the efficiency of its emissions abatement strategies. This model construct can be deployed by airlines or regulators to compare multiple airlines for ASM generation, ASM conversion to RPMs, carbon dioxide emissions abatement, or revenue generation. When required, this model should be deployed with a number of DMUs that exceeds the number of variables being assessed for efficiency.

Additionaly, the results of this study have shown that the results provide greater value when the sample DMUs are similar with respect to business model and operating environment. While FSCs should be directly comparable, the U.S.-based FSCs (American Airlines, Delta Air Lines, and United Airlines) are best compared due to the similarity in the design and deployment of both their domestic and international operations. All Nippon Airways and Japan Airlines presented a similar scenario; while being comparable to non-U.S. FSCs, these two airlines have constraints to the size of their domestic and regional markets. Therefore, they are best compared to major Gulf carriers or another non-U.S. FSC with limited domestic operations (e.g. Air Canada, Emirates), as opposed to large European FSCs such as Air France-KLM or Lufthansa Airlines.

Lynes and Andrachuk (2008) highlight the importance of environmental emissions abatement within the framework of corporate and social repsonsibility. Their research yielded perspectives from the airline industry that improving the environmental footprint of an airline would provide fiduciary benefit to airlines. This benefit could be manifested in improved brand image and sales from customers who appreciate social investment. Alternatively, the benefits could be directly extracted from improved business operating principles with environmental benefits – e.g. recycling or digitization of assets for weight optimization. This research study did not discern a relationship where the airlines with the least environmental abatement generated the most profit. Rather, the results suggest that airlines investing more in emissions abatement are demonstrating improvements in efficiencies in other aspects of their business operations.

Recommendations to airlines. The review of the results (also captured in Appendix A) describes the specific performance of the different airlines through the different stages. The following sub-sections present specific recommendations for each airline, based on the results of the study.

Air Canada. Air Canada consistently demonstrated efficient performance in Phase 2 in all models, signifying efficient revenue generation from RPMs and effective

RPM generation and emissions abatement. However, in all models (including the non-U.S. carrier model and the FSC-focused models) Air Canada demonstrates inefficient performance relative to its sample, and the inefficiencies are always in the second stage of Phase 1. Detailed review of Air Canada's benchmarks in each model shows that in every case, the benchmark for that stage is a large airline with superior RPM generation. For example, Air Canada's ratio of RPMs to ASMs in 2013 was 0.75, while the American Airlines performance benchmark would yield the same ratio of 0.83.

Air Canada consistently demonstrates strong revenue generation from the RPMs it creates, as well as high emissions abatement. Based on the results of this study, the recommendation to improve Air Canada's total operational efficiency would be to address the comparatively lower RPM generation from ASMs. This may be difficult due to Air Canada's responsibility as the national flag carrier to serve a number of small, low volume locations.

Air France-KLM. Air France-KLM typically demonstrated strong Phase 1 performance, always demonstrating efficient performance in one of the two Phase 1 stages. In the non-U.S. carrier model, Air France-KLM was one of two carriers to demonstrate efficient performance in Phase 1. However, in every model, Air France-KLM did not demonstrate efficient performance in Phase 2. As the merger between two large national flag carriers, the literature review establishes that this airline is working to retire aging and less-efficient aircraft, while optimizing the company structure between the two companies.

The results of this study and corroborating literature highlight opportunities for improving emissions abatement and revenue generation. Air France-KLM should execute its fleet modernization strategy that will retire Boeing 747 and 777 aircraft that may be overcapacity for certain long-haul routes, as well as continue to invest in its emissions and weight reduction initiatives. The replacement aircraft coupled with the operational savings initiatives will manifest in increased efficiency.

Alaska Airlines. The results of this study produce rationale to label Alaska Airlines as the most efficient airline in this study. In the single-year and aggregate models including all airlines, Alaska Airlines always performed efficiently through Phase 1 and efficiently in the first stage of Phase 2. In the U.S. carriers model, Alaska Airlines was efficient in all stages except the last. Finally, in the LCC/Point-to-Point dataset, Alaska Airlines set the benchmark for the entire model.

The results of this study cannot add further recommendation over Alaska Airlines' current deployment. The lower revenue generation efficiency scores are directly related to Alaska Airlines' focused market, which is largely regional (there are some limited transcontinental products). Even though the product compares with the domestic products offered by the large American FSCs, there is limited supplemental revenue in the premium cabin space which international products of the larger FSCs can obtain (e.g., lay-flat seats, individual living pods, or suites). On the domestic front, Alaska Airlines operates solely single-aisle aircraft (e.g. Boeing 737 and Airbus A320 models), supplemented by smaller, regional aircraft for small and remote airports. This means the airline will also struggle to match revenue generation that U.S FSCs may enjoy with Boeing 757 or similar aircraft that have additional seat density for transcontinental routes.

Based on the results of this study, Alaska Airlines is executing within the market space it has defined its business strategy around, and is effectively deploying that strategy.

All Nippon Airways. Review of the results from the DEA model and literature review of this study show that All Nippon Airways produces at the performance benchmark for ASM generation and total revenue generation. However, in both phases the airline struggles with execution of ASM conversion into RPMs and environmental abatement. This production performance was duplicated in all models in which All Nippon Airways was evaluated (single year, three-year aggregate, non-U.S. carriers, and FSCs). Examination of the aircraft company reports highlights that during the period of this study, both Japanese carriers recognized challenges in optimizing their operations due to aging aircraft as well as the limitations of their network routes into the U.S. (Pacific intercontinental flights). As such, they began investing in more efficient aircraft (All Nippon Airways was the launch customer for the Boeing 787-8). Opportunities still exist to deploy a network of routes and schedules that will maximize the utilization of their inputs.

Based on the results of this study, the recommendations for All Nippon Airways to improve its operational efficiency would be to continue to review its network and route deployment of its fleet. The airline is already investing in more efficient aircraft, but the fleet composition should also be reviewed against the offered routes to ensure maximization utilization of these aircraft for revenue generation.

American Airlines. Review of the results from the DEA model and literature review of this study show that American Airlines would consistently produce in the second stage of Phase 1 but in no other part of the model. As highlighted in the results discussion, performance in ASM generation from inputs and revenue generation from RPMs were lagging behind the performance of peer airlines. American Airlines is recognized as the largest airline in the world by a variety of statistics – including revenue generation. However, it has substantially more employees compared to its competitors, and a larger fleet.

Based on the results of this study, a recommendation to American Airlines for improving operational efficiency would be to focus on examining the key components of the airline's operating costs. Generation of more ASMs from the production inputs should also influence the last stage efficiency (total revenue generation as a function of RPMs).

British Airways. Due to the unavailability of emissions or abatement data for the year 2015, British Airways could not be included in the single-year 2015, three-year aggregate, or focused models. As the conclusions of this study have relied upon interpretation of performance in multiple models – leveraging the focused models to corroborate production performance in the single-year or three-year aggregate models with all airlines – no conclusions are presented for British Airways.

Delta Air Lines. Review of the results from the DEA model and literature review of this study suggest that Delta Air Lines is the most efficient FSC. In the 2015 single-year analysis model with all airlines, Delta Air Lines was the only airline to demonstrate efficient performance in all stages. In both the three-year aggregate analysis model and U.S. carriers model, Delta Air Lines scored the highest total efficiency rating, was efficient in the 2nd phase of the model, and one of the few airlines that was efficient in three of the four stages. In the FSC analysis model, Delta Air Lines effectively demonstrated the same performance as in the three-year aggregate model: highest overall efficiency rating with efficient performance in the 2nd phase.

In the U.S.-carriers analysis model, Delta Air Lines presents the highest efficiency score. Further review of the results highlights the complexities of utilizing this multi-stage DEA model to compare airline DMUs with different business models. The six airlines included three FSCs, one true LCC (Southwest) and two point-to-point carriers. The results show that the FSCs struggled in efficiently creating ASMs from inputs and in producing RPMs from ASMs. FSCs would inherently have less efficient ASM production from input costs by operating long-haul international routes (whose airplanes may generate more revenue, but also have fewer seats for the input costs). Additionally, the hub-and-spoke network theory (utilized by all FSCs) typically incurs lower load-factor flights as part of the business strategy. The airline allows flight scheduling with partially-filled flights from smaller airports into the hub, in the interest of high margins and economies of scale in the hub-to-hub leg of the route.

Based on the results of this study, a recommendation to Delta Air Lines for improving operational efficiency would be to review its aircraft fleet and look for opportunities to maximize ASM generation. Delta has demonstrated that it is already successfully executing carbon dioxide abatement strategies. The only area where the airline is not fully efficient is with ASM creation from inputs. Review of company publications highlights that Delta Air Lines is pursuing fleet restructuring with respect to the smaller aircraft it utilizes to bring passengers into its hub airports – i.e. Delta is investing in newer regional aircraft to improve their efficiencies and load factor in this aspect of their operations. In 2017, the airline announced the purchase of more than 100 Bombardier "C Series" regional aircraft to replace its aging McDonnel-Douglas 80/88/90 fleet. The Boeing 717s acquired through the Northwest merger earlier this decade have already been retired. Pursuing new aircraft in the regional segment shows that Delta is not just using fleet renewals to obtain larger aircraft but is targeting specific aircraft to optimize the short routes between outside airports and the hub. These aircraft will help improve ASM generation while improving the environmental footprint of the airline's fleet.

Emirates. Review of the results from the DEA model and literature review of this study show that Emirates struggled to consistently produce efficiently in both phases. In the single-year and three-year aggregate models, efficient production would only occur in a single stage of Phase 1. In the non-U.S carrier analysis model, Emirates achieved efficient production through Phase 1 but again demonstrated inefficient production in Phase 2.

Reflection of the model results allows a conclusion that Emirates generally is less competitive at emissions abatement, ASM conversion to RPMs, and revenue generation. The conclusions regarding inefficient emissions abatement and ASM conversion to RPMs are derived from the consistent inefficient production in the first stage of the second phase. Emirates typically operates very large aircraft on long-haul routes, a strategy which helps profitability with economies of scale; their ASM creation from inputs is strong, as presented by the analysis model results. However, unfilled seats (lower load factor) for these large aircraft will result in lower conversion of ASMs to RPMs. Additionally, Emirates prides itself on a high service quality standard. While this may allow a company to demand higher prices, Emirates must ensure that the costs associated with their service offering do not jeopardize their revenue generation.

Based on the results of this study, it is recommended that Emirates evaluate their emissions abatement programs, cost structure, and fleet / route scheduling strategy. Emirates leverages an operational strategy focusing on economies of scale on long-haul international routes, as well as providing a high-level of service. The results of this study suggest that their execution of this business strategy is resulting is less profitable (and less environmentally friendly) operations compared to the other airlines in the study.

Japan Airlines. Review of the results from the DEA model and literature review of this study present performance that is very similar to that of All Nippon Airways. Japan Airlines produces at the performance benchmark for ASM generation and total revenue generation. Similar to All Nippon Airways, it struggles in both phases with execution of ASM conversion into RPMs and environmental abatement. This production performance was witnessed in all models in which Japan Airlines was evaluated (single year, three-year aggregate, non-U.S. carriers, and FSCs) with the exception of the 2014 single-year analysis model where Japan Airlines did not demonstrate efficient production in the second stage of Phase 2 (revenue generation). Examination of the airline's company reports highlights that during the period of this study, both Japanese carriers recognized challenges in optimizing their operations due to aging aircraft as well as the limitations of their network routes into the U.S. (Pacific intercontinental flights). Although not the launch customer of a Boeing 787 model, Japan Airlines still demonstrates its appetite for fielding an efficient fleet by being the second largest Boeing 787 operator in the world. The investment in more efficient aircraft will help improve emissions abatement. Opportunities still exist to deploy a network of routes and schedules that will maximize the utilization of their inputs.

Based on the results of this study, the recommendations for Japan Airlines to improve its operational efficiency would be to continue to review its network and route deployment of its fleet. The airline is already investing in more efficient aircraft, but the fleet composition should also be reviewed against the offered routes to ensure maximization utilization of these aircraft for revenue generation.

JetBlue Airways. Review of the results from the DEA model and literature review of this study establish that JetBlue is consistently strong in ASM generation from input resources, emissions abatement, and conversion of ASMs into RPMs. In the analysis models containing all airlines from the study (single-year and the three-year aggregate model), JetBlue consistently produces at benchmark levels in the first stage of both the first and second phases. In the 2015 single-year model, JetBlue demonstrates efficient production through Phase 1.

The results of the U.S.-carriers model and LCC/P2P model highlight the key differences between JetBlue and Alaska Airlines' operations. JetBlue started its existence as a true LCC. Over time, the airline has evolved its business model to provide a number of amenities, while trying to maintain its low prices. Review of company reports shows that the airline is trying to achieve this balance by leveraging commonality in its aircraft fleet (i.e. operating very similar derivatives of the Airbus A320 family). In the U.S.-carriers model, JetBlue establishes the benchmark for the first stage of Phase 1, the only stage in which Alaska Airlines does not set one of the benchmark frontier boundaries for other airlines. As JetBlue is more of an LCC executing on point-to-point routes than a regional / fixed market business model (such as Alaska Airlines), it makes sense that it is succeeding at maximizing ASMs produced. The results from the other three stages present that JetBlue is not as efficient as Alaska Airlines at emissions abatement, ASM conversion to RPMs, or revenue generation.

In the LCC/P2P model, the results partially contradict those established by the other models. In this model, Jet Blue performs at benchmark for the second stage of each phase (along with Alaska Airlines). As there are only three DMUs in this model, these results are considered at risk due to too few DMUs existing in the multi-stage DEA model.

Analysis of the study results supports a conclusion that JetBlue's deployment of the LCC business model – and the limited number of LCC carriers in this study – is confounding the results for JetBlue in some of the models. JetBlue's performance in the all-carriers and U.S.-carriers analysis models is corroborated by the literature review. However, the LCC/point-to-point carrier analysis presents results that contradict the previous models. Based upon the usable results, the recommendation to JetBlue is to maintain their current business strategy with additional focus given to the operational steps required to improve ASM conversion to RPMs and emissions abatement. The strategy which best improves both fronts will look at network route/scheduling to optimize the aircraft deployed (and deploy newer aircraft where possible). Opportunities for deployment of additional emissions abatement programs will also improve relative efficiency.

Lufthansa Airlines. Review of the results from the DEA model and literature review of this study show Lufthansa Airlines produces consistently at benchmark levels of performance in the second stage of Phase 2 (revenue generation) but does not ever demonstrate efficient performance utilizing the construct of this analysis model. This production performance was witnessed in all models in which Lufthansa Airlines was evaluated (single year, three-year aggregate, non-U.S. carriers, and FSCs). The consistent model results drive the conclusion that Lufthansa is able to show efficient revenue generation from its RPMs when compared to its peers. However, it lags its peers in ASM creation from input resources, emissions abatement, and ASM conversion to RPMs.

Reviewing airline company reports shows that Lufthansa is extensively investing in emissions reduction and means of reducing its cost structure. As an FSC, Lufthansa does not want to reduce its service levels. However, some facets of its fleet strategy are driving costs that require evaluation and adjustment. Lufthansa deployed Boeing 747 aircraft for decades and supported the development of the updated 747-8. Demand for the 747-8 has waned, as airlines want more flexibility with scheduling (driving demand for long-range aircraft that correspond to the size of the Boeing 787, Boeing 777, Airbus A330, and Airbus A350 models). The timing of Lufthansa's fleet replacement activities suggests that there are a number of aging aircraft requiring replacement. While the literature review captured that Lufthansa had some of the most extensive emissions reduction initiatives in the sample group of airlines, aging aircraft and operational inefficiencies that decrease the efficiency scoring establish that Lufthansa is producing inefficiently relative to its peer group.

Based on the results of this study, the recommendation for Lufthansa Airlines to improve its operational efficiency is to continue to review and deploy its fleet renewal strategy to better align efficient and optimally loaded aircraft with the route network. Per the aforementioned results analysis, Lufthansa has been investing heavily in programs that reduce waste and help reduce carbon dioxide emissions; those programs should continue to be pursued in earnest.

Southwest Airlines. Review of the results from the DEA models in this study present inconclusive data regarding Southwest Airlines' operational efficiency. In the analysis models containing all airlines from the study (single-year and the three-year aggregate model), Southwest Airlines consistently produces at benchmark levels in the first stage of Phase 1. However, the benchmark performance in Phase 2 switches between stages depending on the year of study. Similar to JetBlue, the U.S.-carrier and LCC/P2P models have too few DMUs operating with the LCC business model. As such, the DEA analysis models are not able to appropriately compare efficiency between the few similar airlines.

Analysis of the study results supports a conclusion that Southwest Airline's deployment of the LCC business model – and the limited number of LCC carriers in this study – is confounding the results in some of the models. The study results support Southwest Airlines' deployment of the LCC model through its fleet strategy and route/scheduling network, illustrated by the benchmark execution of ASM creation from input resources. Further conclusions or recommendations related to total operating efficiency or emissions abatement are not possible based on the results of this study.

United Airlines. Review of the results from the DEA model and literature review of this study present consistently inefficient performance. United Airlines demonstrated efficient performance in Phase 1 of the 2013 single-year all-carrier model. In the subsequent years – and in the three-year aggregate model – United Airlines consistently underperformed benchmarks set by Emirates and Delta Air Lines. In the 2014 and 2015 single-year analysis models, United Airlines presents benchmark performance in the second stage of Phase 2; suggesting effective revenue generation.

In the U.S.-carriers analysis model, United Airlines presents the second highest total efficiency score. However, these results cannot be interpreted to present effective performance, as the airline does not execute efficient performance in either phase and is one of only two airlines to not deliver benchmark performance in any stage.

Analysis of the study results suggests that United Airlines' execution of its FSC business model and environmental abatement strategies are lagging in performance compared to the other airlines in this study, particularly those also executing as FSCs. The results show that in varying stages, Air Canada, Delta Air Lines, and Emirates all serve as defining benchmarks for United Airlines.

Based on the results of this study, the recommendation to United Airlines is to review all aspects of its operations for opportunities in greater ASM creation from input resources, more effective conversion of ASMs to RPMs, and increased emissions abatement activities. The literature review of airline reports highlights that United Airlines has been investing in a fleet renewal strategy. The efforts to deploy more efficient aircraft effectively into the route network will help realize the aforementioned opportunities in United Airlines' operational efficiency.

Recommendations to regulatory bodies. The model developed in this study provides the ability to compare the relative operational efficiency of multiple airlines for a predefined period, inclusive of environmental efficiency. Governing and law-making entities could use this model to analyze and trend airline efficiencies in the interest of defining future emissions goals or requirements. As the DEA method determines a relative efficiency, the specific efficiency results cannot be used to assess airline performance against an absolute numerical goal over time. However, deployment of the DEA model can generate relative efficiency results to establish an efficient production frontier. As the analysis results will identify the top performing airlines relative to the benchmark frontier, a regulatory agency could review the operational efficiency and environmental abatement performance of these efficient airlines to determine the operational parameters which define efficient performance (e.g. operating revenues, passenger miles flown, tons of carbon dioxide emissions expelled, etc.). By trending efficient operational parameters over consecutive years, a researcher may be able to establish trends in environmental abatement performance by the industry or target sector. This information could be used by regulatory bodies to enact requirements or incentives which foster future improvements in the industry's efficiency evolution.

The regulatory application of this model would supplement and evolve current industry measures to enhance the transparency of emissions generation, and require recognition of emissions through mandatory offsetting programs. Since the inception of this study, the ICAO approved the deployment of the Carbon Offsetting and Reduction Scheme for International Aviation (CORSIA) in a 2016 annex release (Sheelhaase et al, 2018). The approval of a deployment strategy by ICAO represents action toward the first global emissions offsetting requirements (unlike the EU Emissions Trading System which is specifically targeted within the EU). In order to define requirements within a trading system, internationally accepted standards for emissions reporting have been established by the Global Reporting Index leveraging – e.g. ISO 14064 and ISO 14069. The opportunity exists for the programs that are launched to effect CORSIA to leverage operational data gathered within the program to deploy the DEA model from this study and define future program goals.

Future research opportunities. Chapter I of this dissertation identifies a number of limitations and delimitations for this study. This section of Chapter V describes future research opportunities to explore and evolve the capabilities of the analytical model construct developed in this research study.

First, the VRS two-stage DEA components of the analytical model can implement a disproportionate weighting between the two stages as part of the optimization routine. In this study, an equivalency was established for all weighting requirements. This strategy directed the optimization routine to consider the following aspects of business operations equally: (1) the creation of ASMs from labor and material resources, (2) the conversion of ASMs into RPMs through network routes and scheduling, (3) the abatement of carbon dioxide emissions, and (4) the sales of RPMs to realize true revenue. From a holistic perspective, the strategy employed is appropriate for a large sample composed of many different airlines executing different models. However, a more focused research study could be conducted with airlines all operating the same business philosophy (e.g. FSC, LCC, or point-to-point). By narrowing the study to similar business philosophies, the research study could explore whether tailoring the stage weighting to reflect the business priorities of that specific operating model is an appropriate extension of the analysis model.

Irrespective of weighting, the results of this study highlighted the importance of comparing similar DMUs to maximize the efficacy of the comparison analysis. Different operational philosophies prioritize different efficiencies for business requirements: LCCs and point-to-point operators want to maximize ASM conversion to RPMs. Conversely, while FSCs still consider ASM conversion to RPMs an important measure of business efficiency, their operational philosophy inherently creates lower ASM conversion to RPMs from lower load factor flights carrying passengers from smaller spoke airports to the hubs (and vice versa). The FSCs are prioritizing the efficiency of their hub-to-hub operations, as that is where their ASM conversion and profit generation should be greatest. A similar dichotomy occurs with airlines operating the same business philosophy but on networks operating in different parts of the world (as discussed previously in this chapter). In order to best utilize this tool to assess and compare operating efficiencies between airlines, the selection of carriers to be included in the model sample should identify carriers with comparable operating models and networks.

A second opportunity for future research explores the variable selection used to reflect operational success. This study specifically utilized an operating revenue variable in the final stage of the multi-stage model. Following the Mallikarjun (2015) three-stage airline operating model construct, operating revenue was deemed an appropriate method of measuring revenue generation from RPM consumption through successful sales activity. Additionally, the profit realization of the airline was accounted for in the model as operating costs were an input variable for the overall model. Future research and variations of this model could leverage a net profit variable as the output of the final stage, as opposed to total revenue. This variation of the model may be challenging, as net profits are not publicly disclosed by all airlines; however, if a focused study is able to obtain this information, a final output goal of profitability as opposed to revenue generation may further contribute to the body of knowledge with regards to the impacts of emissions abatement activities on overall airline operating efficiency.

An extension of the aforementioned research opportunity could focus on the desired business output of non-traditional business models. Low-cost carriers and other niche operating models do not necessarily focus on maximizing revenue generation. Therefore, the output of the final stage (and overall model) could utilize a success factor that better aligns with the operating – e.g. revenue generating load factor.

A third opportunity for future research exists regarding the selection of carbon dioxide as the environmental impact included in this study. The literature review presented several different environmental impacts – and different foci of abatement initiatives – which the airline industry currently recognizes. Aircraft operations generate many sources of particulate emissions, including carbon oxides and nitrous oxides. As presented in the literature review, exigent research has also discovered that the acoustic emissions of aircraft operations have an impact on people living near areas with airline activity (airport). It is recommended that future research extend this model to other forms of emissions as well.

Data regarding other particulate emissions may be easier to collect as ICAO and GRI mandate reporting requirements for these other emissions in the future. As presented in the literature review, the International Organization for Standardization (ISO) has now created industry specifications for the quantification and reporting of greenhouse gas emissions. As regulatory bodies implement formal requirements for airlines to report emissions of carbon dioxide and other greenhouse gases according to an industry standard, these other emissions will become easier to study. Additionally, this current study could be repeated (for future years when the reporting standard is deployed) to evaluate if there is improved data quality due to standard global reporting requirements.

The final recommendation of this study is to explore variations of the model construct to better isolate the emissions abatement aspects of airline operating efficiency, while retaining the high fidelity of the Mallikarjun (2015) proposed three-stage airline operating model. Ebrahimnejad (2014) proposed a multi-stage DEA construct with parallel stages in a single phase. These stages possessed intermediate outputs which fed a final stage. A variation of the model developed in this study could invoke a three-stage DEA architecture while inserting two parallel stages in the second (of three) phase; one stage would be specific to ASM conversion to RPMs, the other stage would be specific to emissions abatement activity. Development of such a model would require significant scope in formula development and programming. Similar to the Mallikarjun (2015) model, this model would require a forward-backward recursion algorithm between the first-to-second and second-to-third phases. In addition, it would require the recursive programming to separately interact with each of the two parallel stages in the second phase.

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APPENDIX A

Tables

Table A1

2013 Single Year VRS Model – Phase 1, Stage 1 Results

Airline	Stage 1 Efficiency	1st Benchmark	1st Airline Benchmark	2nd Benchmark	2nd Airline Benchmark
Air Canada	1.00000	0.379	Emirates	0.621	JetBlue
Air France – KLM	0.96758	0.992	Emirates	0.008	JetBlue
Alaska Airlines	1.00000	1.000	Alaska Airlines		
All Nippon Airways	1.00000	0.607	Emirates	0.393	JetBlue
American Airlines	0.84710	0.889	Emirates	0.111	JetBlue
British Airways	1.00000	0.776	Emirates	0.224	JetBlue
Delta Air Lines	1.00000	1.000	Delta Air Lines		
Emirates	1.00000	1.000	Emirates		
Japan Airlines	1.00000	0.378	Emirates	0.622	JetBlue
JetBlue Airways	1.00000	1.000	JetBlue		
Lufthansa Airlines	0.52609	1.000	Emirates		
Southwest Airlines	1.00000	0.652	Emirates	0.348	JetBlue
United Airlines	1.00000	1.000	United Air Lines		

Table A2

2013 Single Year VRS Model – Phase 1, Stage 2 Results

Airline	Stage 2 Efficiency	1st Benchmark	1st Airline Benchmark	2nd Benchmark	2nd Airline Benchmark	3rd Benchmark	3rd Airline Benchmark
Air Canada	0.37664	0.462	Air Canada	0.538	American Airlines		
Air France – KLM	1.00000	0.212	Alaska Airlines	0.788	Delta Air Lines		
Alaska Airlines	1.00000	1.000	Alaska Airlines				
All Nippon Airways	0.42117	0.024	Air Canada	0.464	Alaska Airlines	0.512	Delta Air Lines
American Airlines	1.00000	1.000	American Airlines				
British Airways	0.68627	0.080	Air Canada	0.281	Alaska Airlines	0.639	Delta Air Lines
Delta Air Lines	1.00000	1.000	Delta Air Lines				
Emirates	0.93740	0.206	Alaska Airlines	0.794	Delta Air Lines		
Japan Airlines	0.47938	0.122	Air Canada	0.523	Alaska Airlines	0.355	Delta Air Lines
JetBlue Airways	0.97762	0.928	Alaska Airlines	0.072	Delta Air Lines		
Lufthansa Airlines	0.91257	0.206	Alaska Airlines	0.794	Delta Air Lines		
Southwest Airlines	0.85297	0.457	Alaska Airlines	0.543	Delta Air Lines		
United Airlines	1.00000	1.000	United Air Lines				

Table A3

2013 Single Year VRS Model – Phase 2, Stage 1 Results

Airline	Stage 1 Efficiency	1^{st} Benchmark	1^{st} Airline Benchmark	2^{nd} Benchmark	2^{nd} Airline Benchmark	3rd Benchmark	3rd Airline Benchmark
Air Canada	1.00000	1.000	Air Canada				
Air France – KLM	0.90797	0.291	Alaska Airlines	0.709	Delta Air Lines		
Alaska Airlines	1.00000	0.809	Air Canada	0.124	Alaska Airlines	0.067	Delta Air Lines
All Nippon Airways	0.52991	0.765	Air Canada	0.152	Alaska Airlines	0.082	Delta Air Lines
American Airlines	0.99421	0.291	Alaska Airlines	0.709	Delta Air Lines		
British Airways	1.00000	0.598	Alaska Airlines	0.402	Delta Air Lines		
Delta Air Lines	0.75218	0.291	Alaska Airlines	0.709	Delta Air Lines		
Emirates	0.91227	0.291	Alaska Airlines	0.709	Delta Air Lines		
Japan Airlines	0.39998	0.938	Air Canada	0.040	Alaska Airlines	0.022	Delta Air Lines
JetBlue Airways	1.00000	0.645	Air Canada	0.231	Alaska Airlines	0.125	Delta Air Lines
Lufthansa Airlines	0.94162	0.291	Alaska Airlines	0.709	Delta Air Lines		
Southwest Airlines	1.00000	0.527	Alaska Airlines	0.473	Delta Air Lines		
United Airlines	0.72121	0.291	Alaska Airlines	0.709	Delta Air Lines		

Table A4

2013 Single Year VRS Model – Phase 2, Stage 2 Results

Airline	Stage 2 Efficiency	1st Benchmark	1st Airline Benchmark	2nd Benchmark	2nd Airline Benchmark
Air Canada	1.00000	1.000	Air Canada		
Air France – KLM	0.84990	0.291	Alaska Airlines	0.709	Delta Air Lines
Alaska Airlines	0.33143	0.809	Air Canada	0.124	Alaska Airlines
All Nippon Airways	1.00000	0.765	Air Canada	0.152	Alaska Airlines
American Airlines	0.59424	0.291	Alaska Airlines	0.709	Delta Air Lines
British Airways	0.62725	0.598	Alaska Airlines	0.402	Delta Air Lines
Delta Air Lines	0.87240	0.291	Alaska Airlines	0.709	Delta Air Lines
Emirates	0.53433	0.291	Alaska Airlines	0.709	Delta Air Lines
Japan Airlines	1.00000	0.938	Air Canada	0.040	Alaska Airlines
JetBlue Airways	0.29617	0.645	Air Canada	0.231	Alaska Airlines
Lufthansa Airlines	1.00000	0.291	Alaska Airlines	0.709	Delta Air Lines
Southwest Airlines	0.51761	0.527	Alaska Airlines	0.473	Delta Air Lines
United Airlines	0.88322	0.291	Alaska Airlines	0.709	Delta Air Lines

Table A5

2014 Single Year VRS Model – Phase 1, Stage 1 Results

Airline	Stage 1 Efficiency	1st Benchmark	1st Airline Benchmark	2nd Benchmark	2nd Airline Benchmark
Air Canada	1.00000	0.396	Air France - KLM	0.604	JetBlue
Air France – KLM	1.00000	1.000	Air France - KLM		
Alaska Airlines	1.00000	1.000	Alaska Airlines		
All Nippon Airways	1.00000	0.590	Air France - KLM	0.410	JetBlue
American Airlines	0.76157	0.914	Air France - KLM	0.086	JetBlue
British Airways	1.00000	0.815	Air France - KLM	0.185	JetBlue
Delta Air Lines	0.95294	0.060	Emirates	0.940	United Air Lines
Emirates	0.88910	0.799	Air France - KLM	0.201	Emirates
Japan Airlines	1.00000	0.323	Air France - KLM	0.677	JetBlue
JetBlue Airways	1.00000	1.000	JetBlue		
Lufthansa Airlines	0.61330	1.000	Emirates		
Southwest Airlines	1.00000	0.745	Air France - KLM	0.255	JetBlue
United Airlines	0.94792	0.145	Emirates	0.855	United Air Lines

Table A6

2014 Single Year VRS Model – Phase 1, Stage 2 Results

Airline	Stage 2 Efficiency	1st Benchmark	1st Airline Benchmark	2nd Benchmark	2nd Airline Benchmark	3rd Benchmark	3rd Airline Benchmark
Air Canada	0.38800	0.455	Air Canada	0.545	American Airlines		
Air France – KLM	0.99190	0.245	Alaska Airlines	0.755	Delta Air Lines		
Alaska Airlines	1.00000	1.000	Alaska Airlines				
All Nippon Airways	0.45880	0.003	Air Canada	0.523	Alaska Airlines	0.474	Delta Air Lines
American Airlines	1.00000	1.000	American Airlines				
British Airways	0.69286	0.078	Air Canada	0.287	Alaska Airlines	0.635	Delta Air Lines
Delta Air Lines	1.00000	1.000	Delta Air Lines				
Emirates	1.00000	0.228	Alaska Airlines	0.772	Delta Air Lines		
Japan Airlines	0.51641	0.190	Air Canada	0.503	Alaska Airlines	0.307	Delta Air Lines
JetBlue Airways	0.98210	0.930	Alaska Airlines	0.070	Delta Air Lines		
Lufthansa Airlines	0.85003	0.159	Alaska Airlines	0.841	Delta Air Lines		
Southwest Airlines	0.47410	0.148	Air Canada	0.852	American Airlines		
United Airlines	1.00000	0.014	Alaska Airlines	0.986	Delta Air Lines		

Table A7

2014 Single Year VRS Model – Phase 2, Stage 1 Results

Airline	Stage 1 Efficiency	1st Benchmark	1st Airline Benchmark	2nd Benchmark	2nd Airline Benchmark	3rd Benchmark	3rd Airline Benchmark
Air Canada	1.00000	1.000	Air Canada				
Air France – KLM	0.72334	0.504	Alaska Airlines	0.496	Delta Air Lines		
Alaska Airlines	1.00000	0.811	Air Canada	0.121	Alaska Airlines	0.068	Delta Air Lines
All Nippon Airways	0.48085	0.807	Air Canada	0.124	Alaska Airlines	0.069	Delta Air Lines
American Airlines	0.99045	0.312	Alaska Airlines	0.688	Delta Air Lines		
British Airways	1.00000	0.590	Alaska Airlines	0.410	Delta Air Lines		
Delta Air Lines	1.00000	1.000	Delta Air Lines				
Emirates	0.84993	0.312	Alaska Airlines	0.688	Delta Air Lines		
Japan Airlines	0.33361	1.000	Air Canada				
JetBlue Airways	1.00000	0.653	Air Canada	0.222	Alaska Airlines	0.125	Delta Air Lines
Lufthansa Airlines	0.93753	0.312	Alaska Airlines	0.688	Delta Air Lines		
Southwest Airlines	0.87228	0.561	Air Canada	0.281	Alaska Airlines	0.158	Delta Air Lines
United Airlines	0.80145	0.226	Alaska Airlines	0.774	Delta Air Lines		

Table A8

2014 Single Year VRS Model – Phase 2, Stage 2 Results

Airline	Stage 2 Efficiency	1st Benchmark	1st Airline Benchmark	2nd Benchmark	2nd Airline Benchmark
Air Canada	1.00000	1.000	Air Canada		
Air France – KLM	1.00000	0.247	Air Canada	0.753	Lufthansa Airlines
Alaska Airlines	0.36244	0.891	Air Canada	0.109	Lufthansa Airlines
All Nippon Airways	1.00000	0.889	Air Canada	0.111	Lufthansa Airlines
American Airlines	0.70825	1.000	Lufthansa Airlines		
British Airways	0.65765	0.358	Air Canada	0.642	Lufthansa Airlines
Delta Air Lines	1.00000	1.000	Delta Air Lines		
Emirates	0.63898	1.000	Lufthansa Airlines		
Japan Airlines	0.97823	1.000	Air Canada		
JetBlue Airways	0.33803	0.800	Air Canada	0.200	Lufthansa Airlines
Lufthansa Airlines	1.00000	1.000	Lufthansa Airlines		
Southwest Airlines	1.00000	0.747	Air Canada	0.253	Lufthansa Airlines
United Airlines	1.00000	0.275	Delta Air Lines	0.725	Lufthansa Airlines

Table A9

2015 Single Year VRS Model – Phase 1, Stage 1 Results

Airline	Stage 1 Efficiency	1st Benchmark	1st Airline Benchmark	2nd Benchmark	2nd Airline Benchmark
Air Canada	1.00000	0.332	Air France - KLM	0.668	JetBlue
Air France – KLM	1.00000	1.000	Air France - KLM		
Alaska Airlines	1.00000	1.000	Alaska Airlines		
All Nippon Airways	1.00000	0.711	Air France - KLM	0.289	JetBlue
American Airlines	0.73109	0.195	Air France - KLM	0.805	Emirates
Delta Air Lines	1.00000	1.000	Delta Air Lines		
Emirates	1.00000	1.000	Emirates		
Japan Airlines	1.00000	0.351	Air France - KLM	0.649	JetBlue
JetBlue Airways	1.00000	1.000	JetBlue		
Lufthansa Airlines	0.60252	1.000	Emirates		
Southwest Airlines	1.00000	0.840	Air France - KLM	0.160	JetBlue
United Airlines	1.00000	0.976	Delta Air Lines	0.024	Emirates

Note. British Airways is excluded from the 2015 model as they did not have publicly available environmental data.

Table A10

2015 Single Year VRS Model – Phase 1, Stage 2 Results

Airline	Stage 2 Efficiency	1st Benchmark	1st Airline Benchmark	2nd Benchmark	2nd Airline Benchmark	3rd Benchmark	3rd Airline Benchmark
Air Canada	0.49755	0.608	Air Canada	0.392	American Airlines		
Air France – KLM	0.99678	0.263	Alaska Airlines	0.737	Delta Air Lines		
Alaska Airlines	1.00000	1.000	Alaska Airlines				
All Nippon Airways	0.42168	0.042	Air Canada	0.409	Alaska Airlines	0.549	Delta Air Lines
American Airlines	1.00000	1.000	American Airlines				
Delta Air Lines	1.00000	1.000	Delta Air Lines				
Emirates	0.89504	0.065	Air Canada	0.935	Delta Air Lines		
Japan Airlines	0.49273	0.178	Air Canada	0.499	Alaska Airlines	0.323	Delta Air Lines
JetBlue Airways	1.00000	1.000	JetBlue				
Lufthansa Airlines	0.77294	0.071	Alaska Airlines	0.929	Delta Air Lines		
Southwest Airlines	0.96482	0.369	Alaska Airlines	0.631	Delta Air Lines		
United Airlines	0.97621	0.002	Air Canada	0.998	Delta Air Lines		

Note. British Airways is excluded from the 2015 model as they did not have publicly available environmental data.

Table A11

2015 Single Year VRS Model – Phase 2, Stage 1 Results

Airline	Stage 1 Efficiency	1st Benchmark	1st Airline Benchmark	2nd Benchmark	2nd Airline Benchmark	3rd Benchmark	3rd Airline Benchmark
Air Canada	1.00000	1.000	Air Canada				
Air France – KLM	0.93221	0.326	Alaska Airlines	0.674	Delta Air Lines		
Alaska Airlines	1.00000	0.799	Air Canada	0.127	Alaska Airlines	0.074	Delta Air Lines
All Nippon Airways	0.63568	0.691	Air Canada	0.196	Alaska Airlines	0.113	Delta Air Lines
American Airlines	0.79999	0.326	Alaska Airlines	0.674	Delta Air Lines		
Delta Air Lines	1.00000	1.000	Delta Air Lines				
Emirates	0.79046	0.305	Alaska Airlines	0.695	United Air Lines		
Japan Airlines	0.45512	0.942	Air Canada	0.037	Alaska Airlines	0.021	Delta Air Lines
JetBlue Airways	1.00000	0.640	Air Canada	0.228	Alaska Airlines	0.132	Delta Air Lines
Lufthansa Airlines	0.94216	0.326	Alaska Airlines	0.674	Delta Air Lines		
Southwest Airlines	1.00000	0.376	Alaska Airlines	0.624	Delta Air Lines		
United Airlines	0.82812	0.207	Alaska Airlines	0.793	Delta Air Lines		

Note. British Airways is excluded from the 2015 model as they did not have publicly available environmental data.

Table A12

2015 Single Year VRS Model – Phase 2, Stage 2 Results

Airline	Stage 2 Efficiency	1st Benchmark	1st Airline Benchmark	2nd Benchmark	2nd Airline Benchmark
Air Canada	1.00000	1.000	Air Canada		
Air France – KLM	0.81323	1.000	Lufthansa Airlines		
Alaska Airlines	0.41158	0.879	Air Canada	0.121	Lufthansa Airlines
All Nippon Airways	1.00000	0.814	Air Canada	0.186	Lufthansa Airlines
American Airlines	0.92818	1.000	Lufthansa Airlines		
Delta Air Lines	1.00000	1.000	Delta Air Lines		
Emirates	0.65101	1.000	Lufthansa Airlines		
Japan Airlines	1.00000	0.965	Air Canada	0.035	Lufthansa Airlines
JetBlue Airways	0.40008	0.784	Air Canada	0.216	Lufthansa Airlines
Lufthansa Airlines	1.00000	1.000	Lufthansa Airlines		
Southwest Airlines	0.57415	0.065	Air Canada	0.935	Lufthansa Airlines
United Airlines	1.00000	0.363	Delta Air Lines	0.637	Lufthansa Airlines

Note. British Airways is excluded from the 2015 model as they did not have publicly available environmental data.

Table A13

3 Year Combined (2013-2015) VRS Model – Phase 1, Stage 1 Results

Airline	Stage 1 Efficiency	1st Benchmark	1st Airline Benchmark	2nd Benchmark	2nd Airline Benchmark
Air Canada	1.00000	0.367	Air France - KLM	0.633	JetBlue
Air France – KLM	0.99233	0.990	Air France - KLM	0.010	JetBlue
Alaska Airlines	1.00000	1.000	Alaska Airlines		
All Nippon Airways	1.00000	0.622	Air France - KLM	0.378	JetBlue
American Airlines	0.79069	0.936	Air France - KLM	0.064	Emirates
British Airways	1.00000	0.795	Air France - KLM	0.205	JetBlue
Delta Air Lines	0.98210	0.115	Emirates	0.885	United Air Lines
Emirates	0.91302	0.892	Air France - KLM	0.108	Emirates
Japan Airlines	1.00000	0.348	Air France - KLM	0.652	JetBlue
JetBlue Airways	1.00000	1.000	JetBlue		
Lufthansa Airlines	0.57807	1.000	Emirates		
Southwest Airlines	1.00000	0.726	Air France - KLM	0.274	JetBlue
United Airlines	0.95086	0.133	Emirates	0.867	United Air Lines

Note. British Airways data includes flight capacity (seat miles) and revenue generation from 2015, but no environmental data.

Table A14

3 Year Combined (2013-2015) VRS Model – Phase 1, Stage 2 Results

Airline	Stage 2 Efficiency	1st Benchmark	1st Airline Benchmark	2nd Benchmark	2nd Airline Benchmark	3rd Benchmark	3rd Airline Benchmark
Air Canada	0.42264	0.519	Air Canada	0.481	American Airlines		
Air France – KLM	1.00000	0.244	Alaska Airlines	0.756	Delta Air Lines		
Alaska Airlines	1.00000	1.000	Alaska Airlines				
All Nippon Airways	0.43871	0.024	Air Canada	0.473	Alaska Airlines	0.503	Delta Air Lines
American Airlines	1.00000	1.000	American Airlines				
British Airways	0.69325	0.379	Alaska Airlines	0.621	Delta Air Lines		
Delta Air Lines	1.00000	1.000	Delta Air Lines				
Emirates	1.00000	0.227	Alaska Airlines	0.773	Delta Air Lines		
Japan Airlines	0.49746	0.166	Air Canada	0.508	Alaska Airlines	0.326	Delta Air Lines
JetBlue Airways	0.98628	0.929	Alaska Airlines	0.071	Delta Air Lines		
Lufthansa Airlines	0.84035	0.144	Alaska Airlines	0.856	Delta Air Lines		
Southwest Airlines	0.76289	0.427	Alaska Airlines	0.573	Delta Air Lines		
United Airlines	1.00000	0.003	Alaska Airlines	0.997	Delta Air Lines		

Note. British Airways data includes flight capacity (seat miles) and revenue generation from 2015, but no environmental data.

Table A15

3 Year Combined (2013-2015) VRS Model – Phase 2, Stage 1 Results

Airline	Stage 1 Efficiency	1st Benchmark	1st Airline Benchmark	2nd Benchmark	2nd Airline Benchmark	3rd Benchmark	3rd Airline Benchmark
Air Canada	1.00000	1.000	Air Canada				
Air France – KLM	0.92276	0.310	Alaska Airlines	0.690	Delta Air Lines		
Alaska Airlines	1.00000	0.806	Air Canada	0.124	Alaska Airlines	0.070	Delta Air Lines
All Nippon Airways	0.54746	0.756	Air Canada	0.157	Alaska Airlines	0.088	Delta Air Lines
American Airlines	0.91702	0.310	Alaska Airlines	0.690	Delta Air Lines		
British Airways	1.00000	0.599	Alaska Airlines	0.401	Delta Air Lines		
Delta Air Lines	1.00000	1.000	Delta Air Lines				
Emirates	0.84028	0.310	Alaska Airlines	0.690	Delta Air Lines		
Japan Airlines	0.38924	0.965	Air Canada	0.023	Alaska Airlines	0.013	Delta Air Lines
JetBlue Airways	1.00000	0.646	Air Canada	0.227	Alaska Airlines	0.127	Delta Air Lines
Lufthansa Airlines	0.94035	0.310	Alaska Airlines	0.690	Delta Air Lines		
Southwest Airlines	0.95937	0.010	Air Canada	0.596	Alaska Airlines	0.395	Delta Air Lines
United Airlines	0.72635	0.310	Alaska Airlines	0.690	Delta Air Lines		

Note. British Airways data includes flight capacity (seat miles) and revenue generation from 2015, but no environmental data.

Table A16

3 Year Combined (2013-2015) VRS Model – Phase 2, Stage 2 Results

Airline	Stage 2 Efficiency	1st Benchmark	1st Airline Benchmark	2nd Benchmark	2nd Airline Benchmark
Air Canada	1.00000	1.000	Air Canada		
Air France – KLM	0.83220	1.000	Lufthansa Airlines		
Alaska Airlines	0.36631	0.888	Air Canada	0.112	Lufthansa Airlines
All Nippon Airways	1.00000	0.859	Air Canada	0.141	Lufthansa Airlines
American Airlines	0.73383	1.000	Lufthansa Airlines		
British Airways	0.64631	0.369	Air Canada	0.631	Lufthansa Airlines
Delta Air Lines	1.00000	1.000	Delta Air Lines		
Emirates	0.60418	1.000	Lufthansa Airlines		
Japan Airlines	1.00000	0.980	Air Canada	0.020	Lufthansa Airlines
JetBlue Airways	0.34205	0.796	Air Canada	0.204	Lufthansa Airlines
Lufthansa Airlines	1.00000	1.000	Lufthansa Airlines		
Southwest Airlines	1.00000	1.000	Southwest Airlines		
United Airlines	0.97626	1.000	Lufthansa Airlines		

Note. British Airways data includes flight capacity (seat miles) and revenue generation from 2015, but no environmental data.

Table A17

U.S. Airlines (2013-2015) VRS Model – Phase 1, Stage 1 Results

Airline	Stage 1 Efficiency	1st Benchmark	1st Airline Benchmark	2nd Benchmark	2nd Airline Benchmark
Alaska Airlines	1.00000	1.000	Alaska Airlines		
American Airlines	0.74644	0.807	Delta Air Lines	0.293	JetBlue
Delta Air Lines	0.81072	0.856	Delta Air Lines	0.144	JetBlue
JetBlue Airways	1.00000	1.000	JetBlue		
Southwest Airlines	1.00000	0.743	Delta Air Lines	0.257	JetBlue
United Airlines	0.79160	0.823	Delta Air Lines	0.177	JetBlue

Table A18

U.S. Airlines (2013-2015) VRS Model – Phase 1, Stage 2 Results

Airline	Stage 2 Efficiency	1st Benchmark	1st Airline Benchmark	2nd Benchmark	2nd Airline Benchmark
Alaska Airlines	1.00000	1.000	Alaska Airlines		
American Airlines	0.86405	0.143	Alaska Airlines	0.857	Delta Air Lines
Delta Air Lines	1.00000	1.000	Delta Air Lines		
JetBlue Airways	0.72353	0.775	Alaska Airlines	0.225	Delta Air Lines
Southwest Airlines	0.53671	0.448	Alaska Airlines	0.552	Delta Air Lines
United Airlines	0.92979	0.102	Alaska Airlines	0.898	Delta Air Lines

Table A19

U.S. Airlines (2013-2015) VRS Model – Phase 2, Stage 1 Results

Airline	Stage 1 Efficiency	1st Benchmark	1st Airline Benchmark	2nd Benchmark	2nd Airline Benchmark
Alaska Airlines	1.00000	1.000	Alaska Airlines		
American Airlines	0.88940	0.276	Alaska Airlines	0.724	Delta Air Lines
Delta Air Lines	1.00000	1.000	Delta Air Lines		
JetBlue Airways	0.96313	0.998	Alaska Airlines	0.002	Delta Air Lines
Southwest Airlines	0.92038	0.619	Alaska Airlines	0.381	Delta Air Lines
United Airlines	0.85647	0.276	Alaska Airlines	0.724	Delta Air Lines

Table A20

U.S. Airlines (2013-2015) VRS Model – Phase 2, Stage 2 Results

Airline	Stage 2 Efficiency	1st Benchmark	1st Airline Benchmark	2nd Benchmark	2nd Airline Benchmark
Alaska Airlines	0.37194	1.000	Southwest Airlines		
American Airlines	0.85779	1.000	Delta Air Lines		
Delta Air Lines	1.00000	1.000	Delta Air Lines		
JetBlue Airways	0.34852	1.000	Southwest Airlines		
Southwest Airlines	1.00000	1.000	Southwest Airlines		
United Airlines	0.95622	1.000	Delta Air Lines		

Table A21

Non U.S. Airlines (2013-2015) VRS Model Phase 1, Stage 1 Results

Airline	Stage 1 Efficiency	1st Benchmark	1st Airline Benchmark	2nd Benchmark	2nd Airline Benchmark
Air Canada	1.00000	0.029	Air France - KLM	0.971	Japan Airlines
Air France – KLM	1.00000	1.000	Air France - KLM		
All Nippon Airways	1.00000	0.420	Air France - KLM	0.580	Japan Airlines
British Airways	1.00000	0.686	Air France - KLM	0.314	Japan Airlines
Emirates	1.00000	1.000	Emirates		
Japan Airlines	1.00000	1.000	Japan Airlines		
Lufthansa Airlines	0.52171	1.000	Air France - KLM		

Note. British Airways data includes flight capacity (seat miles) and revenue generation from 2015, but no environmental data.

Table A22

Non U.S. Airlines (2013-2015) VRS Model Phase 1, Stage 2 Results

Airline	Stage 2 Efficiency	1st Benchmark	1st Airline Benchmark	2nd Benchmark	2nd Airline Benchmark
Air Canada	0.72415	0.750	Air Canada	0.250	Air France - KLM
Air France – KLM	1.00000	1.000	Air France - KLM		
All Nippon Airways	0.53671	0.448	Air Canada	0.552	Air France - KLM
British Airways	0.76049	0.243	Air Canada	0.757	Air France - KLM
Emirates	1.00000	1.000	Emirates		
Japan Airlines	0.86405	0.773	Air Canada	0.227	Air France - KLM
Lufthansa Airlines	0.92979	1.000	Air France - KLM		

Note. British Airways data includes flight capacity (seat miles) and revenue generation from 2015, but no environmental data.

Table A23

Non U.S. Airlines (2013-2015) VRS Model Phase 2, Stage 1 Results

Airline	Stage 1 Efficiency	1st Benchmark	1st Airline Benchmark	2nd Benchmark	2nd Airline Benchmark
Air Canada	1.00000	1.000	Air Canada		
Air France – KLM	0.93014	0.078	Air Canada	0.922	Air France - KLM
All Nippon Airways	0.55155	0.870	Air Canada	0.130	Air France - KLM
British Airways	1.00000	0.426	Air Canada	0.574	Air France - KLM
Emirates	0.84700	0.078	Air Canada	0.922	Air France - KLM
Japan Airlines	0.39001	0.981	Air Canada	0.019	Air France - KLM
Lufthansa Airlines	0.94787	0.078	Air Canada	0.922	Air France - KLM

Note. British Airways data includes flight capacity (seat miles) and revenue generation from 2015, but no environmental data.

Table A24

Non U.S. Airlines (2013-2015) VRS Model Phase 2, Stage 2 Results

Airline	Stage 2 Efficiency	1st Benchmark	1st Airline Benchmark	2nd Benchmark	2nd Airline Benchmark
Air Canada	1.00000	1.000	Air Canada		
Air France – KLM	0.83220	1.000	Lufthansa Airlines		
All Nippon Airways	1.00000	0.859	Air Canada	0.141	Lufthansa Airlines
British Airways	0.65138	0.378	Air Canada	0.622	Lufthansa Airlines
Emirates	0.60418	1.000	Lufthansa Airlines		
Japan Airlines	1.00000	0.980	Air Canada	0.020	Lufthansa Airlines
Lufthansa Airlines	1.00000	1.000	Lufthansa Airlines		

Note. British Airways data includes flight capacity (seat miles) and revenue generation from 2015, but no environmental data.

Table A25

Full Service Carriers (2013-2015) VRS Model – Phase 1, Stage 1 Results

Airline	Stage 1 Efficiency	1st Benchmark	1st Airline Benchmark	2nd Benchmark	2nd Airline Benchmark
Air Canada	1.00000	0.029	Air France - KLM	0.971	Japan Airlines
Air France – KLM	1.00000	1.000	Air France - KLM		
All Nippon Airways	1.00000	0.420	Air France - KLM	0.580	Japan Airlines
American Airlines	0.79069	0.936	Air France - KLM	0.064	Emirates
British Airways	1.00000	0.686	Air France - KLM	0.314	Japan Airlines
Delta Air Lines	0.98210	0.115	Emirates	0.885	United Air Lines
Emirates	1.00000	1.000	Emirates		
Japan Airlines	1.00000	1.000	Japan Airlines		
Lufthansa Airlines	0.57807	1.000	Emirates		
United Airlines	0.95089	0.133	Emirates	0.867	United Air Lines

Note. British Airways data includes flight capacity (seat miles) and revenue generation from 2015, but no environmental data.

Table A26

Full Service Carriers (2013-2015) VRS Model – Phase 1, Stage 2 Results

Airline	Stage 1 Efficiency	1st Benchmark	1st Airline Benchmark	2nd Benchmark	2nd Airline Benchmark
Air Canada	0.58662	0.752	Air Canada	0.248	American Airlines
Air France – KLM	0.99371	0.218	Air Canada	0.782	Delta Air Lines
All Nippon Airways	0.53358	0.568	Air Canada	0.432	Delta Air Lines
American Airlines	1.00000	1.000	American Airlines		
British Airways	0.76049	0.243	Air Canada	0.757	Air France - KLM
Delta Air Lines	1.00000	1.000	Delta Air Lines		
Emirates	0.92094	0.133	Air Canada	0.867	Delta Air Lines
Japan Airlines	0.85998	0.822	Air Canada	0.178	Delta Air Lines
Lufthansa Airlines	0.84093	0.133	Air Canada	0.867	Delta Air Lines
United Airlines	1.00000	0.003	Air Canada	0.997	Delta Air Lines

Note. British Airways data includes flight capacity (seat miles) and revenue generation from 2015, but no environmental data.

Table A27

Full Service Carriers (2013-2015) VRS Model – Phase 2, Stage 1 Results

Airline	Stage 1 Efficiency	1st Benchmark	1st Airline Benchmark	2nd Benchmark	2nd Airline Benchmark
Air Canada	1.00000	1.000	Air Canada		
Air France – KLM	0.92437	0.284	Air Canada	0.716	Delta Air Lines
All Nippon Airways	0.54951	0.899	Air Canada	0.101	Delta Air Lines
American Airlines	0.91863	0.284	Air Canada	0.716	Delta Air Lines
British Airways	1.00000	0.551	Air Canada	0.449	Delta Air Lines
Delta Air Lines	1.00000	1.000	Delta Air Lines		
Emirates	0.84175	0.284	Air Canada	0.716	Delta Air Lines
Japan Airlines	0.38963	0.985	Air Canada	0.015	Delta Air Lines
Lufthansa Airlines	0.94200	0.284	Air Canada	0.716	Delta Air Lines
United Airlines	0.72762	0.284	Air Canada	0.716	Delta Air Lines

Note. British Airways data includes flight capacity (seat miles) and revenue generation from 2015, but no environmental data.

Table A28

Full Service Carriers (2013-2015) VRS Model – Phase 2, Stage 2 Results

Airline	Stage 1 Efficiency	1st Benchmark	1st Airline Benchmark	2nd Benchmark	2nd Airline Benchmark
Air Canada	1.00000	1.000	Air Canada		
Air France – KLM	0.83220	1.000	Lufthansa Airlines		
All Nippon Airways	1.00000	0.859	Air Canada	0.141	Lufthansa Airlines
American Airlines	0.73383	1.000	Lufthansa Airlines		
British Airways	0.64866	0.373	Air Canada	0.627	Lufthansa Airlines
Delta Air Lines	1.00000	1.000	Delta Air Lines		
Emirates	0.60418	1.000	Lufthansa Airlines		
Japan Airlines	1.00000	0.980	Air Canada	0.020	Lufthansa Airlines
Lufthansa Airlines	1.00000	1.000	Lufthansa Airlines		
United Airlines	0.97626	1.000	Lufthansa Airlines		

Note. British Airways data includes flight capacity (seat miles) and revenue generation from 2015, but no environmental data.

Table A29

P2P / LCC Carriers (2013-2015) VRS Model – Phase 1, Stage 1 Results

Airline	Stage 1 Efficiency	1st Benchmark	1st Airline Benchmark	2nd Benchmark	2nd Airline Benchmark
Alaska Airlines	1.00000	1.000	Alaska Airlines		
JetBlue Airways	0.83594	1.000	Alaska Airlines		
Southwest Airlines	0.26806	1.000	Alaska Airlines		

Table A30

P2P / LCC Carriers (2013-2015) VRS Model – Phase 1, Stage 2 Results

Airline	Stage 2 Efficiency	1st Benchmark	1st Airline Benchmark	2nd Benchmark	2nd Airline Benchmark
Alaska Airlines	1.00000				
JetBlue Airways	1.00000				
Southwest Airlines	1.00000				

Table A31

P2P / LCC Carriers (2013-2015) VRS Model – Phase 2, Stage 1 Results

Airline	Stage 1 Efficiency	1st Benchmark	1st Airline Benchmark	2nd Benchmark	2nd Airline Benchmark
Alaska Airlines	1.00000	1.000	Alaska Airlines		
JetBlue Airways	0.71975	1.000	Alaska Airlines		
Southwest Airlines	0.30502	1.000	Alaska Airlines		

Table A32

P2P / LCC Carriers (2013-2015) VRS Model – Phase 2, Stage 2 Results

Airline	Stage 2 Efficiency	1^{st} Benchmark	1^{st} Airline Benchmark	2^{nd} Benchmark	2^{nd} Airline Benchmark
Alaska Airlines	1.00000				
JetBlue Airways	1.00000				
Southwest Airlines	1.00000				