European Airline Performance: A Data Envelopment Analysis with Extrapolations Based on Model Outputs

By

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Declaration

I hereby certify that this material, which I now submit for assessment on the programme of study leading to the award of M.B.S. is entirely my own work, that I have exercised reasonable care to ensure that the work is original, and does not to the best of my knowledge breach any law of copyright, and has not been taken from the work of others save and to the extent that such work has been cited and acknowledged within the text of my work.

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Acronyms

AHP	Analytical Hierarchy Process
AT & T	Aircraft Transport and Travel
BCC	Banker, Charnes & Cooper (Model of DEA)
BEA	British European Airways
BSC	Balanced Score Card
CCR	Charnes, Cooper & Rhodes (Model of DEA)
CKI	Cost of Capital Invested
CRS	Constant Returns to Scale
DEA	Data Envelopment Analysis
DM	Decision Maker
DMU	Decision Making Unit
EASA	European Aviation Safety Agency
ENAC	Ente Nazionale Per L'Aviazione Civile
EVA	Economic Value Added
IAA	Irish Aviation Authority
IATA	International Air Transport Association
ICAO	International Civil Aviation Organisation
KLM	Koninklijke Luchtvaart Maatschappij N.V. (Royal Dutch Airlines)
KPI	Key Performance Indicator
MADM	Multi Attribute Decision Making
MCDM	Multi Criteria Decision Making
MODM	Multi Objective Decision Making
NOPAT	Net Operating Profit After Tax
OCF	Operating Cash Flow
PIM	Performance Improvement Management

RA	Ratio Analysis
RPK	Revenue Passenger Kilometres
SFA	Stochastic Frontier Analysis
TFP	Total Factor Productivity
VRS	Variable Returns to Scale

Abstract

European Airline Performance: A Data Envelopment Analysis with Extrapolations Based on Model Outputs

Martin Phillips

Airlines are notoriously difficult to run successfully. In the 40 years to 2010 the airline industry generated a cumulative profit margin of only 0.1 per cent. Airlines are complex and heavily regulated entities which makes like for like comparisons difficult. This makes the identification of 'best practice' challenging and as a result airlines, while performing the same basic function, do so very differently. This study set out to identify the best performing airlines in Europe in an attempt to rank airlines in terms of company performance.

Previous empirical work in this area was reviewed and Data Envelopment Analysis (DEA) was identified as a suitable performance measurement and ranking technique. The analysis was further developed through the application of sensitivity analyses and robustness measurement methodologies.

This study identifies Ryanair as one of Europe's most efficient airlines and KLM as one of Europe's least efficient airlines. As a result of further analysis various financial, operational and strategic elements of airlines were selected for further investigation. This in turn led to the identification of various 'best practices' and exemplars that poorer performing airlines may wish to emulate.

Chapter One Introduction & Rationale

1.1 Introduction

Profit has always been elusive for the airline industry. In the 40 years to 2010 the airline industry generated over $12,000 billion of revenue in today's prices but a total of only $19 billion of net post tax profit, a margin of only 0.1 per cent (Akbar, Nemeth & Niemeier, 2014). Despite this historic elusiveness of profit the future for the air transport industry looks bright. Growth is predicted to continue at 4.7 per cent until 2028 resulting in global airlines carrying 5.7 billion passengers (O'Connell, 2011). However, as a result of ongoing deregulation in the worldwide aviation industry competition for these passengers is fiercer than ever and airlines need to look for ways to maximise profits. Consequently it is those airlines that develop and implement strategies to manage costs, improve productivity and deliver a product for which customers are willing to pay a compensatory price that will ultimately survive and prosper into the future (Belobaba, 2011). Simply put, in order to compete airlines must "do more with less" and grow the top line while holding the costs down (Coby, 2011). This research sets about examining European airlines in an attempt to not only identify those airlines that are embracing the necessary productivity, but to also identify areas or characteristics of commonality across the best performers. These characteristics may then be suitable for emulation by poorer performing airlines in an attempt to improve productivity.

1.2 Evolution of the Aviation Industry

The world's first heavier than air flight took place in Yorkshire, England in 1804. The designer and builder of the craft was George Cayley. Cayley was an engineer who had originally drawn up plans for the aircraft five years previously. The craft was basic in the extreme and was essentially a glider with no control surfaces. Control was by means of shifting weight and thus the centre of gravity of the aircraft (Ackroyd, 2011). Cayley continued to develop aircraft and in 1849 built a biplane in which it is generally accepted a young child accompanied him during a flight thus becoming the world's first passenger in a heavier than air aircraft. The issues surrounding in-flight control presented quite a challenge for early aeronautical engineers. Up until this point Cayleys success had come about as a result of studying the aerodynamics of birds in flight and it was still not determined whether or not in flight control could be achieved without wings that flap.

Otto Lilienthal was a Prussian engineer who was born in 1848, a year before the world's first aircraft passenger took flight. Like Cayley, Lilienthal was fascinated by manned flight and also looked to birds for inspiration. Lilienthal flew his first glider in 1891. In total he made over 2000 flights in various gliders some of which covered distances of up to 25 meters. Control of Lilienthals craft was also by means of weight shifting and as with previous gliders, this method only allowed for minimal control. In order to help with maneuverability on landing Lilienthal developed a hinged tailplane that could be manipulated in flight. This is accepted as the first control surface used in flight and ultimately led to the elevators, ailerons and rudders seen in modern aircraft (Lukasch, 2003). As a result of this simple addition Otto Lilienthal became the first person to successfully control a heavier than air craft in flight. Lilienthal's contribution to aerodynamics was enormous (Berlins Tegel Airport is named in his honour) and the work of both he and George Cayley was instrumental in the world's first powered controlled flight at Kittyhawk Hill, North Carolina in 1903.

In 1899 in response to the request for information on designing and building aircraft, the Smithsonian Institution forwarded the research and design notes of both George Cayley and Otto Lilienthal among others to Wilbur Wright of Dayton, Ohio. Wilbur and his brother Orville were bicycle manufacturers and publishers, both of whom had an interest in engineering. Although they lacked formal education (both men dropped out of high school) they were both talented engineers who started their first business with a printing press that they had designed and built themselves. Their interest in aviation is credited to a toy helicopter bought for them by their father in 1878 (Crouch, 2003).

The Wright brothers differed from previous fliers in that they conducted experimental research, even going so far as to build their own wind tunnel. This approach alongside witnessing the untimely demise of many of their predecessors convinced them that the secret to successful flight lay in an adequate control system. Just like Lilienthal before them, the Wrights turned to nature and observed birds in flight in an effort to understand in flight control. They observed that birds can change the shape of their wings in order to affect turns and set about replicating this capability in their own flying machines. They achieved this by means of a technique known as wing warping. By "twisting" one wing, extra lift could be produced on that side of the aircraft resulting in banking and thus turning in the required direction. Wing warping along with a vertical stabilizer, the idea for which they got from shipbuilding, gave the Wright brothers the in flight control they sought.

The Wright brothers employed several engine shops all of whom were unable to produce an engine not only of sufficient power, but light enough for sustained flight. Ultimately, an engine was designed and built by their in-house mechanic. This "Wright/Taylor" engine was the world's first practical aeronautical power plant. It was extremely innovative having been cast from aluminum in order to save weight and fitted with a fuel injection system. Earlier attempts to produce an aero engine by George Cayley had resulted in a gunpowder fuelled engine whose ignition source was a candle. In a culmination of over a century of experimentation and development and at the cost of many lives, the Wright brothers found themselves standing at Kittyhawk Ohio on the 17th December 1903. Orville took the controls of their aircraft, the Wright Flyer 1 and at 10:35am became the pilot of the world's first powered and controlled flight in a heavier than air aircraft. The flight lasted 12 seconds and covered a distance of 37 meters. Over the following 90 minutes the brothers made three further flights, the greatest of which lasted 59 seconds and covered a distance of just under 260 meters (Collins, 1999). Over the next three years the brothers continued to develop their flying machines but made relatively minor advances. During 1906 and 1907 the brothers ceased all aviation activity in an unsuccessful attempt to sell their machines both in the US and Europe. Although initially unsuccessful, these promotional tours ultimately led to the U.S. Army requesting bids for flying machines. A stipulation of any bid made was that the machine must be capable of carrying a passenger. In answer to this the Wrights modified one of their existing aircraft by adding an extra seat and on the 14th May 1908, the world's first passenger in a controlled, powered, heavier than air craft took to the skies. It was as a result of the outbreak of World War I that aviation evolved from little more than a hobby into a massive industry in its own right (MacLeod, 2013).

Although aircraft have been in use in revenue services since 1909, the aircraft in use at that time were hydrogen filled airships and were very different from today's fast, efficient and safe aircraft. The first airline to operate with aircraft as they would be recognised today was Aircraft Transport and Travel (AT & T) which was founded in 1916. AT & T's aircraft were capable of carrying only two passengers and the fare for the first flight between London and Paris was £21 (Crouch, 2014). The average weekly wage at the time was approximately seven shillings which equates to 1.7 per cent of the aforementioned air fare (conversion figures from www.royalmint.com). By 1919 the company was operating the world's first international scheduled service on that route. In the following years, on the back of AT & T's success, airlines began to appear all over Europe. KLM was also established in 1919 (www.klm.com) and is still in existence today making it the world's oldest operating airline. In 1923 Finnair was established (www.finnair.com) and the airline now known as Aeroflot also began operations.

Ireland's first airline Aer Lingus was established in 1936 by the Irish Government (www.aerlingus.com). This rapid growth in the number of airlines operating in Europe at that time gave rise to the high levels of competition that is a feature of the airline industry to this day.

Given the proliferation of smaller airlines in Europe during the 1920's and 30's, competition was intense and many simply could not compete. In order to survive, many of the smaller airlines consolidated into larger operators. These consolidations ultimately led to the emergence of airlines such as British Airways, Air France and Lufthansa. These airlines were heavily subsidised by their respective states and thus became "national" airlines. They were state funded, state controlled and heavily regulated. This regulation and control persisted until the early 1990s and allowed for such practices as route allocation, fare fixing and revenue sharing. Capacity on routes was often split between two carriers with each providing 50 per cent of the available seats and cargo capacity. Essentially each market was operated as a network of duopolies. This was facilitated through various governmental bilateral agreements. These practices and the highly regulatory environment resulted in virtually no competition in the European airline market (Scharpenseel, 2001).

Originally the rules governing the conduct of the aviation industry were intended to provide a safe reliable and affordable service. However, since the mid 1970s concern had been expressed that the regulations had become inflexible and unduly protective of those they were supposed to control (McGowan & Seabright, 1992). In an effort to address these issues the EU Council of Ministers agreed a range of measures designed to encourage competition in the European airline market. These measures were to be introduced as three "packages". The first two packages introduced in 1989 related only to scheduled passenger services and freight. The pricing benefits of these packages were full cargo pricing freedom, the lifting of some passenger capacity restriction and the liberalisation of passenger fare setting. The third package which was implemented between 1993 and 1997 removed the distinction between scheduled and non-scheduled operations. The most significant elements of the third package however were the common licensing and operational standards, the fact that licensed carriers were no longer required to own their own aircraft, the abolition of capacity restrictions, the allowing of multiple operators on international routes, the allowing of a carrier from one state to operate between two other states (cabotage) and the right to carry passengers and/or freight between two foreign countries on a route originating or terminating in the state of registration of the carrier (Fifth Freedom rights) (Reynolds-Feighan, 1999).

This deregulation lowered the "barriers to entry" to the European airline market and took the duopolistic control away from the state carriers. An airline registered in a member state could now operate a route of its choice, set its own fares and frequency, and with leased aircraft which greatly reduced capital costs. Between 1993 and 1996 eighty new operator licenses were issued (Scharpenseel, 2001). Many failed, but these new entrants to the market were the first salvos in the upcoming battle between state owned flag carriers and privately operated enterprises. This was the beginning of real competition in the European market. In addition the introduction of the "low cost" model into Europe by Ryanair in 1991 was a game changer in the European airline market and ultimately resulted in the state carriers losing their stranglehold on the market (Dobruszkes, 2009) and forced them to compete with the low cost carriers in terms of financial and operational efficiencies (Lee & Worthington, 2014).

Ryanair operated their first flight between Waterford and London Gatwick with a 15 seater aircraft in July 1985. It is interesting to note that this is approximately the same capacity as the aircraft that Imperial Airways (the forerunner to British Airways) were operating in the 1930s. In 1986 Ryanair began operations between Dublin and London Luton with fares of IR£94.99. This was well below the IR£208 charged by both

Aer Lingus and British Airways, the only other operators on the route (Barrett, 2008). In 1986 the average industrial wage was approximately IR£232 per week (Casey, 2004). Despite the competitiveness of Ryanair's fares its first years were turbulent. Between 1985 and 1990 Ryanair lost IR£25 million (Morrell, 2003). In 1991 Ryanair Deputy Chief Executive Michael O'Leary visited Southwest Airlines based in Dallas, Texas. Southwest was the innovator of the "low cost" model for airlines. O'Leary returned to Ryanair and implemented many of the strategies he had observed while at Southwest. In its first year as a low cost airline Ryanair reported its first ever profit of IR£293,000 (www.ryanair.com). As Ryanair success continued unabated, other "low cost" airlines started to appear in Europe. These new players presented a very real challenge to the incumbent national airlines who for the first time found themselves facing competition from leaner, more efficient operators who could compete on a level playing field.

The term deregulation implies a lack of regulation but this is not the case. Airlines are still regulated and subject to oversight by various industry bodies, associations and regulators such as International Civil Aviation Organisation (ICAO), International Air Transport Association (IATA), European Aviation Safety Agency (EASA) and the regulator of the state of registration. In the case of airlines registered in Ireland the regulator is the Irish Aviation Authority (IAA).

The International Air Transport Association (IATA) - was founded in Cuba in 1945. It is the trade association for the world's airlines representing 240 airlines or 84 per cent of total air traffic. IATA is instrumental in formulating industry policy on aviation issues. IATA is the advocate for the international air transport industry and challenges unreasonable rules and charges, holds regulators to account and considers sensible regulation its core mission (www.iata.org).

The European Aviation Safety Agency (EASA) - has been in operation since 2004. The main purpose of EASA is to draft aviation safety legislation for the European

Commission and its member states. EASA are also responsible for inspection and training in order to ensure the uniform implementation of European aviation safety legislation in all member states. EASA also approve maintenance and production facilities that are located outside of the European Union (www.easa.europa.eu).

The Irish Aviation Authority (IAA) - is a commercial semi state body which is responsible for the safety regulation of the civil aviation industry in Ireland. They are also responsible for aviation security oversight. These roles were assumed by the IAA from the Department of Transport in 1993. The IAA ensures compliance through regular inspections and audits of airports, air carriers, cargo companies and suppliers. The IAA is also responsible for the licensing of aviation professionals (pilots, air traffic controllers and maintenance personnel) and entities such as airlines and airports within the Irish state (www.iaa.ie).

The International Civil Aviation Organization (ICAO) - was created in 1944 with the signing of the Convention on International Civil Aviation (The Chicago Convention). There are currently 191 signatory states and various industry organizations who work together to develop international standards and recommended practices with regard to safety, security and civil aviation policy. These standards and recommended practices form the basis of the legally binding National Civil Aviation Guidelines developed by signatory states (www.icao.int). The original signatory states of the Chicago Convention agreed nine “Freedoms of the Air”. The purpose of these freedoms of the air was to provide a framework for the development of civil air transport. Any states that are signatories to the Chicago Convention may enter into bilateral agreements with other signatory states and grant each other any or all of the freedoms as defined by the convention.

The Nine Freedoms of the Air are:

1) The right or privilege, in respect of scheduled international air services, granted by one state to another state or states to fly across its territory without landing.

2) The right or privilege, in respect of scheduled international air services, granted by one state to another state or states to land in its territory for non-traffic purposes.

3) The right or privilege, in respect of scheduled international air services, granted by one state to another state to put down, in the territory of the first state, traffic coming from the home state of the carrier.

4) The right or privilege, in respect of scheduled international air services, granted by one state to another state to take on, in the territory of the first state, traffic destined for the home state of the carrier.

5) The right or privilege, in respect of scheduled international air services, granted by one state to another state to put down and to take on, in the territory of the first state, traffic coming from or destined to a third state.

6) The right or privilege, in respect of scheduled international air services, of transporting, via the home state of the carrier, traffic moving between two other states.

7) The right or privilege, in respect of scheduled international air services, granted by one state to another state, of transporting traffic between the territory of the granting state and any third state with no requirement to include on such operation any point in the territory of the recipient state, i.e. the service need not connect to or be an extension of any service to/from the home state of the carrier.

8) The right or privilege, in respect of scheduled international air services, of transporting cabotage traffic between two points in the territory of the granting state on a service which originates or terminates in the home country of the foreign carrier or (in connection with the so-called Seventh Freedom of the Air) outside the territory of the granting state.

9) The right or privilege of transporting cabotage traffic of the granting state on a service performed entirely within the territory of the granting state. (www.icao.int)

Cabotage is defined in the Chicago convention as "Each contracting state shall have the right to refuse permission to the aircraft of other contracting States to take on in its territory passengers, mail and cargo carried for remuneration or hire and destined for another point within its territory. Each contracting state undertakes not to enter into any arrangement which specifically grant any such privilege on an exclusive basis to any other state or an airline of any other state, and not to obtain any such exclusive privilege from any other state." (www.icao.int).

This framework was not agreed between the USA and the UK who reached a separate compromised agreement in Bermuda in 1976. This agreement was later revisited and an updated "Bermuda II Agreement" was brokered in 1977. This second agreement was actually more restrictive than the original and restricted capacity, reduced US carrier fifth freedom rights and added provisions concerning international charter services (Chang, Williams & Hsu, 2009). In terms of liberalisation this was a retrograde step, however efforts are ongoing in an attempt to achieve the ultimate goal of full freedom or "Open Skies" for international air transport.

Even though the airline industry is some way off a true "Open Skies" scenario there is little doubt that the liberalization achieved to date has been beneficial. Air travel has grown while average fares continue to decline and with no apparent impact on safety. These improvements have come about as a result of the former legacy carriers having to compete with the new entrant low-cost carriers on a direct commercial basis.

However, competing on a like for like basis is often extremely difficult due to the varying strategic, financial and operational approaches taken by the different airlines. For example, legacy airlines tend to operate hub and spoke networks with their associated complexities such as integrated ticketing and baggage transfer. Low cost airlines operate simpler point to point networks which allow for quick turnarounds and higher aircraft and staff productivity. They also differ in terms of fleet i.e. single type or mixed types, maintenance arrangements, the carriage of freight and other key areas. The legacy carriers have had to reduce costs, improve efficiency and increase productivity. Despite their best efforts sustained profitability still remains elusive for many airlines (Belobaba, 2011). This lack of profitability may be directly attributed to “high fixed cost structure, overleveraged balance sheets, low barriers to entry, high barriers to exit, fragmentation, militant unions, cyclical macroeconomics, fluctuating fuel prices, a unique regulatory environment and monopolistic/oligopolistic suppliers – which are just a small sample of the varying dynamics that reside when managing airlines.” (O’Connell, 2011).

1.3 Motivation for this study

There is an adage in the airline industry that states “The quickest way to make a million dollars in aviation is to start with a billion”. Airlines are notoriously difficult to run successfully. This is due not only to the high initial and ongoing costs involved, but to the complexity of the commercial space in which they operate. Airlines operate within single markets, across markets, long haul, short haul, full service and low cost. Some provide freight services and allow code shares, others are much more streamlined and do not offer either. All airlines are regulated bodies of the state in which they are registered. Despite efforts to harmonise this regulation, differences do exist. It is these complexities that make performance measurement and comparisons across airlines so difficult. Consider two airlines, one of which operates a mixed fleet of 20 aircraft and offers passenger and cargo services while employing 1000 people. The second airline operates a single type fleet of 25 aircraft offers passenger services only and employs 750 people. Airline One returns a profit of €8 million and Airline Two returns a profit of €7 million. By that metric both are successful but given the complexity of their structure it is difficult to establish which airline is making the best use of its resources.

The researcher works in the aviation industry in Ireland and has watched industry leaders such as Ryanair and easyJet achieve the seemingly impossible: consistent, profitable growth. Given the apparent simplicity of the concept, i.e. provide a seat from A to B, determine the cost of providing the seat and then sell the seat for 'cost + profit margin' it seems remarkable that other airlines are not emulating industry leaders with greater success (Sparaco, 2012).

In his role within the operations department of a major aviation company the researcher is familiar with the importance of operational performance measures. However, he realised that there was a lack of awareness amongst his operational colleagues of financial performance measures outside of the headline profit figures. On further investigation it became apparent that the reverse was true for staff in the financial departments, i.e. they were familiar with financial performance measures but not operational performance measures.

This led to an initial review of the literature in the area of performance measurement in the airline industry. With regard to financial and operational performance measurement there does appear to be a bias in favour of financial measures. A google.scholar search using the search string "airline financial performance" carried out on 15/10/13 returned 151,000 results. A second search using "airline operational performance" returned 76,000 results, while a search using the string "airline financial operational performance" returned 86,000 results. This gives some indication of the proclivity towards a single category of performance measure in the body of literature.

Eccles (1991) highlighted the importance of combining operational and financial indicators in performance measurement. He also drew attention to the potential advantages in benchmarking a company's performance with competitors so that best practice in various areas may be identified and emulated.

Comparing performance across airlines is difficult due to the complexity of their structure (MacKenzie-Williams, 2005). While an airlines core business activity is always the same, the elements which make up the airline itself are often vastly different. Fleet size, route structure, staff numbers and even the regulatory environment in which they operate are all factors that must be considered. Direct performance comparisons can be useful when assessing firms' market position.

1.4 Financial Performance Measures

Some of the most frequently used financial ratios in evaluating accounting performance across industries are: Liquidity ratios, Activity ratios, Financing ratios and Profitability ratios. These metrics are also valid in an aviation context. Flouris and Walker (2005) used these four ratios when analysing the accounting performance of airlines. They are explained and calculated as follows;

1) Liquidity ratios: These may be explained as the company's ability to pay its bills while allowing for a safety margin. For example, current ratio provides a measure of a company's ability to satisfy short term obligations.

2) Activity ratios: Total asset turnover effectively measures a company's efficiency in managing its assets. The total asset turnover is an example of an activity ratio. The higher the total asset turnover ratio the more efficiently a firm's assets have been used.

3) Financing Ratios: They provide an indication of a company's ability to pay long term debts. Debt ratio represents the percentage of assets financed by creditors and helps to determine the level of protection of these creditors in case of insolvency. A high debt ratio indicates that a company has more debt and is therefore more of a risk for creditors.

The interest coverage ratio measures the ability of the company to service all debts. The higher the ratio, the more likely it is that a company can meet its obligations. Debt ratio and interest coverage are two possible financing ratios.

4) Profitability Ratios: These ratios provide information on profit performance. Net profit margin, return on assets and return on equity are all examples of profitability ratios. The net profit margin is the amount of profit available to shareholders after interest and taxes. The return on assets ratio measures how efficiently a firm is utilizing its assets while the return on equity ratio measures the return earned by a stakeholder's equity in the firm. The higher the rate, the higher the earning for the stakeholder.

The same measures were used by the same authors in a similar study "Financial Comparisons across different business models in the Canadian Airline Industry" (Flouris and Walker, 2007). These measures have also been identified as traditional accountancy measures by Davila and Venkatachalam (2004).

1.5 Non-Financial Performance Measures

The study by Davila and Venkatachalam (2004) which investigated non-financial performance measures as a means of rewarding CEO's identified "passenger load factor" as one such measure. It is stated that passenger load factor is a measure of an airline's operational efficiency and as such is a better indicator of a firm's "current" performance. Passenger load factor was also identified as a preferred performance metric by Francis, Schipper and Vincent (2003) who also identified "revenue per passenger mile (yield)" and "cost per available seat mile" as non financial performance metrics for the airline industry. These three measures were also used to demonstrate the operating trends of British European Airways (BEA) by Lyth (1993).

1.6 Aim of This Study

This research sets out to examine the performance of European airlines across both financial and operational measures. The aim of this study is to identify the best and worst performers through a benchmarking process. A review of performance measurement techniques will be carried out. These performance techniques are: Economic Value Added (EVA) which is a method of measuring a company's profitability. EVA goes beyond traditional measures of profit by taking account of the cost of the capital employed in producing a company's profit; The Balanced Scorecard (BSC) combines both financial and operational measures to provide managers with a comprehensive overview of their company's performance; Multi Criteria Decision Making (MCDM) which is concerned with managerial level decision making in the pursuit of a single goal, usually profit. MCDM takes account of financial and non-financial data available to decision makers in order to formulate strategy and Data Envelopment Analysis (DEA) which is "a methodology whereby within a set of comparable decision making units (DMU's) those exhibiting best practice could be identified and would form an efficient frontier" (Cook & Seiford, 2009). DEA also utilises both financial and non-financial measures.

These four methods of performance measurement were chosen for consideration as they are well known and commonly used for evaluating company performance. A literature review of each technique was performed which allowed for evaluation of each method across a number of headings. As is outlined in later sections, DEA was chosen for this study as it has already been widely used in airline studies, is capable of including both financial and non-financial measures and provides rankings. DEA also allows for efficiency ranking in terms of overall efficiency, managerial efficiency and scale efficiency which provides a comprehensive insight into company performance.

For the purposes of this study three DEA models are employed.

1) Constant Returns to Scale (CRS) – This model provides an overall efficiency score and includes both technical and scale efficiency.

2) Variable Returns to Scale (VRS) – This model provides a technical efficiency score only. Technical efficiency is the measure of how efficient a company is at turning input x into output y. It is also known as Managerial or Process efficiency.

3) Pure Scale – This model provides a scale efficiency score only. It is a measure of whether or not a company is operating optimally for its size.

The best and worst performers across these three models are identified and a comparative analysis is performed.

1.7 Structure of the Thesis

Chapter one introduced the subject matter and basis for the thesis. It provided an overview of the development of the airline industry from its inception up to and including the deregulation of the European airline market. An outline of the performance measurement models was also introduced. The remainder of the thesis is structured as follows. Chapter two presents a literature review. The current state of the literature around various performance measurement techniques is presented. This forms the basis for this thesis. The literature surrounding performance measurement, airline performance measurement and several specific performance measurement techniques are reviewed. Based on this review a performance measurement model is constructed and applied to European passenger airlines. Chapter three provides the methodological approach taken in the design and execution of this study. This includes data identification & gathering, sample selection, software selection & validation and data analysis. Chapter four presents the DEA efficiency scores from all three models for each of the airlines examined. The best and worst performing airlines are then evaluated by means of a comparative analysis. The output targets that are required in order for each airline to achieve pareto optimal efficiency are also provided. Robustness scores for each airline identified as efficient are determined. Chapter five consists of a sensitivity analysis of the three DEA models. The sensitivity of the models is ascertained and findings are reported with respect to airline specific findings. Chapter six outlines the conclusions, limitations of the study, and recommendations for future research.

Chapter Two Literature Review

2.1 Introduction

This chapter presents a review of the literature surrounding performance measurement both generally and pertaining specifically to aviation. An in depth review of four performance measurement techniques; Economic Value Added, The Balanced Scorecard, Multi Criteria Decision Making and Data Envelopment Analysis, is performed and a thematic bibliography of the current state of the aviation performance literature is also presented. This review draws from the fields of strategy and operations management. In doing so it seeks to influence not only each of these fields individually, but also as a result of focusing these fields through an aviation lens to have an impact in the sphere of aviation management. The literature is primarily sourced from academic journals and text books but in some cases periodicals are used.

The key studies drawn upon are; The EVA Financial Management System (Stern, Stewart & Chew, 1996), The Balanced Scorecard: Translating Strategy Into Action (Kaplan & Norton, 1996), MCDM – If Not a Roman Numeral, Then What? (Zionts, 1979), Multi-Criteria Decision Making Methods: A Compatitive Study (Triantaphyllou, 2000), Measuring the Efficiency of Decision Making Units (Charnes, Cooper & Rhodes, 1978), Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis (Banker, Charnes & Cooper, 1984).

2.2 Measuring performance

In business, performance measurement has historically been based almost exclusively on financial performance. This has been recorded as far back as the middle ages (Bruns, 1998). Specifically, profit was generally considered to be the primary metric when measuring the performance of a business. At the most basic level this is a reasonable assumption. Profit may be defined as “Revenue realised in excess of costs incurred” (Roberts, 1988). Thus, in order to survive a company must make profit. Profit, however, should not be mistaken as a measure of company performance (Tulvinschi, 2013). Company performance is an evolutionary measure which takes a holistic approach over time. Conversely, profit is a singular measure attributable to a single defined accounting period. As a result, concentrating solely on profit as a performance measure leads to short term-ism (Hayes & Abernathy, 1980) and may lead to profit chasing at the expense of the business as a whole. Greene & Segal (2004) demonstrated a direct link between the inefficient use of resources and an adverse affect on profit. This suggests that a more efficient use of resources will result in a positive effect on profit. Thus the inclusion of non financial performance measures when assessing overall company performance gives greater insight into the current state of a company and can identify areas where, if efficiencies were made, profits may be increased. This approach has the added benefit of promoting more long term strategic planning.

Ndlovu (2010) identified a paradigm change in how business performance is evaluated. The emerging paradigm places much stronger emphasis on combining financial and non financial performance measures when assessing business performance. These non financial performance measures include operational efficiency, productivity and customer satisfaction. The catalyst for this shift towards a combined measure approach was the rise of the technology industry. Technology companies are often built on human capital and non physical assets, making valuation difficult. This resulted in the need to find new ways to assess performance as simple profit and loss measures became ever more inadequate as sole indicators of business performance. This approach spread to other industries with Kurtzmann (1997) reporting that by the mid 1990's 64 per cent of US companies were experimenting with new methods of measuring the performance of their business. Increasingly companies began to recognise the benefits that could be gained through the inclusion of operational measures in performance measurement (Marr & Schiuma, 2003; Radner & Barnes, 2007). The inclusion of non financial performance measures also opened up the possibility of comparing a company's performance with that of its peers on an operational as well as a financial level with potentially advantageous results (Adebanjo, Abbas & Mann, 2010). The advantages of combining financial and non financial performance measures include enhanced cash flow, reduced operational risk and improved levels of working capital (Protopappa-Sieke & Seifort, 2010). These benefits highlight how multi dimensional performance measuring methods are preferable and more informative than basic profit and loss depicted performance (Sardana, 2008) which measures the effectiveness of managerial decisions which have already been taken. The inclusion of non financial performance measures transforms business performance measurement into a forward looking proactive exercise. It does this by allowing a company to examine how it is currently utilising its resources and identify any efficiencies that may be made in the future thus increasing profitability (Kanji, 2002).

2.3 Measuring Performance in Aviation

Much research has been carried out on company performance in the field of aviation. The majority of this research is concerned with examining the performance of airport operators and airlines. This section examines the current literature surrounding these topics.

2.3.1 Airport Performance

The application of efficiency evaluation techniques to the airport sector is a relatively recent concept. While efficiency evaluation studies on other industries (electricity, water, banking health and agriculture) were commonplace, these techniques were not applied to the airport sector until the mid-1990's. Since then the most commonly used techniques when evaluating airport performance are Multi Criteria

Analysis and Frontier Analysis i.e. Stochastic Frontier Analysis, Total Factor Productivity and Data Envelopment Analysis (Lai, Potter & Benyon, 2012).

Despite its identification as one of the most commonly used methods, Multi Criteria Analysis has been used relatively infrequently when analysing airport performance. Multi Criteria based studies tend to make use of qualitative data for analysis. Yeo, Wang & Chou (2013) made use of this method by means of surveys in their paper which evaluated the competitiveness of Aerotropolisis in East Asia. They identified various important criteria for a successful Aerotropolis including geographic location and airport access modes. Multi Criteria type analysis strengths lie in identifying optimal criteria when making decisions. However, a limitation of this approach is the inability to compare the optimal criteria once they have been identified. For example, in the above study airport accesses modes have been identified as an important criteria for success but no metrics are provided that allow direct comparisons across airport access modes.

The most common techniques used in airport performance studies are Frontier type analyses; Stochastic Frontier Analysis (SFA), Total Factor Productivity (TFP) and Data Envelopment Analysis (DEA). All three of these techniques are similar in that they establish an efficient frontier from which relative inefficiencies are determined. Beyond that they differ in how they estimate and explain these inefficiencies (Pels, Nijkamp & Rietreld, 2003). SFA is often used in conjunction with DEA when examining airport performance. Assaf (2011) and Assaf, Gillen & Barros (2012) both used a combination of SFA and DEA when investigating airport performance. In both cases the input/output variables were chosen based on the previous literature in the area and the data were drawn from annual reports and the University of Bath. Scotti, Malighetti, Martini & Volta (2012) made sole use of SFA for their study of Italian airports with data drawn from Ente Nazionale Per L'Aviazone Civile (ENAC) and the Italian National Institute for Statistics while Marques & Barros (2011) made use of the Cost Frontier Model in their study of airport managerial efficiency. In all of these studies data were drawn from primary and secondary sources which has the potential to give rise to consistency issues.

One of the most common Frontier methods employed in airport performance studies is Data Envelopment Analysis (DEA). Lozano, Gutierre & Moreno (2013) make use of the Variable Returns to Scale (also known as the Banker, Charnes & Cooper or BCC) model of DEA. This model (BCC) is a measure of technical or process/managerial efficiency. Another DEA model is the Constant Returns to Scale (also known as the Charnes, Cooper & Rhodes or CCR) model which is a measure of overall efficiency. The ratio CCR/BCC provides a measure of pure scale efficiency. Data were collected from third party sources. Two DEA models, BCC and CCR were used by Wanke (2013) when analysing the efficiency of Brazillian Airports again data were drawn from a third party. Chang, Yu & Chen (2013) made use of all three models CCR, BCC and CCR/BCC when they examined 41 Chinese airports. However, while their paper focused on geographical characteristics as opposed to the more typical financial and operational measures it is notable in that all three DEA models were applied. In some instances it is not possible or at least difficult to ascertain which model of DEA was used (Zhang, Wang, Liu & Zhao, 2012). In many cases these studies drew their data from third party sources which while not necessarily problematic in itself can lead to the data used being data of convenience.

Key Performance Indicator (KPI) identification and comparison was used by two studies that sought to measure and benchmark airport performance (Painvin, 2011; Goulmy, Stern & Eggenkamp, 2013) These studies were “high level” in comparison with the previous MCDM and DEA studies and gave little insight into the identification of inefficient practices within the airports examined.

2.3.2 Airline Performance

Along with airports, airline performance studies comprise the majority of aviation industry research. In a similar way to airport performance studies, various methods have been employed. A quantitative approach such as the Balanced Scorecard (Wu & Liao, 2014) and surveys (Wen & Chen, 2011) have been used in order to evaluate airline performance. This approach can be useful for introducing information and opinions from passengers on service quality into performance investigations. MCDM was used to rank and benchmark Turkish domestic airlines based on their service quality (Kazancoglu & Kazancoglu, 2013), The link between service quality was also investigated by Stevenm Dong & Dresner (2012) using non-linearities and modelling effects. Direct comparisons of business models and practices have also been used to evaluate airline performance (Klophaus, Conraddy & Fichert, 2012). However, these types of study are relatively high level and struggle to assist in the identification of areas to be targeted for performance improvement. Data sources were provided by means of survey and third party sources which led to data of convenience being used in at least one instance.

DEA is one of the most prolific performance measurement methods used in airport performance studies and this is also the case for the airline industry. As with airport performance studies various models of DEA are used by researchers investigating the airline industry. While not making direct use of DEA, Akbar, Nemeth & Niemeier (2014) make several references to its use in terms of airline performance. Lin (2012) while using DEA gave no indication of which model was used, i.e. BCC, CCR or pure scale. Other studies use one model only (Arjomandi & Seutert, 2014; Zhu, J, 2011; Assaf & Jesiassen, 2011; Lu, Wang, Hung & Lu, 2012; Lee & Worthington, 2014) More comprehensive results are achieved by studies that apply to two or more DEA methodologies (Merkert & Morrell, 2012; Joo & Fowler, 2014). While Merket &

Williams (2013) used all three models (BCC, CCR and Pure Scale) only technical efficiency was reported (results for pure scale and pure technical efficiency are available on request). Again, data were drawn from both primary and secondary sources which gives rise to the previously documented issues.

Other methods have been used sporadically in airline performance measurement. Zuidberg (2014) used econometric analysis to identify the influence of airline characteristics on average operating cost per aircraft movement. Barros & Couto (2013) and Jentabadi & Ismail (2014) used the Luenberger Productivity Indicators and Structural Equation Modelling respectively to evaluate productivity and overall airline performance. Both of these studies used financial and operational data. Squalli (2014) used the Estimated Specifications technique to compare airline passenger traffic openness and the performance of Emirates Airlines. Cashflow has been used in conjunction with Ratio Analysis (RA) as a metric for comparing airline performance (Armen, 2013) however this approach provides a measure of liquidity more than actual company performance.

2.3.3 Performance Measurement Technique Review

As has been shown above there are many different performance measurement techniques available to the researcher wishing to investigate company performance in aviation. These range from the less common cash flow and service quality type analyses to the prolific use of Frontier type analyses. All of these techniques are valid research tools and this validity is not dependent on prolificacy of usage. This research is concerned specifically with airline performance measurement and comparison and as such requires the identification of a suitable technique.

Comparing performance across airlines is difficult due to the complexity of their structure. While an airlines core business activity is always the same, the elements which make up the airline itself are often vastly different. Fleet type and size, route network and structure, staff numbers, airports served and even the regulatory environment in which they operate are all factors that must be considered making direct comparison difficult. Direct performance comparisons can be useful when assessing a firms' market position. When attempting to compare the financial and operating performances of airlines a difficulty arises when trying to take account of their differing business models. This issue was addressed by Mason and Morrison (2008). Their paper identified the key components of both the product and organisational architecture present in the airline industry which could be used as benchmark metrics. However some of the key components identified by Mason and Morrison such as promotional spend per passenger and yield figures are commercially sensitive and thus not always available to the researcher.

This gives rise to a trend in the literature whereby when airline performance is being measured or compared there is a clear tendency towards publicly available financial only measures. Flouris and Walker (2005), Gittel, Von Nordenflycht and Kochan (2004), Smith, Grim, Gannon and Chen (1991) and Potter (2011) are examples of studies that use publicly available financial measures.

In an attempt to identify a process that considers both financial and non financial measures in an airline context the following four methods of performance measurement where chosen for review primarily because they are relatively well known and widely used both in academia and in industry. This results in a sufficient body of literature from which to make decisions regarding suitability and practicality for the purposes of this research. The four performance evaluation techniques are:

1) Economic Value Added – A measure of profit which accounts for the cost of capital invested in realising that profit.
2) The Balanced Scorecard – Well established method for identifying financial and operational measures of a company,

3) Multi Criteria Decision Making – Concerned with managerial level planning and decision making, the ultimate goal of which is pareto optimisation – the point at which no further gains can be made in one objective at no cost to another objective.
4) Data Envelopment Analysis – Originally developed for evaluating not-for-profit entities whereby those exhibiting best practice could be identified.

2.4 Economic Value Added (EVA)

Economic Value Added is a performance metric that was developed by the Stern Stewart Company in the early 1990’s. It is a measure of the after tax cash net profit less a charge for the capital employed to produce those profits. In other words EVA is a measure of profit – the cost of the capital invested. For example a company with a 10 per cent cost of capital that earns a 20 per cent return on $100 million of net operating assets has an EVA of $10 million (Stern, Stewart & Chew, 1996). EVA may be expressed fractionally as

$$EVA = NOPAT - CKI$$

where:

NOPAT = Net Operating Profit After Tax – determined for a certain period of time

CKI = Cost of Capital Invested

(Vasile, 2013)

EVA like many performance metrics is calculated over a defined calendar period. However, it differs from traditional performance metrics in how it measures a company’s economic performance. Traditionally this is achieved through performance measures such as profit, earnings and cash flow (Burksaitiene, 2009). EVA goes beyond these baseline performance measures by measuring the value created in excess of traditional performance measures and this excess value is then used for evaluating the performance of firms (Salehi, Enayati & Javadi, 2014). However, one of the original creators of EVA, Joel Stern stated that it was not intended as a pure measure of firm performance like the conventional performance measures, but rather a system that could be used to create a compensation structure that would encourage employees across the board to work towards maximising shareholder wealth (Kramer & Peters, 2001). From this perspective EVA is not just a simple performance measure, but may constitute the core element of an integrated financial management system. Thus EVA is not just concerned with measuring performance but also highlighting areas within a firm that may benefit from a different managerial approach (Stern, Stewart & Chew, 1997).

2.4.1 Usage

Economic Value Added is a widely used measure of operating performance (Ferguson & Leistikow, 1998). This is because it is not subject to industry specific bias and therefore is suitable for use across a wide range of sectors (Kramer & Peters, 2001). EVA as a technique is proprietary to the Stern Stewart strategic consulting company. For that reason, information on specific usage is not necessarily readily available. However, there is existing research that gives some indication of the use of EVA across various industries, for example, the automobile industry (Ghanbari & More, 2007), the banking industry (Oberholzer & Van der Westhuizen, 2010), information technology (Yao, Sutton & Chan, 2010), air navigation service provision (Austin, 2005), hospitality and tourism (Kim, 2006) and agribusiness (Geyser & Liebenberg, 2003).

There are numerous studies on EVA, but reference to a specific company or industry is relatively rare, for example, Sharma & Kumar (2010) conducted a review of EVA literature which examined 112 papers, but concentrated on identifying the countries in which EVA was used rather than focusing on specific industries or companies. These countries were USA, India, South Africa, Australia, UK, China, Malaysia, Canada, Brazil, Greece, Russia, New Zealand, Kuwait, Turkey and Indonesia. EVA is used both in industry and research settings. It is widely accepted as a performance measure by corporate management services and is increasingly being adopted by financial and management researchers (Yao, Sutton & Chan, 2009).

2.4.2 Benefits

Proponents of EVA argue that as a performance metric it is superior to traditional performance measures because it concentrates on maximizing shareholder value. The most vocal of these proponents is the Stewart Stern company who were the original developers of the EVA technique and who claim that “The best practical periodic performance measure is EVA” (Stewart, 1991) and ‘EVA is almost 50 per cent better than accounting based measures in explaining changes in the shareholders wealth” (Stewart, 1994). This view was further supported by Ehrbar (1999) in an in-house study for Stewart Stern which compared returns for companies grouped according to industry and size. This found that EVA adopters outperformed non-adopters over a period of up to five years. Kleiman (1999) also found improved returns for EVA adopters compared to non-adopters for companies in the same industry.

EVA has also been shown to be a superior metric when considering performance based bonus schemes for CEOs. Traditional performance based compensation schemes (i.e. those based on profit and/or earnings) are sensitive to anomalies whereby an exceptional event causes a one-off unsustainable spike in profits. Yet it is this figure that the CEOs bonus is based on. EVA avoids these issues by calculating bonuses based on value created for the shareholder and is thus a better indicator by which to evaluate CEO performance (Ferguson & Leistikow, 1998). This view is supported by Coles, McWilliams & Sen (2001) who carried out a review of performance measures including traditional metrics and found that while traditional performance metrics were valid indicators of performance, EVA is a preferred measure as a tool for assessing CEO performance. When justifying CEO bonuses to shareholders with respect to company performance, EVA is one of the strongest measures that can be used to do this and at the same time demonstrate improved company performance (Ghanbari & More, 2007).

In addition to being a performance metric EVA is also a financial management system in its own right. Firms which have adopted it as a management system have shown improvement in terms of stock performance and profitability relative to their peers (Ferguson, Rentzler & Yu, 2005). Alternatively, in certain circumstances such as de facto monopolies (Air Navigation Service Provision) and industries subject to regulation, EVA may also be used to demonstrate that profits are not excessive (Austin, 2005).

2.4.3 Limitations

The creators of EVA, the Stern Stewart company assert that EVA is a superior company performance metric when compared with traditional performance metrics. Dunbar (2013) points to numerous studies that refute these claims. These criticisms are founded on a lack of clarity in the literature as a result of the confidential nature of corporate privacy. This view is supported by Ivanov, Leong & Zaima (2014) who state that while EVA has theoretical appeal, empirical evidence regarding its efficacy are mixed. Paulo (2010) goes a step further and states that the empirical evidence is not compelling. This paper also examined the methodology of EVA and found it to be deficient and claimed that overall there was insufficient supportive evidence to validate the claims that EVA makes with respect to being a superior performance metric. Previous to this Paulo (2002) had also contended that EVA was of dubious value due to being construct deficient. It is also argued that there are fundamental issues with the economic and financial factors that are the very basis of EVA and that these have been demonstrated to have minimal effect on variation in share price and consequently share returns. Paulos findings supported earlier research by Biddle, Bowan & Wallace (1997) which found that traditional measures such as earnings were more highly associated with returns and firm value than EVA. They also suggested that EVA provided information that was only marginally useful beyond that of earnings. Paulos assertions are contradicted by Chen & Dodd (2002) where they claim that Paulo makes fundamental errors and assumptions when evaluating EVA. They contend that Paulo omits fundamental factors such as earnings in his calculations. This contention is also levelled at analysts by Machuga, Pfeiffer & Kerma (2002) who state that the information within EVA is often used inappropriately.

Kumar & Sherma (2011) conducted a study of 873 firms in order to examine the claims of EVA proponents that it is superior to traditional performance measures as a corporate financial performance metric. Their findings revealed that NOPAT (Net Operating Profit After Tax) and OCF (Operating Cash Flow) outperform EVA as a company performance metric. This study also supported Biddle, Bowan &Wallace (1997) findings that EVA components add only marginally to the information content beyond earnings. Kumar and Sherma also concluded that non-financial variables such as employees should be considered when measuring company performance.

Silverman (2010) found a marked disparity between present EVA estimates and the actual market value of firms in the US technology sector which suggests that there may be questions surrounding the validity of EVA as a performance measure. This disparity may be due to EVA neglecting to account for long-term investment by concentrating on assets in place, thus making it suitable only as a short-term performance measure (Johnson & Soenen, 2003). This means that the adoption of EVA is not appropriate for all firms as it does not account for long term investment (Griffith, 2004).

2.4.4 Summary – Economic Value Added

Economic Value Added was originally developed by the Stern Stewart company and is a measure of the after tax cash net profit less a charge for the capital employed. It is not just a performance measuring tool, but may also be incorporated into a managerial system that promotes the creation of shareholder wealth by employees across the board. It is widely used across many industries worldwide although specific data can be difficult to obtain due to company privacy issues. Despite the issues with data collection, EVA is popular with financial and management researchers.

The primary advocate of EVA is the Stern Stewart company, who developed the technique as a means of going beyond the traditional company performance measures in attempt to create a metric that also promotes the creation of shareholder wealth. EVA has also been identified as a superior performance metric when evaluating and remunerating CEO performance. In terms of stock performance companies that have adopted EVA as a core element of their financial management systems have been demonstrated to perform better than non adopters.

Numerous studies have refuted Stern Stewarts claims of EVA's superiority claiming that while EVA has theoretical appeal, results from empirical work vary. This is primarily due to difficulty with data collection as a result of corporate privacy issues. Various studies have shown EVA to provide only marginally greater information content than traditional performance measures such as profit while others have found EVA to be inferior to NOPAT and OCF as performance metrics. EVA has also been accused of short term-ism and as a result is not suitable for all firms and industries.

2.5 The Balanced Scorecard

The Balanced Scorecard was devised by Kaplan and Norton (1996) in an attempt to provide managers with a fast and comprehensive overview of their business. It combines financial measures (lagging) and operational measures (leading) to provide a dashboard which can be read to give an indication of a company's performance. Kaplan and Norton compare the balanced scorecard to the instruments in an airplane's cockpit. They all must be monitored and fixation on any one instrument may prove fatal. The Balanced Scorecard considers a company from four important perspectives;

1) The Customer perspective – How do customers see us?

2) The Internal Perspective – What must we excel at?

3) The Innovation and Learning Perspective – Can we continue to improve and create value?

4) The Financial Perspective - How do we look to shareholders?

An important element of the Balanced Scorecard is limiting the number of measures examined from each perspective. This forces managers to focus on the measures that are most critical. Another important element is that it forces managers to consider all operational measures no matter how disparate, allowing them to identify if improvements in one area are coming about at the expense of standards in another area. This is a crucial principle of the Balanced Scorecard – a failure to convert improved operational performance into improved financial performance is a failure of the process and requires re-examination. The Balanced Scorecard is about strategy not individual control. Goals are established and it is assumed that management and staff will do whatever is necessary to achieve them. These goals are strategic and apply to the company as a whole. As a result no one goal may be achieved to the detriment of individual sections of the company. It is this understanding of interdependent relationships that promotes strategic thinking which keeps companies moving forward.

2.5.1 Usage

The Balanced Scorecard (BSC) is a highly adaptable tool and has been successfully utilised across a wide range of industries including engineering, computing, technology, semiconductors (Kaplan & Norton, 1993) manufacturing (Hoque & James, 2000) education (Haddad, 1999), insurance, chemical, hotel and banking (Juhmani, 2007). Silk (1998) reported that 60 per cent of Fortune 1000 firms had experimented with the Balanced Scorecard. This included firms which had not fully embraced the BSC process and had used a diluted form of the process. Thompson & Mathys (2008) found that 40 per cent of Fortune 1000 companies used the BSC in 2007. Banchier, Planas & Sanchez (2011) stated that 53 per cent of 1430 companies surveyed used BSC making it the sixth most commonly used management tool. It would appear from these studies that usage of the method has remained reasonably constant over time. It is difficult to pin down precise usage of the BSC as some companies have been found to be using it unknowingly. Its use is widespread across the banking sector in Pakistan where a large number of banks surveyed were following all four perspectives without any specific knowledge or formalisation of the process (Ahmed, Ahmed, Ahmed & Nawraz, 2010); it was simply how they did business.

2.5.2 Awareness

A general knowledge of the process appears to be quite high. For example, Juhmani (2007) found that of the 83 usable replies returned, 54 of the companies surveyed formally applied the BSC but there was a high level of awareness of the process among the respondents (various industries in Bahrain). All respondents to this survey considered the BSC to be useful whether they used it or not. This may suggest that the BSC is being utilised to varying degrees across various industries, but that companies do not necessarily consider themselves to be users of the BSC.

2.5.3 Implementation

Developing a Balanced Scorecard can be a complex, costly and lengthy process (Haddad, 1999), (Lipe & Salterio, 2000). It is also not without risks. Venkatraman & Gering (2000) state that there are as many failures as successes in implementing a BSC, while Williams (2004) states that fewer than 20 per cent of companies utilising the BSC have realised performance improvements. One of the primary issues with implementation of the BSC is its top down approach. The research for and development of the scorecard itself is carried out at senior management level and then filtered down despite the fact that the managers involved may have no experience of the process (Niven, 2006). This combined with scepticism and a lack of trust from the staff side may lead to the process being effectively defeated before it begins. Othmen, Khairy, Domil, Senik, Abdullah and Hamzah (2006) also identified the top down approach as being problematic to successful implementation of the BSC for similar reasons.

2.5.4 Benefits

Companies that are formal users of the BSC believe it brings many benefits. The BSC can help streamline highly diversified companies whose various business units need to be realigned with one unifying corporate strategy. This was the case with F.M.C., a highly diversified company which produced over 300 product lines in 21 divisions organised into five business segments. In 1992 F.M.C. embarked on a growth strategy with the help of a BSC. It was so successful that the BSC is now considered a cornerstone of the management system (Kaplan, 1993). This is an important point; the BSC is not a quick fix, it requires integration into the company's culture and ethos. This allows for long term growth and improvement (Haddad, 1999). Greater BSC usage has been associated with increased organisational performance (Hoque & James, 2000). There are other positives for companies that use the BSC. Chen & Jones (2009) found that these companies are more likely to link strategic objectives to long term targets, thus avoiding short term-ism. They also tend to be more flexible and open to restructuring working environments if required. Employees see an attitude that is less resistant to change and individual business units have the autonomy to make adjustments in organisational procedures which may facilitate any changes required. These companies are also viewed by their employees as promoting continuous improvement. Ittner & Larcker (2003) found that 23 per cent of the 157 organisations they surveyed consistently built upon and improved their models and that all 23 per cent that did so achieved a superior level of performance. This is particularly true when the BSC used complements the company's strategy as opposed to being a measurement focused process (Braam & Nijssen, 2004). There is also evidence to suggest that the BSC is positively correlated to managers levels of job satisfaction. Burney & Swanson (2010) found that managers whose emphasis was on the Financial, Customer and Innovation & Learning perspectives had higher levels of job satisfaction than those whose emphasis was on the Internal Business perspective, although no reason is given as to why this may be the case. Also, Gonzalez-Padron, Chabowski, Hult & Ketchen Jr. (2010) found a positive correlation between a focus on the customer perspective and financial performance but found no such correlation for the other perspectives. Overall BSC usage has remained reasonably consistent over the last fifteen years. It is popular with its users with 88 per cent of regular users believing it has led to improved operating performance (DeBusk & Crabtree, 2006). It has also been associated with flexibility, openness to change and increased job satisfaction.

2.5.5 Limitations

As with every performance measurement technique there are some issues with the BSC model. In a review of the literature Banchieri et al. (2011) analysed 309 articles and identified three areas of concern in the model – perspectives, indicators and cause & effect relationships. Essentially the BSC views an organisation from a mechanistic perspective; it does not consider any outside influence and reduces the complexity of the company to a simplistic cause and effect relationship. There have been calls for these issues to be addressed by, for example, adding an external perspective (Epstein & Manzoni, 1998) but this should not be regarded as a major issue as Kaplan & Norton do allow for the addition of other perspectives if required (Kaplan & Norton, 1996). The oversimplification of the cause and effect model is a larger issue. The main issue is that the BSC does not consider the time lag factor and views the cause and effect relationship as simultaneous (Kune, 2008). These views are supported by Rillo (2005) who also criticises the BSC’s top down approach to implementation and its unsuitability for small and medium sized companies. The lag in the cause and effect relationship must be monitored closely as the entire BSC concept is about harmonisation and it is pointless improving, for example, quality at the expense of volume or productivity (Norreklit, Jacobson & Mitchel, 2008). Another major issue with the BSC is the tendency towards financial measures. Lipe & Salterio (2000) reported that managers may pay insufficient attention to leading and non-financial measures. This of course defeats the purpose of the Balanced Scorecard. Neumann, Roberts & Cauvin (2010) found that managers preferred financial measures over non-financial measures at a rate of two to one. Another study by Herath, Wayne, Bremser & Birnberg (2010) identified this phenomenon and proposed a method for counteracting it. However, this method was based around the assumption that “there is a full open truthful exchange of information between the parties, that the parties are analytically minded and that they have agreed upon the strategic objectives, performance measures and hypothesised cause-effect linkages”. If the above assumption was in fact the reality then perhaps the problem wouldn’t arise in the first instance. The core of this issue lies in the fact that it is usually the financial measures against which performance bonuses for managers are set. This combined with the understandable scepticism of mangers, whose bonus may be at stake, may lead to a lack of openness and honesty (Tate, 2000). This was also highlighted by Chen & Jones (2009) who reported that the employees in BSC companies indicated that the company pays more attention to the financial measures. The manner in which the metrics themselves are developed can also be problematic. The goals and metrics are constructed by senior management and then filtered down through the company. There are several challenges with this process. Top management may not have a complete view of the area for which they are setting the benchmarks. There is also a tendency for groups to favour decision consensus over decision quality. Communication lines must be open and honest, although even if they are there may be no opportunity for middle management to have any real input into the process as the decisions have already been made at a higher level (Hughes, Cauldwell & Paulson, 2005). This process is dependent on the assumptions of a good knowledge of the concept as well as openness and honesty.

The BSC has been criticised on a very fundamental level by Norreklit (2003) "What the model offers is not particularly innovative and lacks a reliable theoretical base". This study also criticises the lack of monitoring of technological developments, the fact that the model takes no account of external risks to strategy and that it is a top down process. Many concepts such as employee empowerment and organisational learning as well as issues such as implementation problems and gaining support for the process are assumed to be completely unproblematic by Kaplan & Norton. Norreklit even takes issue with how the model is presented and described as is evidenced by the question "is the Balanced Scorecard a new and convincing theory or just persuasive rhetoric?"

2.5.6 Summary – Balanced Scorecard

The Balanced Scorecard was introduced by Kaplan and Norton in 1992. It was an attempt to combine financial and non-financial measures of a company's performance in order to drive improvements in a company's strategic performance. It has been successfully implemented across a wide number of industries and geographical locations. It has much support from its users who believe it has brought about improvements to their organisation's performance. It is however not without its issues. It is complex and costly to develop. It relies on an assumption that a company adopting it is open, honest and willing to embrace it from the top down. It is not really suitable for small companies. Organisations must foster involvement, consistency and adaptability in order to achieve measurable results from the implementation of a BSC (Deem, Barnes, Segal & Perziosi, 2010). This would imply that company culture also plays a large part in the usefulness of the Balanced Scorecard (Chavan, 2009).

BSC usage only leads to higher performance if managers understand the cause and effect relationships that link drivers with future financial performance (Capelo & Dias, 2009) and that a BSC which focuses purely on measurement and not strategy or improvement may in fact have a negative effect on performance (Braam & Nijssen, 2004).

The primary issues faced by the BSC are that it is costly and complex to develop and implement. It takes no account of many dimensions such as external forces. It assumes no lag in the cause and effect relationship. There still appears to be a bias towards financial measurements by managers. These challenges may be overcome if management are fully open, honest and not resistant to change. Management must have good lines of communication with their staff who must feel involved and who must also trust management (Dyball, Cummings & Yu, 2011). These points are summed up by Albright, Burgess, Davis & Juras (2007) who state that there are five elements required for the successful implementation of the BSC;

1) Fairness
2) Communication

3) Involvement in developing measures and standards

4) Stretch Goals

5) A meaningful reward system

This gives rise to the question that if a company has knowledgeable, open, honest management with good lines of communication to staff who trust management, feel involved and who are well rewarded, how much of an improvement can the formal BSC offer as it is likely that management are already operating under some form of BSC. Conversely, if these attributes are not present then it is unlikely that management would be receptive to the BSC. Due to these issues the BSC is usually only suitable for larger companies and despite all the work involved reliance on the BSC does not necessarily translate to a strong market position (Hoque & James, 2000)

2.6 MCDM - Multi Criteria Decision Making

Multi Criteria Decision Making (MCDM) is concerned with the managerial level planning and decision-making process. This process ranges from a single decision maker (DM) making the decision in the pursuit of a single goal, usually profit, up to theoretically any number of DM's being involved in the decision-making process, the results of which may not necessarily be purely profit driven and may be subject to any number of constraints. The two primary perspectives of MCDM are;

Multi Objective Decision Making (MODM). In these cases the alternatives are not explicitly known and the number of possible solutions are infinite. This method requires the application of complex mathematics and is of limited value to the practitioner. And, Multi Attribute Decision Making (MADM). In these cases the alternatives are explicitly known and are countable. The mathematics required for this method are not as complex and given the fact that the number of alternatives are finite, is of much greater value to the practitioner.

1) The basic elements of the MCDM process which are common to the majority of MCDM methods are:
2) Alternatives- represent the different set of choices of action available to the decision maker.
3) Multiple attributes- also known as "goals" or "decision criteria". These represent the different perspectives from which the alternatives may be viewed. If the number of criteria is large (generally greater than 12) they may be weighted and arranged in a hierarchical manner.
4) Conflicts among criteria- different criteria representing different dimensions of the alternatives may conflict with each other.

Incommensurable units- different criteria may use different units of measure

Decision weights- most MCDM methods require that the criteria be assigned weights of importance these rates are normalised and add up to 1. (Triantaphyllou, 2000)

Although the mathematics involved can be complex the following example using the Weighted Score Method is basic and gives a good insight into how the concept works;

Let S_{ij} be the score of option i using criterion j

Let W_j be the weight for criterion j

Let S_i be the score of option i

Hence,

$$S_i = \sum_j W_j \, S_{ij}$$

This operation is carried out on each option using each criteria and the option with the best score is then selected. (Triantaphyllou, Shu, Nieto-Shanchez & Ray, 1998)

Zionts (1979) realised that in spite of all of the research done in MCDM, most of it was not comprehensible to managers because of the mathematics involved. He wrote a paper in an attempt to explain the concept in plain English and used the possible decision making process employed when purchasing a car.

In every decision there are conflicting objectives, in this case (buying a car) there are four.

1) The price. The cheaper the better.
2) The economy. The more economical the better.
3) The roominess. The larger the better.
4) The sportiness. The sportier the better.

These objectives produce the following conflicts; the sportiest is not the cheapest, the roomiest is not the most economical, the largest is not the sportiest and so on. This means that tradeoffs will have to be made in order to affect a solution. When studying decision making, three assumptions are often made which are not necessarily true. 1) There is a fixed set of alternatives; one has to be chosen. 2) There is a decision maker who knows the alternatives; he chooses one of these alternatives and 3) The alternative selected is in some sense optimal or best. Regardless of the specific scenario preference information from the DM's is required in order to reach a solution. This solution is not necessarily the best choice but the optimal alternative from a set of available alternatives derived from the methods described above incorporating the DM's preferences. The same problem with the same constraints may provide a very different set of alternatives depending on the DM's preferences. The "all knowing" decision maker is a myth. Nobody can know everything. Many decision makers depend on advisors when making decisions; further to this many decisions are made by committee. The committee scenario presents its own obvious problems. Ultimately the alternative chosen may not be the one that scores highest in each category, but the one that is the best overall fit or in some cases may even be the "least bad" option. The ultimate goal is "Pareto Optimisation" which is the point at which no further gains can be made in one objective at no cost to another objective.

2.6.1Usage

MCDM is a highly adaptable process and has been applied to many different areas including: Transportation and logistics, Business and financial management, Agriculture and forestry management, Project management, Manufacturing and assembly, Environmental management, water management, Managerial and strategic planning, Energy management, Military services and social services (Toloie-Eshlaghy & Homayonfar, 2011). These applications were all from a research/academic perspective suggesting that MCDM is more suited to research than industry. In fact, Steuer, Gardiner & Gray (1996) reported that MCDM has been ranked by various surveys as the 5th and 7th most useful operations research/ management science tool. The majority of the studies carried out on MCDM are from the academic perspective with very few of the studies being initiated from industry. However, MCDM's flexibility means that it can also be used to resolve concrete problems in industry such as end of life solutions (Bufardi, Sakara, Gheorghe, Kiristis & Xirouchakis, 2003) or more abstract concepts such as corporate image and reputation (Liou & Chuang, 2010). This would suggest that either industry awareness of the process is low or that it is of little value to industry. It could also be argued that the simple weighing up of "pros" and "cons" is MCDM in its most basic form and that from this perspective usage of the method runs at 100 per cent.

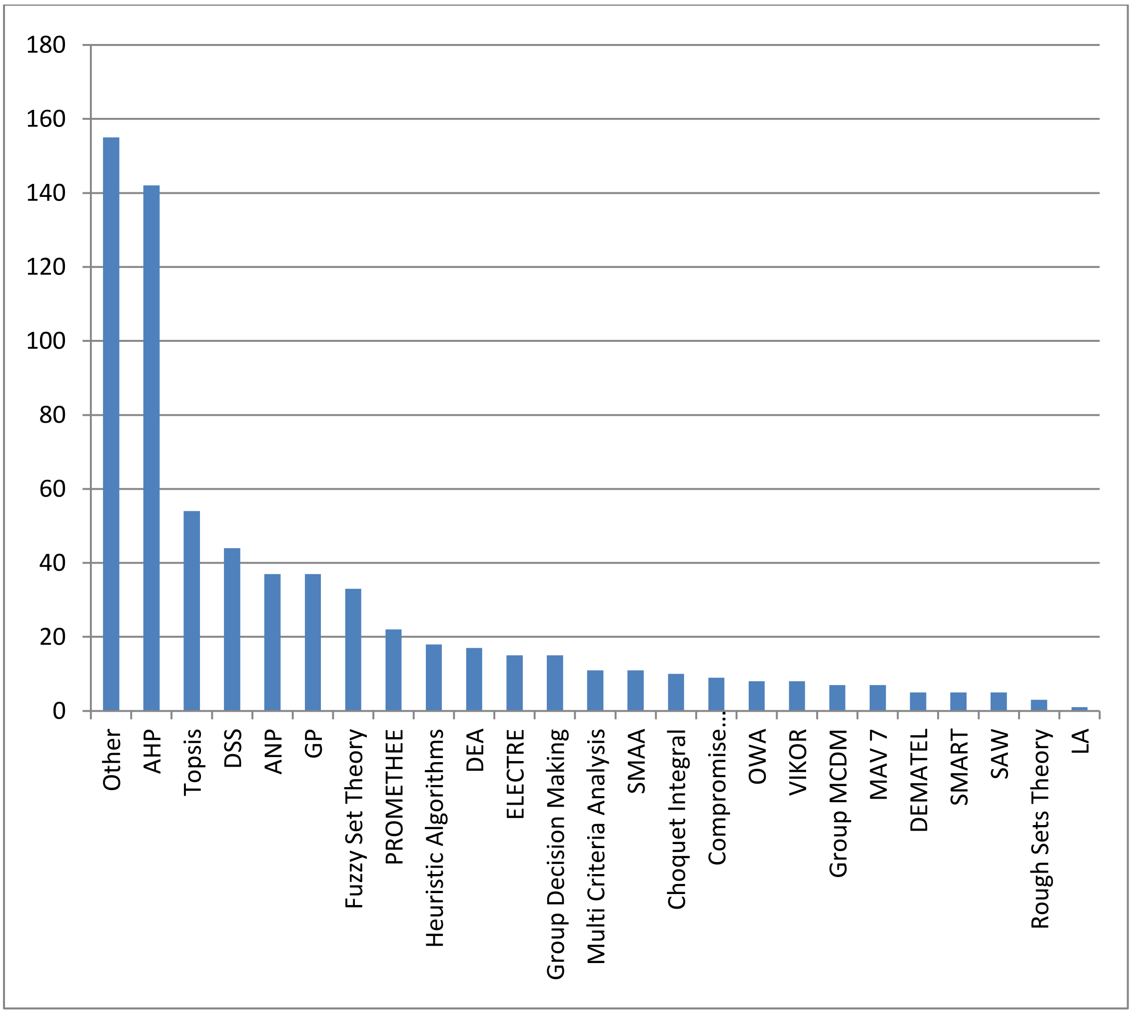

Figure 1. MCDM Methods Identified in Order of Frequency of Use (Authors own)

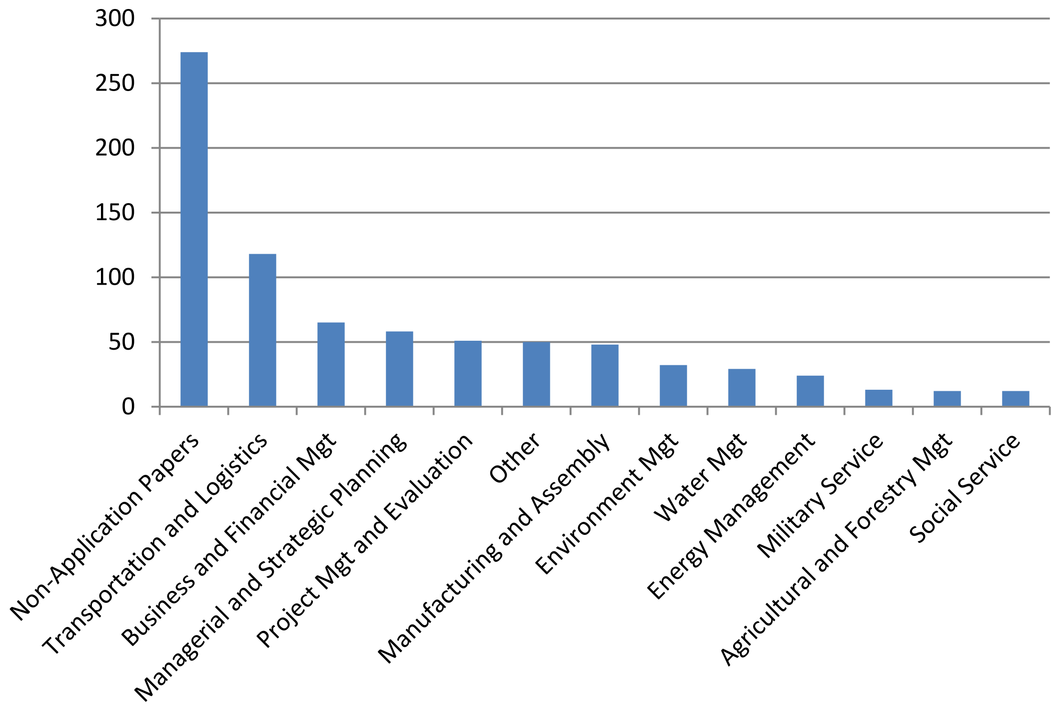

Figure 2. Areas of Application of MCDM in Order of Use (Authors own)

2.6.2 Awareness

Awareness of the formal method of MCDM within industry appears to be quite low. However, Toloie-Eshlaghy & Homayonfar, (2011) conducted a review of MCDM methodologies and applications between 1999 and 2009 and found 628 scholarly papers on the subject. These findings make sense as MCDM is primarily an operations research tool, so awareness of the process is high in academia/research but low in industry even though MCDM can and has been applied to real world industry scenarios. For example Bellver, Royo & Augistin, (2011) combined AHP (Analytical Hierarchy Process) and valuation ratios in order to place valuations on recently merged Spanish banks. This produced methods for valuation but gave no indication of how accurate or correct the value estimates were. In this case the variables are both quantitative and qualitative demonstrating the flexibility of the MCDM process. Seven expert decision-makers were chosen from the financial and banking industries to take part in the determination and weighting of the criteria and to prioritise the alternatives for each criterion. No selection process is described for the selection of these experts nor is a definition of what constitutes an expert.

2.6.3 Implementation

Applying an MCDM technique can be a costly and lengthy process. Before the actual computation itself takes place experts must be identified and agree to come on board the project. Parameters must be agreed upon and complex and lengthy questionnaires must be completed by decision makers and experts (Zionts & Wallenius, 1976). Again no method is provided for the choosing of expert decision makers nor is "expert" defined. These are traits shared with the Balanced Scorecard. These selections can only be made after a suitable MCDM method has been evaluated and chosen. In a review Toloie-Eshlaghy & Homayonfar, (2011) identified over 26 different MCDM methodologies (see Fig. 1). There is no systematic process available to assist with the selection of the most suitable method (Bufardi, Sakara, Gheorghe, Kiristis & Xirouchakis, 2003) although efforts have been made to present guidelines which may assist with the selection process (Gurrouni & Martel, 1998). One of the biggest issues with MCDM is its lack of “real world” applications. While it is undoubtedly highly utilised in research settings, there is a definite shortage of real world interventions (Montibeller, Gummer & Tumidei, 2006). This is not necessarily a criticism or failing of the process as MCDM is after all primarily a research tool.

2.6.4 Benefits

MCDM is a widely used decision making research tool (Steuer, Gardiner & Grey, 1996; Toloie-Eshlaghy & Homayonfar, 2011) and its users believe it brings many benefits. It is usable over short and long term timeframes of two to ten years (Zionts & Wallenius, 1976) and is therefore useful in long term strategic planning (Montibeller, Gummer & Tumidei, 2006). With regard to strategic planning the MCDM process, as a by-product, highlights any lack of cohesiveness or strategic awareness on the part of managers during the questionnaire phase (Kim, Kwak & Yoo, 1988). This in turn can result in managers taking a fresher approach to problems (Montibeller, Gummer and Tumidei, 2006). These strategies can be more flexible and efficient with minimal extra cost through the addition of extra parameters (Linares, 2002). As well as strategic and policy planning, MCDM can be used in more “concrete” situations such as selecting computer systems (Klersey, Ko & Lin, 1988). The ability of MCDM to handle both concrete and more abstract issues such as corporate image (Liou & Chuang, 2010) is down to the fact that the model can deal effectively with both qualitative and quantitative data (Mardle & Pascoe, 1999). This ability to deal effectively with qualitative data is especially useful when dealing with opinions from large and diverse groups. The “expert groups” and decision makers all have a role in the refining of parameters and these parameters are not necessarily numeric values. The MCDM process accommodates these differing opinions and results in agreed aggregate weighting (Baucells & Sarin, 2003). This allows for a greater input from expert groups which in turn leads to more informed decision making. That said, quantitative data is more efficient than qualitative data as quantitative data requires further manipulation with the application of fuzzy logic (Rao & Patel, 2010). MCDM can also account for multiple uncertain conditions simultaneously (Kuo, 2011). This is an important feature as it allows multiple scenarios to be examined in a single operation instead of taking each one in turn which demonstrates MCDM’s efficiency. Most levels of uncertainties can be accommodated. There are two broad categories of uncertainty; External uncertainty – related to the consequences of our actions and Internal uncertainty – related to the decision makers values and judgements. The levels of these uncertainties vary from “low level” that can be handled probabilistically right up to deep uncertainty (unknown unknowns). There are no MCDM methods for dealing with deep uncertainty (Van Der Pas, Walker, Marchan, Van Wee & Agusdinata, 2010) despite the great diversity of the MCDM procedures available (Bouysson, Perny, Pirlot, Tsoukias & Vincke, 1993). To this end and in so far as is possible some MCDM methods, for example Analytic Hierarchy Process (AHP), can be predictive. AHP has been successful in predicting the rise and fall of stocks, political candidacy, oil prices, energy rationing, predicting family size in rural India and the outcomes of chess games (Saaty, 1997). Despite the complexity of the decisions aided by MCDM the practical application of the process itself should be straightforward for the decision makers. The real complexity of the process lies in the complex mathematics required, but this is usually performed by dedicated software packages. Indeed for relatively simple decisions, the process can be executed on an excel spreadsheet (Fischer, 2009).

2.6.5 Limitations

Perhaps one of the biggest issues with MCDM is the subjectivity of the decision makers. The decision makers input into the process is essentially their opinion. Granted this is usually an informed opinion, but it is an opinion nonetheless. This opinion may not be the best option in the given context (Zionts & Wallenius, 1976). This is especially true if only one decision maker is utilised as a result of biases that may be present (Linares, 2002). Even in a situation where there are multiple decision makers, they may have conflicting objectives or opinions resulting in a situation where a single best solution is unlikely (Mardle & Pascoe, 1999). This scenario results in difficulty aggregating the preferences of the decision makers. This is achieved through reducing the total number of decision makers to a number of coalitions (Baucells & Sarin, 2003) which would seem to degrade any advantage gained through having a large number of decision makers in the first instance. The realistic accommodation of these limitations of judgement has been an ongoing concern in MCDM research and merits further attention (Fishburn & Lavalle, 1999). In order to reach an optimal solution a greater number of questions must be answered by the decision makers. This results in a higher computational cost, also the more questions that are asked the greater the lack of decision maker consistency (Zionts & Wallenius, 1976). Similarly with criteria, the more criteria included, the more flexible the resulting strategy will be but again this results in higher costs (Linares, 2002). A large amount of DMs results in a higher number of possible alternatives (Mardle & Pascoe, 1999) so it would appear that in an effort to include as much as possible in a decision making process may in fact lead to a broader set of alternatives instead of narrowing them down. Another concern with extra input is that of "entrenched thinking" or "analysis paralysis". This type of approach does not encourage innovative "outside the box" thinking and with so many opinions, there is the danger of a trade off between agreeing on the correct answer and simply making a decision (Snowden & Boone, 2007). This highlights another serious issue with MCDM, the lack of guidelines for choosing decision makers and the lack of a definition of "expert" in that context. Some studies employ the services of academics (it is often unknown if these academics have interests in the decision making process or the industry being investigated) some, industry leaders and others make use of a mix of both. There is a shortage of real world interventions using MCDM techniques (Montibellar, Gummer & Tumidei, 2006). That is not to say that MCDM techniques have not been applied to real world scenarios because they have (Blair, Mandelkar, Saaty & Whitaker, 2010) but mostly from a research perspective only. This is possibly as a result of MCDM's inability to cope with deep uncertainty or unknown unknowns (Linares, 2002), There have been attempts to develop models that deal with deep uncertainty (Van Der Pas, Walker, Marchan, Van Wee & Agusdinata, 2010) but as they are dealing with unknown future events, evaluation can be difficult and any correlation beyond coincidence would be difficult to prove. When applying MCDM, most studies control for deep uncertainty by simplifying parameters and evaluation procedures to a level that is rarely so clearly defined and simplistic in real world scenarios (Belton, Ackerman & Isheperd, 1997). Value ranges may be predetermined by the researcher in order to avoid complications (Klersey, Ko & Lin, 1998), (Kim, Kwak & Yoo, 1998). This required manipulation supports the notion that MCDM may not be a viable option when making a "real world" decision that does not have clearly defined parameters and high levels of uncertainty. This gives rise to the question why use a complex process to solve a relatively simple problem? In fact this complexity, particularly the high level of mathematics required can in itself put managers off using the process (Fischer, 2009). Another deterrent may be the sheer number of MCDM techniques available (Bouysson, Perny, Pirlot, Tsoukias & Vincke, 1993) (see Fig. 1) with no clear selection criteria available (Bufaardi, Sakara, Gheorghe, Kiristis & Xironchakis, 2003) the process of choosing a decision making technique almost requires the application of a decision making technique.

2.6.6 Summary – Multi Criteria Decision Making

MCDM is a decision making framework consisting of many different methods that may be applied as per their suitability. It is widely used in the field of operations research although it lacks "real world" applications. It is highly mathematical and complex process and is capable of dealing with low to mid level uncertainty. There is a large number of techniques which may be applied and while no formal solutions procedure exists for finding the most suitable technique guidelines were produced by Gurrouni & Martel (1998) which include: the type of data, the nature of the data – crisp, fuzzy, etc.; the objective of comparing alternatives; Compensation between criteria – total, partial, not allowed; Articulation of preference and the type of criteria – pseudo criteria, semi criteria or true criteria. While the techniques are widely used by researchers (Toloie-Eshlaghy & Homayonfar, 2011) it would appear that managers and decision makers struggle with the process in reality (Montibeller, Gummer & Tumidei, 2006) despite the simplification of criteria selection and parameters (Kaleta, Ogryczak, Toczylowski & Zoltanska, 2003). It would appear that MCDM is best suited to research problems with low to medium levels of uncertainty. However the ability to deal with deep uncertainty (essentially the ability to predict the future) is an unreasonable expectation of any decision making framework, be it research or industry based.

2.7 Data Envelopment Analysis

Data Envelopment Analysis (DEA) was developed “to provide a methodology whereby within a set of comparable decision making units (DMU), those exhibiting best practice could be identified and would form an efficient Frontier” (Cook & Seiford, 2009).

The following is an example of how the efficiency of a group of airlines may be measured using DEA. Each airline has a single output measure which is the number of economy passengers carried in a year. Each airline also has a single input measure which is the total number of staff employed.

Airline	Passengers (000's)	No. of Staff
Airline A	125	18
Airline B	44	16
Airline C	80	17
Airline D	23	11

Table 1. Airlines with Single Input and Single Output Measure

Expressing the above as a ratio of passengers per staff member gives us the following;

Airline A......6.94 passengers per staff member

Airline B......2.75 passengers per staff member

Airline C.......4.71 passengers per staff member

Airline D.......2.09 passengers per staff member

Airline A has the highest ratio so is the most efficient of the examined airlines. The relative efficiency of the other airlines can be calculated by dividing the ratio of any airline by 6.94 and multiplying by 100 to give a percentage.

Airline A 100(6.94/6.94) = 100%

Airline B 100(2.75/6.94) = 40%

Airline C 100(4.71/6.94) = 68%

Airline D 100(2.09/6.94) = 30%

This shows that the other airlines are not performing as well when compared to Airline A. They are relatively less efficient at producing an output from the given input. Airline A in this instance could be used to set performance targets for the other less efficient airlines. For example, Airline D could carry the same number of passengers but with less staff members, this is known as an input target. Alternatively Airline D could increase the number of passengers carried while retaining the same number of staff, this is known as an output target. In practice a mix of input and output targets would be set.

Typically there are more than one input and one output. Suppose business class passengers carried was included as an output but with the same staff numbers;

Airline	**Economy Passengers (000's)**	**Business Passengers (000's)**	**No. of Staff**
Airline A	125	50	18
Airline B	44	20	16
Airline C	80	55	17
Airline D	23	12	11

Table 2. Airlines with Single Input and Two Output Measures

Again using ratios for comparison purposes;

Airline	**Staff Members per Economy Passenger**	**Staff Members per Business Passenger**
Airline A	6.94	2.78
Airline B	2.75	1.25
Airline C	4.71	3.24
Airline D	2.09	1.09

Table 3. Ratios of Input to Outputs for Airlines

Now consider Airline C and Airline A. Airline C is (4.71/6.94) = 67.86 per cent as efficient as Airline A with regard to economy passengers but (3.24/2.78) = 116.55 per cent as efficient with regard to business passengers. DEA is a method whereby these two figures may be aggregated into a single score allowing the airlines examined to be benchmarked against their peers.

DEA can trace its origins back to “Measuring the efficiency of decision making units” (Charnes, Cooper & Rhodes, 1978). The method was originally developed for evaluating public/not-for-profit programs hence the terminology “DMU” and “programme” as opposed to terms such as “firms” and “industry”. Charnes, Cooper and Rhodes proposed that the measure of efficiency of any DMU is obtained as the maximum of a ratio of weighted outputs to weighted inputs subject to the condition that similar ratios for every DMU be less than or equal to unity.

This may be expressed mathematically as:

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

Subject to;

$$\frac{\sum_{r=1}^{s} u_r\, y_{rj}}{\sum_{i=1}^{m} v_i\, x_{ij}} \ \leq\ 1 : j = 1 \ldots\ldots\ldots, n.$$

u_r,v_i ≥ 0; r = 1.........,s. ; i = 1.........,m.

(Charnes, Cooper & Rhodes, 1978)

“Here the y_{rj}, x_{ij} (all positive) are the known outputs and inputs of the j^{th} DMU and the u_r, v_i ≥ 0 as the variable weights to be determined by the solution of this problem e.g. by the data on all of the DMU’s which are being used as a reference set. The efficiency of one member of this on reference set of j=1.........n DMU’s is to be rated relative to the others for the DMU’s that concern us. These x_{ij} and y_{rj} values which are constants will usually be observations from past decisions on inputs and the outputs that resulted there from. We can, however, replace some or all observations by theoretically determined values if we wish (and are able) to conduct the efficiency evaluations in that manner." (Charnes, Cooper & Rhodes, 1978)

The CCR (Charnes, Cooper & Rhodes) ratio is a measure of overall efficiency and is comprised of both technical and scale inefficiencies combined. In 1984 Banker, Charnes & Cooper (BCC) developed this concept further to allow separation into technical and scale inefficiencies without altering the conditions for the use of DEA directly on observational data.

The identification of technical efficiencies is achieved by identifying the failure to achieve the best possible output levels and/or excessive inputs.

This is described mathematically as follows:

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

Subject to;

$$\sum_{i=1}^{m} v_i x_{i0} = 1,$$

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

$j = 1, \dots, n, u_r, v_i \geq \varepsilon \, \forall r, i$, and u_0 is unconstrained in sign.

(Banker, Charnes & Cooper, 1984)

The CCR model provides a measure of technical and scale efficiency combined (overall efficiency) and the BCC model provides a pure technical efficiency score, while pure scale efficiency may be determined by dividing the CCR score by the BCC score.

In order to provide clarity the concepts of overall, technical and pure scale efficiency are presented graphically in figure 3. For demonstration purposes a simple one input one output model is used.

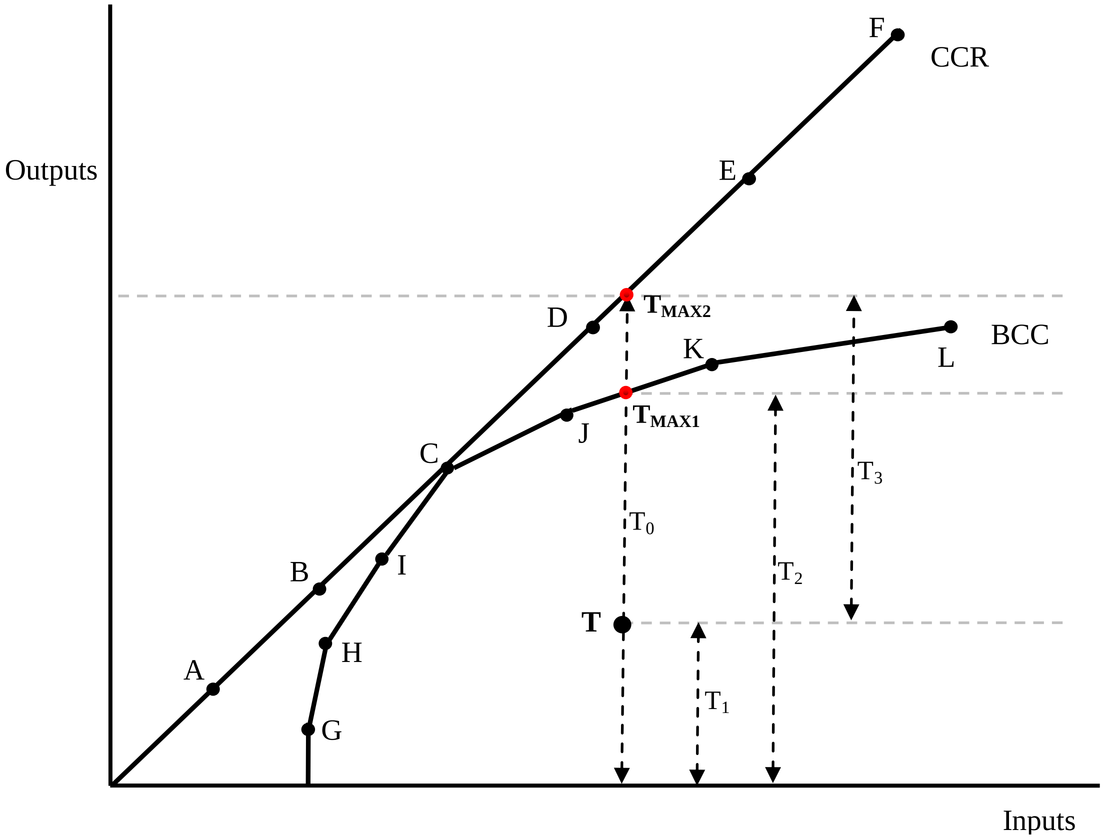

Figure 3. Graph of the Relationship Between the Three DEA Models

In the above graph the DMUs A, B, C, D, E and F form the efficiency frontier, i.e. are 100 per cent efficient, according to the Charnes, Cooper and Rhodes (CCR) model which assumes constant returns to scale. This is a measure of overall efficiency. DMUs G, H, I, C, J, K and L form the efficiency frontier, i.e. are 100 per cent efficient, according to the Banker, Charnes and Cooper (BCC) model which assumes variable returns to scale. This is a measure of pure technical (or managerial) efficiency. The ratio of overall efficiency score/pure technical score provides a measure of pure scale efficiency.

Consider the target DMU "T" which is inefficient.

The efficiency score for DMU T according to the CCR model (overall efficiency) is the distance T_1 expressed as a percentage of T_0.

The efficiency score for DMU T according to the BCC model (technical efficiency) is the distance T_1 expressed as a percentage of T_2.

If DMU T were to achieve 100 per cent technical efficiency it would reach the point T_{MAX1}. This implies any inefficiencies that are preventing DMU T from reaching overall efficiency (T_{MAX2}) are pure scale inefficiencies. Thus the distance T_2 represents pure scale efficiency when expressed as a percentage of T_0. This percentage may be calculated by dividing the CCR score for DMU T by the BCC score for DMU T.

Returns to scale refers to the change of total output due to the change in total input. In cases where the changes are directly proportional i.e. a doubling of inputs results in a doubling of outputs this is known as constant returns to scale. If however outputs change at increasing or decreasing rates this is known as varying returns to scale. There are various causes of each type of return to scale. Constant returns to scale may occur when a production process is easily replicable. For example a manufacturing company may build a second identical factory hence double the inputs results in double the outputs. Increasing returns to scale are often a result of various factors. A heavy engineering company may need large expensive machinery and these machines must be used no matter how small the scale of production. If scale of production increases then there is a more efficient use of the machine and hence an increasing return to scale. Decreasing returns to scale can often occur as a result of increased complexity. If a manufacturing company buys a second factory some distance from the first there is now a requirement for extra coordination, management and logistics these extra inputs are additional costs that would not be required with only one factory hence double the inputs does not result in double the outputs.

2.7.1 Usage

Data Envelopment Analysis (DEA) as developed by Charnes, Cooper and Rhodes (1978) was originally intended as a tool to measure efficiency in not-for-profit entities as opposed to firms and industries. However when the process is defined as "the measure of the efficiency of any DMU is obtained as the maximum of a ratio of weighted outputs to weighted inputs subject to the condition that the similar ratios for every DMU be less than or equal to unity" (Charnes, Cooper & Rhodes, 1978) it is not surprising to find that DEA has become a popular method of efficiency measurement outside of the not-for-profit sector. DEA has been used to measure efficiency in the hotel industry (Huang, Lee & Lee, 2012), the airline industry (Zhu, 2011; Merkert & Morrell, 2012), healthcare (Assaf & Matawie, 2010), the banking sector (Barr, Seiford & Siems, 1993), airports (Martin & Roman, 2006), electricity provision (Sueyoshi & Goto, 2012) and government policy analysis (Whittaker, 1994) among others. All of the examples provided above are from a research/academic perspective. There is, however, evidence to suggest that DEA is a commonly used tool in a "real world" context. This is in spite of the relatively complex mathematics involved and specific expertise required to carry out a DEA analysis. There is also evidence which suggests that DEA has a role to play in developing early warning tools in failure prediction (Gumus & Celikkol, 2011). This indicates that DEA may have the potential for an even more significant role in industry than it currently does.

Input and Output Selection

A feature of Data Envelopment Analysis is the requirement to choose the inputs and outputs which are to be compared/measured. There are no firm rules pertaining to these selections. In order to reduce any arbitrariness**,** a further review was conducted focusing on the area of input/output selection. A review of 20 airline efficiency studies was conducted (see Appendix A). These studies included techniques such as DEA, Total Factor Productivity and Stochastic Frontier Analysis. All of the techniques included in this review make use of the input/output model as applied to an airline. The purpose of this exercise was to identify the most commonly used inputs and outputs utilized in airline efficiency studies (see figures 4 and 5 below).

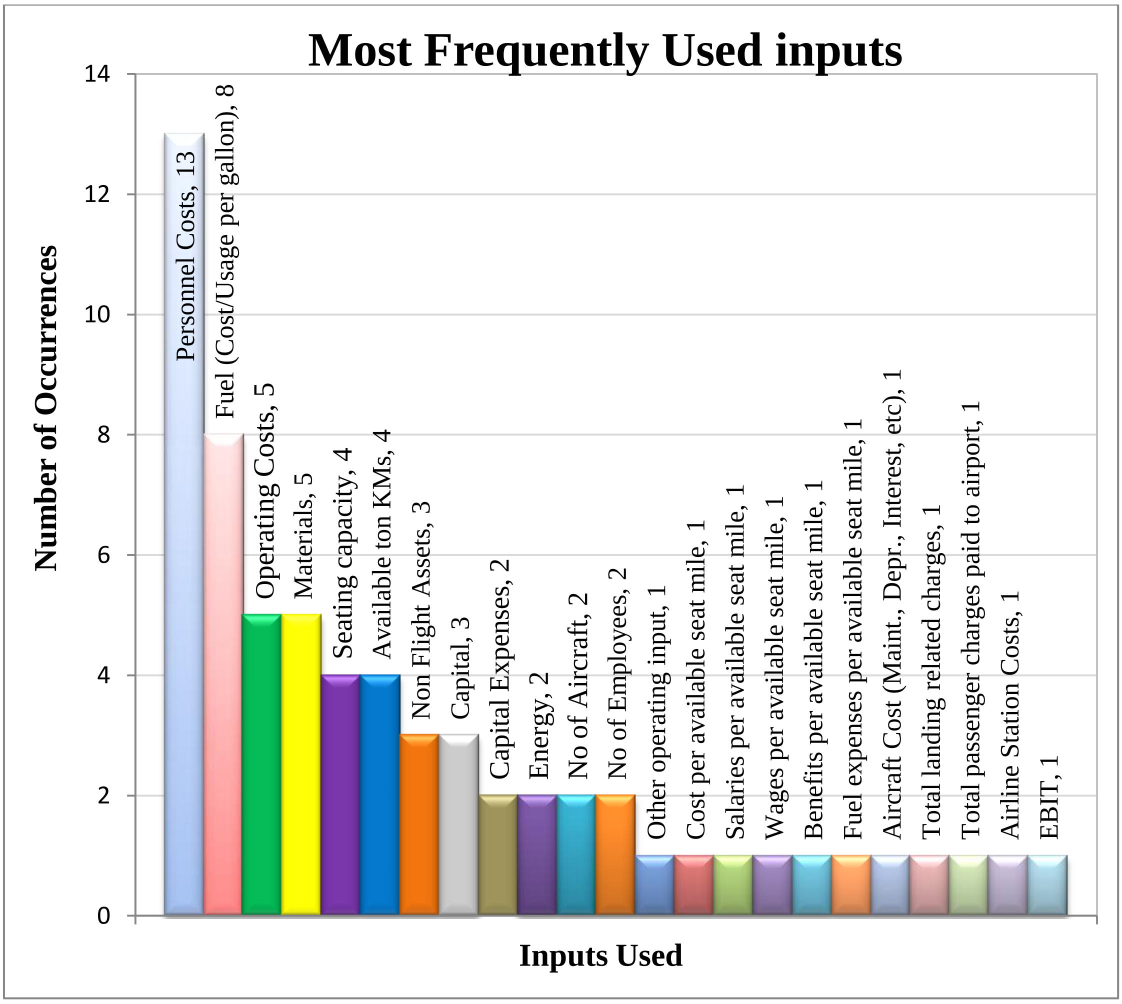

Figure 4. Most Frequently Used Inputs

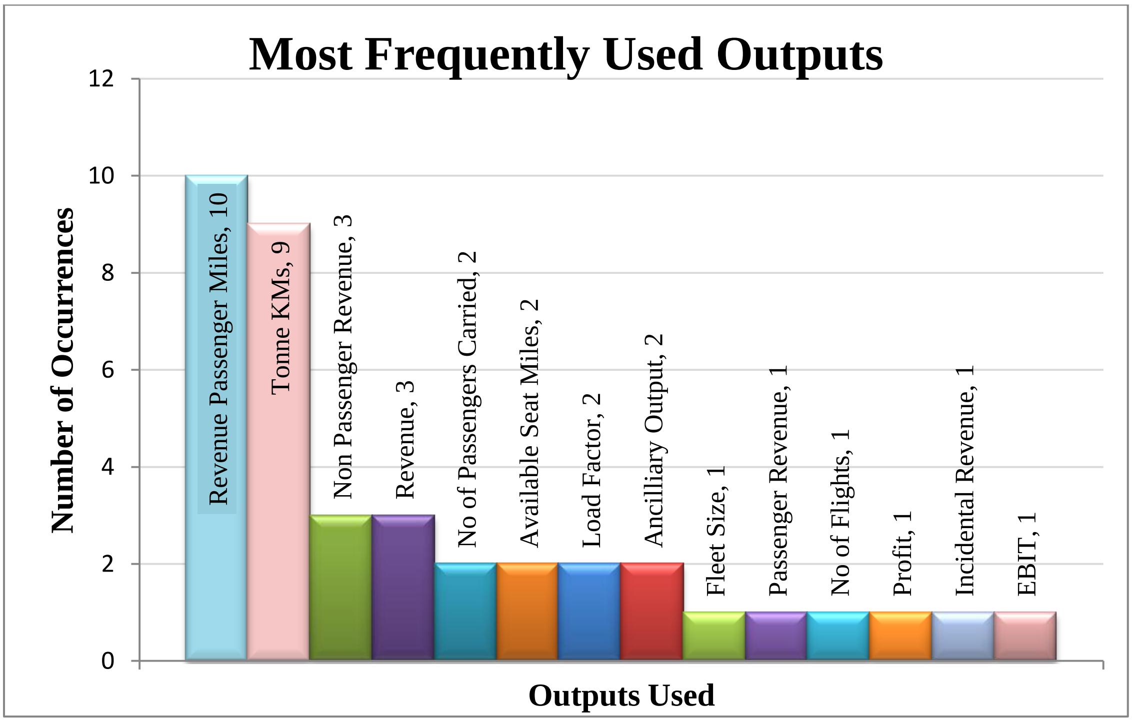

Figure 5. Most Frequently Used Outputs

This analysis shows that the average airline based study that made use of an input/output based technique (DEA, TFP, SFA) consists of three inputs and two outputs. From figure 4, the three most commonly used inputs are:

- Personnel Costs
- Fuel
- Operating Cost (total operating expenses) or Materials (fuel, flight/non flight equipment and other materials)

From figure 5, the two most commonly used outputs are:

- Revenue passenger miles
- Tonne KMs

These input and output parameters formed the initial basis for parameter selection during the empirical stage of the project.

2.7.2 Benefits

When measuring anything the validity of the measure is crucially important and efficiency is no different. DEA provides a technique for accurately measuring efficiency and identifying potential areas of improvement. DEA is suitable for a wide variety of applications including banking, mergers and acquisitions, public transport and program evaluation (Seiford, 1996). Many of these applications are from a real-world perspective (Gattouffi, Oral, Kumar & Reisman, 2004). This gives DEA an advantage over many other performance measurement techniques which are often concentrated on research or academic settings. The popularity of DEA is evidenced by the 3000+ publications which have cited the use of DEA (Tavares, 2002). The widespread popularity of DEA is attributable to four facts:

1) Its ability to handle multiple inputs and outputs,
2) It does not require a priori a relative weighting scheme for the input/output variables,
3) It returns a simple summary measure for the efficiency of each DMU,
4) It identifies the sources and amounts of relative inefficiency for each DMU.

(Lee & Choi, 2010).

These four attributes demonstrate how relatively uncomplicated yet comprehensive DEA is as a performance measurement technique. This is further emphasised by how unrestrictive the underlying modeling of DEA is including the permissive approach to defining what inputs and outputs may consist of (Parkin & Hollingsworth, 1997). DEA can also accommodate both financial and operational data (Martin & Roman, 2008). Again, this puts DEA ahead of those techniques already capable of processing either one or the other data types. Meaningful conclusions may be reached by using relatively basic, publicly available data (Barr, Seiford & Seims, 1993; Scheraga, 2004). This means that efficiency comparisons can be made across industries without the direct involvement of specific firms. This is a useful property if a firm wishes to benchmark itself within its own industry. When combined with the more traditional ratio analysis (RA) measures such as liquidity, debt and profitability ratios, DEA provides a more comprehensive perspective on resource adjustment (Huang, Lee & Lee, 2012) than RA alone. It has also been suggested that future research employing DEA in conjunction with RA could be useful in developing early warning tools for failure prediction (Gumus & Celikkol, 2011). One of the reasons DEA provides further insight than RA is its ability to quantify variables such as managerial efficiency (Barr, Seiford & Seims, 1993) which RA alone cannot (Sherman & Gold, 1985). Further refining of the DEA approach can provide even further insight into efficiency (Zhu, 2011). This combining of financial and operational ratios can be used in the creation of standards against which to measure other firms (Guerra, de Souza & Moreira, 2012). The data required for such an analysis may be in the form of theoretically prescribed values or they may be in the form of observations (Banker, Charnes & Cooper, 1984). DEA is capable of suggesting financial and operational improvements into the future (Charnes, Cooper & Rhodes, 1978). These suggestions may be quite specific with regard to improvements required for any given criterion (Chakraborty, Majumder & Sarkar, 2011). Some forms of DEA may even account for unobserved DMUs (Gajewski, Lee, Botti, Pramjariyakul & Taunton, 2009). This demonstrates just how efficient DEA is as a process in its own right.

2.7.3 Limitations

DEA provides relative efficiency scores (Charnes, Cooper & Rhodes, 1978) meaning that efficiency is not ranked in absolute terms. This should be borne in mind when using DEA as a DMU may score number one (100 per cent) for efficiency but this is only relative to the other DMU’s examined and still may fall far short of true optimal efficiency. This gives rise to another issue. If several DMU's are positioned on the efficiency frontier they cannot be ranked relative to each other (Martin & Roman, 2006) as all deviations from the frontier are assumed to be random (Scherga, 2004). This makes the identification of specific problem areas impossible as all DMU's are equally efficient. One of the assumptions of DEA is that all DMU's of interest are observed and all relevant inputs and outputs have been measured (Gajewski, Lee, Botti, Pramjariyakul & Taunton, 2009). This leaves the DEA process open to manipulation by vested interests, for example a management team may wish to exclude or manipulate measurements from a particular underperforming DMU. This can lead to some DEA results being nonsensical (Liu, 2009). This issue was specifically identified by Martin & Roman (2008). In their study of Spanish airports managers influenced their efficiency scores by manipulating the inputs i.e. runways, terminal buildings etc. in a particular manner to produce the desired results. DEA is also very permissive of what actually constitutes a DMU and an input or output. No guidance is provided for analysts and choosing the parameters (Parkin & Hollingsworth, 1997). The lack of definition of DMU is also highlighted by Charnes, Cooper & Rhodes (1978) in their original paper so clearly this is a long-running issue. DEA also suffers from methodological difficulties such as:

1) Producing many different DMU's. This is mathematically acceptable but as has been discussed previously is managerially problematic as the efficient DMU's cannot be ranked if several are positioned on the production frontier,
2) Multiple projections and multiple reference sets,
3) A conventional use of DEA cannot provide an industry wide evaluation. Efficiency can only be compared from within the reference set,
4) DEA cannot provide statistical inferences,

(Sueyoshi & Goto, 2012)

The issue of data integrity was also highlighted by Kuo & Lin (2012) who suggested that data should be homogenised into values within the same value range which would ensure that the weight range of evaluation indicators is meaningful. It was also suggested that the number of DMU's should be at least two to three times larger than the sum of the number of inputs + outputs. This places an operational limitation on the use of DEA. As DEA is nonparametric no statistical inferences can be made (Chakraborty, Majunder & Sarkar, 2011; Assaf & Matawie, 2010). This also places a limitation on sample size and comes with an associated lack of inferential power when compared to parametric methods.

2.7.4 Summary – Data Envelopment Analysis

While Data Envelopment Analysis was originally developed for use in the not-for-profit sector its flexibility allowed it to make the crossover into commercial applications. DEA theory is dominated by two primary theories; The CCR model which measures overall efficiency and the BCC model which allows for the separation of technical and scale inefficiencies.

DEA is a relatively straightforward yet comprehensive method of efficiency measurement. It is capable of identifying specific organizational units which are falling short on efficiency. In order to do this however it is assumed that all relevant inputs and outputs are honestly reported. This leaves DEA open to interference by vested interests. As long as this issue is recognised and controlled for it is not a major concern in itself. A greater and ongoing issue is the lack of definition of what constitutes a DMU and an input or output. There are guidelines available with regard to maximum numbers of DMUs and inputs/outputs.

While DEA is widely used across many industries it does require open and honest engagement by managers in reporting their figures. Beyond that, a prudent and systematic application of the process should yield useful and, perhaps even more importantly, actionable information regarding a firms efficiency.

2.8 Conclusion

While EVA, the BSC and MCDM are all valid methodologies they only account for a company's performance in its own right. They do not provide any form of ranking or "built in" comparative function. EVA scores could be calculated and compared but this is essentially another way of reporting profit and does not account for the complexity of airline business models or practices. There are also confidentiality issues surrounding the necessary data which make EVA unsuited for a study of this type. The BSC is a widely used means of assessing company performance and does allow for the inclusion of financial and non financial data. However, many aspects of it are largely subjective which results in large amounts of quantitative data which makes direct comparison difficult. Confidentiality and data availability are also issues for an outside researcher seeking to create multiple balanced scorecards for comparison purposes. Multi criteria decision making is primarily a research tool that allows researchers to investigate and develop strategy and overall is not particularly suited to performance measurement and/or comparison.

	Economic Value Added	Balanced Scorecard	Multi Criteria Decision Making	Data Envelopment Analysis
Financial Measures	✓		✓	✓
Non Financial Measures		✓	✓	✓
Strategic		✓	✓	✓
Proprietary	✓			
Qualitative		✓	✓	✓
Quantitative	✓	✓	✓	✓
Benchmarking				✓

Table 4. Comparison of four key Performance Measurement Methodologies

Data Envelopment Analysis is highly suited to and widely used in performance measurement studies of airlines. However, there are some issues surrounding its use. An ongoing issue with DEA is data availability and input/output selection. Many studies use convenience data which often results in studies of DEA as opposed to DEA studies of airlines. In other words the method rather than the sector is the main focus of the research. Also, 100 per cent efficiency scores are reported as absolutes and while this is technically correct (in fact it is necessary in order to form the efficient frontier) in terms of the DEA model it is highly unlikely that two or more complex entities achieve identical efficiency scores. There are three DEA models available to the researcher CRS, VRS and Pure Scale. The majority of the studies reviewed use only one while some used two and only one used all three.

This study intends to address these issues by first selecting the airlines for analysis and then investigating the data availability in a reversal of the more common direction which tends to focus on data availability first. Those airlines identified as 100 per cent efficient will be further investigated in an attempt to ascertain their “degree” of 100 per cent efficiency and finally all three DEA models will be utilised and used as the basis for a further analysis in order to identify any common best practices that may exist across the best performing airlines.

Chapter Three Research Design and Methodology

3.1 Introduction

This chapter introduces the research designs and methodology including research tool selection and validation; data availability and collection; and airline selection. Empiricism is an approach taken in the pursuit of knowledge that asserts that only when that knowledge is gained through experience and the senses can it be considered sound.

This approach emphasises the need for ideas and hypotheses to be subject to rigorous testing before being accepted as knowledge. The methods and procedures used in this testing must be based on measurable and observable evidence. The methodological approach used by the researcher should provide a framework for how data is collected, categorised and presented (Arbnor & Bjerke, 1996). However, before work of this nature begins it is important to consider the matters of ontology and epistemology. Ontology and epistemology describe the perceptions, assumptions, beliefs and biases present in the researcher and how they might influence how the research is conducted.

Ontology has been described as “the science or study of being“(Blaikie, 1993) and is concerned with an individual’s view on the nature of reality. Simply put, is an individual’s perception of reality actually real or what they think is real? Further, does this reality only exist through experience (subjective), or does it exist independent of experience (objective).

Epistemology is concerned with the question “what is knowledge and what are the sources and limits of knowledge?” (Eriksson & Kovalainen, 2000). Similarly to ontology epistemology may be subjective or objective. If these matters are not understood and addressed it is very easy for the researcher to miss or ignore certain aspects of the research as a result of presupposition.

Once these issues have been acknowledged it is then possible to proceed with the empirical enquiry itself. The basic format of this enquiry is represented by de Groot's Empirical Cycle below in figure 6.

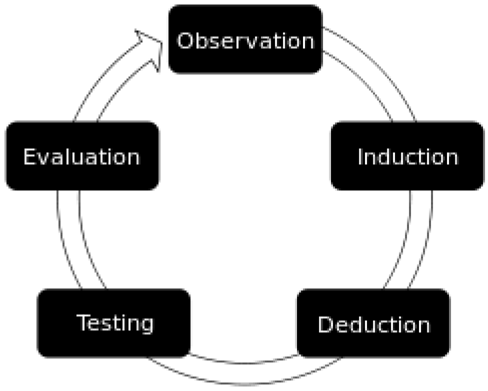

Figure 6. de Groot's Empirical Cycle (Heitink, 1999)

1. Observation: The collecting and organisation of empirical facts; forming hypothesis.
2. Induction: Formulating hypothesis.
3. Deduction: Deducting consequences of hypothesis as testable predictions.
4. Testing: Testing the hypothesis with new empirical material.
5. Evaluation: Evaluating the outcome of testing (Heitink, 1999).

When conducting research it is important to adhere to three principles: reliability, replication and validity (Bryman & Bell, 2007). This section briefly describes these three principles and examines how they relate to this study. Reliability refers to the question of whether or not the measures that are devised for business and management concepts such as staff morale and team working are consistent. This consistency can be difficult if not impossible to achieve when dealing with more "abstract" concepts such as those previously mentioned. As a result it can be difficult to replicate research as the measures are unreliable. This study uses stable measures such as number of employees and fuel costs. These are “concrete” values and so are reliable and make replication possible.

Replication or replicability is a measure of how easy it is to repeat research work. There are various reasons for replicating other researchers’ findings such as confirming the results are correct or conducting the research again in light of new or updated theories. In order for this replication to be possible it is important for researchers to describe the processes and procedures in detail. The processes and procedures for this study are presented in the following pages. Validity is concerned with the integrity of the results and conclusions of a research work. There are various types of validity.

Measurement or construct validity raises the question of whether or not a measure is actually a measure of the concept that is under examination. For example, in the context of this study the variables used; number of employees, fuel costs, staff costs, EBIT and passengers carried are all reliable measures of their constructs. Similarly with performance measurement techniques, several were investigated and ultimately identified as valid measures of their respective constructs and have been widely used in research studies.

Internal validity is concerned primarily with causality. In other words it questions whether or not a conclusion that supposes a causal relationship between two or more variables is valid. This study does not assume causal relationships although such relationships are identifiable through various means such as regression analysis. Such relationships are beyond the scope of this study but are undoubtedly grounds for further research.

External validity asks whether the results of a study can be generalized beyond a specific context. As this study necessarily uses convenience sampling generalisations and inferences about the entire population cannot be made hence external validity is low. This is a limitation of this study but was beyond the control of the researcher as data availability was an issue. Again, this is an area for further research as there is possible value in replicating this research using random sampling and hence providing inferences.

These principles are important as they allow for a considered and structured research strategy. This in turn allows for clear communication between researchers and allows for easy replication of work. The empirical work for this study was carried out in three phases: firstly, a total of 75 annual reports of European airlines were examined; secondly, a formal DEA model was built and the performance of 17 airlines was examined in detail using the model; thirdly, three representative airlines were further examined as mini-case studies. The benefits of this structured approach are protection against errors and the provision of groundwork for future research (Remenyi, Williams, Money & Swartz, 1998).

3.2 Research Process

Watson (1994) illustrated a what, why and how framework that may be used when considering research:

What?	**Why?**
What puzzles/intrigues me? What do I want to know more about/understand better? What are my key research questions?	Why will this be of enough interest to others to be published as a thesis, book, paper, guide to practitioners or policy-makers? Can the research be justified as a contribution to knowledge?
How – conceptually? What models, concepts and theories can I draw on/develop to answer my research questions? How can these be brought together into a basic conceptual framework to guide my investigation?	**How – practically?** What investigative styles and techniques shall I use to apply my conceptual framework (both to gather material and analyse it)? How shall I gain and maintain access to information sources?

Figure 7. What, Why & How Framework (Watson, 1994)

This framework provides an excellent overview and starting point when considering a research project. It gives insight into not only the thought process but also into what is required procedurally in order to execute a research project.

Saunders, Lewis & Thornhill (2007) presented a more detailed and formal approach to research with their Research Onion diagram. The research onion identifies and examines each major step in the research process and provides the researcher with an overview of each step. According to the research onion the research process should be approached from the outer ring or layer towards the centre. The outermost ring describes the philosophies of research; positivism, realism, objectivism, subjectivism, pragmatism, functionalist, interpretive, radical humanist or radical structuralist. The second layer deals with approaches to research; deductive or inductive. Strategies are described in the third layer; experiment, survey, case study, grounded theory, ethnography and archival research. Next there are choices; mono method, mixed method or multi method. The fifth layer is concerned with time horizons i.e. should the study be cross sectional or longitudinal. Finally, the bulb of the onion describes the process of data collection and data analysis.

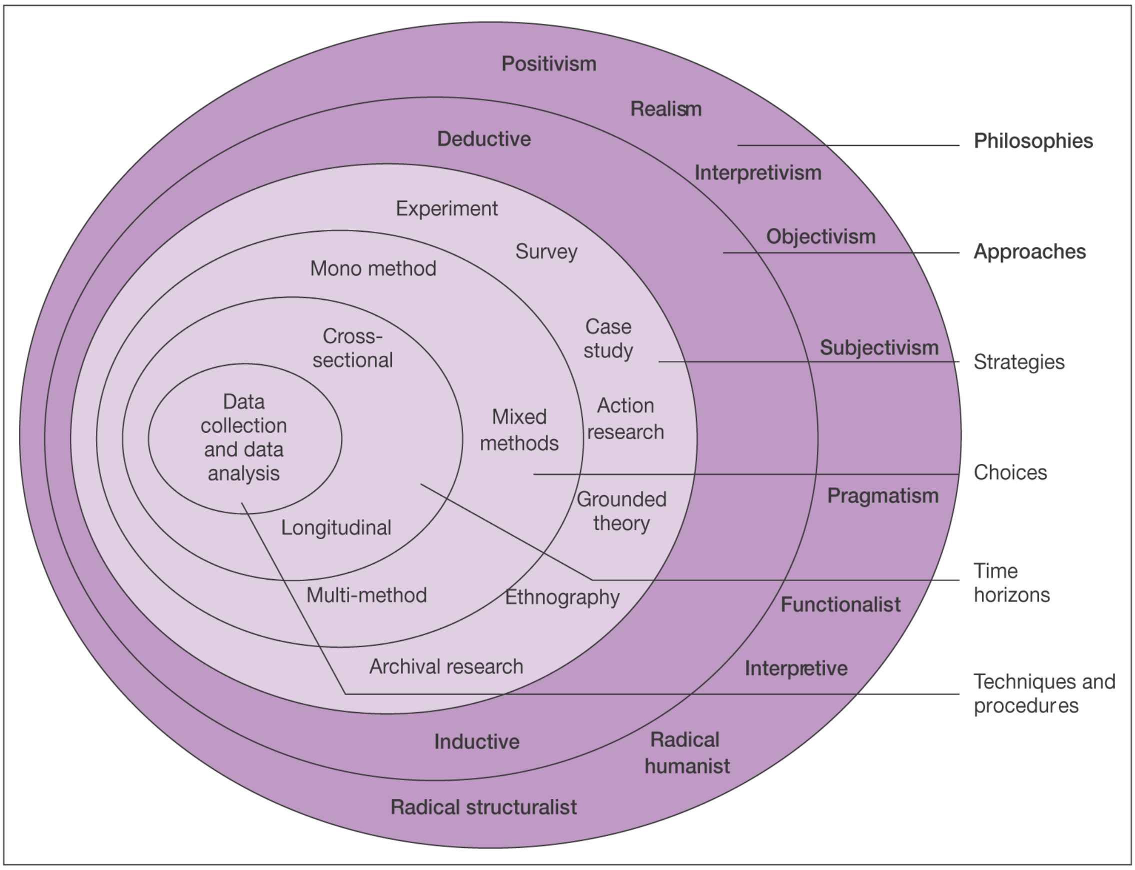

Figure 8. Research Onion (Saunders, Lewis & Thornhill, 2007)

This study is multi faceted and makes use of multiple options available in each layer. The scientific approach to the development of knowledge in this study invokes the philosophy of realism. This philosophy asserts the basic assumption of fact as opposed to belief. There are however also elements of pragmatism in the direct reporting of results and the interpretive approach in the further analysis of these results. As a result the research approach is necessarily inductive as the researcher makes observations which lead to a result. There then follows a deductive element as conclusions are made from previously identified facts. With regard to the research strategy again several elements of the onion are used. Action research - solving a particular problem, case study – analysis of a particular entity and a form of grounded theory – data collected and analysed to identify common factors are all research strategies utilised by this study. The choice of method includes both mixed i.e. qualitative and quantitative approaches as well as multi methods as several research methods are brought together to complete the work. The timeline is a straightforward cross section. The data used are primary data as they are taken directly from the "subjects" and not a third party. The airlines included in this study were selected on the basis of the availability of annual reports, the annual reports being in English and the report containing the required data.

Overall, the research onion provides a comprehensive six step approach to research. McNabb (2004) presents a similar but more detailed approach to research:

Step 1 – Identify Research Question

Step 2 – Establish Research Objectives

Step 3 – Select Research Strategy

Step 4 – Prepare a Research Plan

Step 5 – Review the Literature

Step 6 – Gather the Data

Step 7 – Analyse and Interpret the Data

Step 8 – Prepare and Present the Findings

In terms of describing the research process used in this study with reference to reliability, replicability and validity the philosophies of both the Research Onion and

McNabb are used as underlying guiding principles. Each piece of research is, by its very nature, a unique process and as such may not fit a pre prescribed structure. With this in mind the following describes the steps taken by the researcher in carrying out this study.

3.2.1 Step 1 – Identify Research Question

The researcher has been working in the aviation industry since 1995 and during that time has witnessed the massive changes that have taken place across the European industry as a result of the arrival of the low cost carriers to the marketplace. Younger and leaner low cost carriers such as Ryanair and easyJet have taken on the established leviathan legacy carriers such as Aer Lingus and British Airways with phenomenal success. During this time other companies tried and failed to successfully emulate the low cost model including attempted moves to this model by legacy carriers. This would suggest that emulating the low cost model is not as straightforward as it might appear, nor is it a guarantee of success. Thus the research question becomes 'What elements constitute a successful airline?'

3.2.2 Step 2 – Establish Research Objectives

Fundamentally, this research sets out to examine European airlines in an attempt to identify those who are leading the field in terms of company performance. In addition, it is intended to benchmark the airlines examined and investigate their financial, operational and strategic activities in an attempt to identify best practices or common characteristics that may be emulated by the poorer performing airlines.

3.2.3 Step 3 – Literature Review

A review of the relevant literature was carried out. This review covered two main areas performance measurement techniques and the current literature surrounding performance measurement in aviation. Chapter 2 looked specifically at performance measurement techniques. The goal was to identify a suitable technique that would measure financial and operational performance. It was necessary that publicly available data could be used as the researcher had no access to proprietary data. Economic Value Added, The Balanced Scorecard, Multi Criteria Decision Making and Data Envelopment Analysis were all reviewed. The reviews were conducted in both a general context and more specifically within the context of airline performance measurement.

Chapter 2 also reviewed the literature specific to performance measurement from an aviation perspective. This was carried out with a view to identifying a gap in the literature. From this review DEA was identified as one of the most commonly used analysis techniques with regard to assessing company performance in aviation. This highlights DEAs suitability for performance analysis in the aviation sector above that of EVA, the BSC and MCDM methods. None of the studies reviewed used DEA to its full potential. DEA consists of three different methodologies for assessing efficiency, but in the majority of the studies reviewed only one methodology was employed. In a small number of cases two DEA methodologies were used and only one study, which looked at airports, applied all three (overall efficiency, pure technical efficiency and pure scale efficiency). In the majority of the studies data sources were either not provided or the data were obtained from a mix of third party agencies i.e. ICAO or IATA and some cases included data that were taken from the airlines themselves.

Although DEA is a frequently used method for assessing company performance in an aviation context, to date the structure of the majority of the empirical work appears to be; investigate general data availability (i.e. investigate what data has been collected and made available by a third party such as ICAO or www.wikinvest.com) → apply DEA → report result. This approach ultimately results in a study of DEA using airline data. This researcher proposes the opposite, a study of airlines using DEA, by adopting the following structure, select target group for investigation (airlines) → investigate specific data availability directly from target group → apply DEA → report result → further analysis. This approach not only allows for more targeted results i.e. a DEA study on a group of specifically selected airlines as opposed to a "group of airlines" but gives a deeper insight into how these airlines are performing, why they appear where they do when ranked alongside their peers and then provides specific, actionable targets in order to improve performance. The further analysis aspect of the study consisted of case studies of high, medium and low performing airlines as identified from the Data Envelopment Analysis. This allowed for the identification of best practice across a range of financial and non financial headings.

The result of the review was the identification of Data Envelopment Analysis as a suitable technique for the purpose of the study. DEA was chosen as it was the only method of those reviewed that could handle operational and financial data combined, did not require specialised knowledge or "insider" information and could cope with variables of differing units.

3.2.4 Step 4 – Research Plan

Research strategy is primarily concerned with the orientation of the research i.e. quantitative or qualitative. Bryman & Bell (2007) describe the fundamental differences between quantitative and qualitative research strategies thus: Quantitative research is deductive, tests theories and is objective whereas qualitative research is inductive, generates theories and is constructive.

Initially it was intended that this study would be qualitative and make use of interviews with senior airline managers. It was envisaged that through cross referencing of pre-defined questions in conjunction with open ended questioning a pattern would emerge pointing to various "best practices" which could then be recommended for application to varying degrees across the industry. This course of action proved to be unrealistic very early in the process for various reasons including access to the relevant personnel, time constraints and commercial sensitivities.

These practical considerations gave rise to the decision to use publicly available, accessible data which necessitated a quantitative approach. A quantitative approach by definition is concerned with measurement through the collection of numerical data. This allows for reliability of measure and makes the research easier to replicate. Unusually for quantitative type research this study is not concerned with causality relationships between variables. This study is concerned with the identification of the best performing airlines and then identifying common characteristics that they may share. This in turn required the identification of a performance measurement technique that could make valid use of such data. Finally, the availability of the data required investigation. Several techniques were considered but given the constraints of data availability and the lack of requirement for "industry expert" input and its flexibility Data Envelopment Analysis was chosen.

In order to "define" a data set it was decided to limit the study to European IATA registered passenger airlines, of which there were 75. IATA membership was used as a preliminary requirement for inclusion in the study as it is one of the largest airline industry associations with approximately 84% of available seat kilometres worldwide provided by IATA members. The next step was to investigate the availability and content of each airlines annual report. The 75 annual reports were accessed online through the relevant airlines website. Any reports not available in English were discarded. The remaining reports were read in their entirety. Of the 75 airlines, only 17 had sufficient commonality of data to perform a Data Envelopment Analysis. This commonality was identified through the systematic reading of each available annual report and recording potential inputs and outputs that may be used in a Data Envelopment Analysis. Ryanair and easyJet, while not IATA members, are two of the most successful airlines in Europe. The researcher felt it would be remiss not to include two such successful airlines in an efficiency ranking study. For this reason their annual reports were examined and found to contain sufficient data that they may be included.

3.2.4.1 DEA Model Parameter Selection

With respect to data availability this study uses staff costs (in place of personnel costs), fuel costs and total number of staff (operating costs were not provided in absolute terms in many annual reports, whereas total number of staff was) as inputs. The outputs are passengers carried (in place of revenue passenger miles which were not provided in all annual reports) and EBIT (Tonne KMs not used as this study did not include cargo figures, EBIT was routinely reported in the annual reports). Regarding the availability of data an effort was made to align these chosen variables with the most commonly used variables as identified in figures 4 and 5 above since exact matches were not possible. It should be noted that there is a certain level of distortion when using inputs/outputs such as number of employees and EBIT. In the case of number of employees this distortion arises through the use of outsourcing. Contract workers are not counted as employees but do contribute to input. EBIT may also be distorted depending on whether or not an airline owns or leases some or all of its fleet. It should also be noted however that in the cases of those airlines that do carry cargo the resources utilised to deliver this service are included in all of the inputs used for this study but only one of the outputs (EBIT).

There is no agreement on the number of DMUs that should be used in a data envelopment analysis. There is a general consensus that the minimum number of DMUs should be total number of inputs × total number of outputs, which in this case would give six DMUs. A DMU may constitute another airline within the group to be examined i.e. revenue passenger miles flown by Aer Lingus, Ryanair etc. or it may constitute values from the same airline but from different time periods i.e. revenue passenger miles flown in each quarter. It is accepted that the more DMUs included the more accurate the results will be. There are obvious limitations to this approach and many studies use a rule of thumb which suggests: total number of inputs × total number of outputs × two as the minimum number of DMUs used. Using this rule of thumb (total number of inputs × total number of outputs × two) gives three inputs × two outputs × two which results in a recommended minimum of 12 DMUs. This study uses 17 DMU's which is greater than the recommended minimum.

DEA may be input or output oriented. In the case of an input oriented DEA the focus is on making changes to the input variables in order to achieve efficiencies. For example, a company may achieve an efficiency score of 80 per cent in an input oriented DEA meaning that it needs to reduce its inputs while maintaining output values in order to achieve a higher efficiency score. Conversely, a company may achieve an efficiency score of 80 per cent in an output oriented DEA meaning that it needs to increase its outputs while maintaining input levels in order to improve efficiency.

This study uses an output oriented model as this provides an indication of capacity shortfall and encourages a more strategic approach to improving efficiency as opposed to the often "blunt instrument" approach of reducing inputs.

3.2.5 Step 5 – Gather the Data

At the time of this study there were 75 European passenger airlines registered as IATA members (Appendix B). Cargo only airlines were excluded as one of the input variables selected was total number of passengers. Mixed cargo/passenger airlines were accepted. It might be more correct to define these airlines as passenger carriers who also carry cargo. The time period selected for the data collection was the year 2011. Data collection took place late in 2012 and early 2013 and so 2011 was the latest period for which annual reports were available.

A technique known as "Free Floating Attention" is often used by psychoanalysts when analysing a patient. The theory behind the technique is that the analyst takes in or absorbs what the analysand is saying with a certain detachment while attempting to identify common themes or patterns in the patients discourse (Freud, 1973). This was essentially the approach taken to the data collection from each airlines annual report. Each report was read and if a particular report was felt to be providing sufficient data, it was put aside for closer investigation. Several of the annual reports were not available in English and were discounted. Others were quite brief documents with little substance or usable data. As a result of this process, 23 reports were selected for further attention. This was further refined based on the inputs/outputs identified above, of the original 75 airlines investigated 17 provided enough commonality of data to be used in this study.

3.2.6 Step 6 – Analyse and Interpret the Data

Once the various elements of the proposed Data Envelopment Analysis were established (i.e. inputs/outputs and number of DMUs) the analysis was performed.

Initially it was intended to use the "Solver" function in Microsoft Excel to execute the analysis. This is a relatively straightforward process when applied to simple DEA analyses. It does however become cumbersome as the complexity of the model increases. There are several DEA software packages available. Many of these are available on a "free trial" basis, but offer extremely limited usage, i.e. the number of DMUs and inputs/outputs are limited as are, in some cases, the type of model allowed (e.g. constant returns to scale or variable returns to scale).

It was decided to purchase PIM – 3.0, a DEA software package provided by Dr. Ali Emrouznejad and available to download from **www.deazone.com**. A student version is available at relatively low cost which provides full modeling functionality but with some limitations on data usage. For example, limitations on the number of DMUs are in place but are well within the requirement for this study. PIM – 3.0 allows for data input by importing an Excel file (see toolbar in figure 9 below). Once the data has been imported it is then a matter of selecting the desired model (CRS, VRS, Pure Scale) and orientation from the menu illustrated below in figure 9.

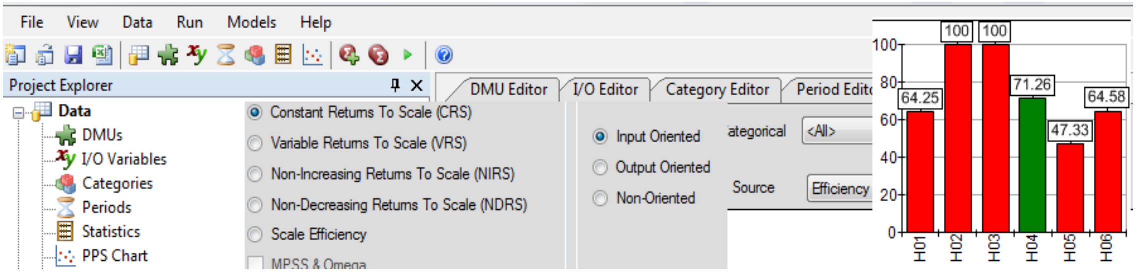

Figure 9. PIM - 3.0 Software Screenshot

Appendix D contains the raw data as collected from each airline annual report and processed data for use in the analyses. In order to standardize the data it was necessary to convert some financial data into Euros. This was completed using the conversion rate in effect on the 31st of December 2011 which was taken from www.xe.com.

DEA requires that all variable values be positive. As some of the airlines examined had recorded losses it was necessary to apply an across the board increase of €71 million to the EBIT values in order to ensure that all values were positive (Air Berlin reported a loss of €70 million). Three DEA model runs were then performed using this data.

1) A Constant Returns To Scale Model (CRS) which provides overall efficiency scores
2) A Varying Returns To Scale Model (VRS) which provides technical efficiency scores
3) CRS/VRS which provides pure scale efficiency scores

A robustness score was determined for each of the efficient airlines as identified in each of the three DEA models. Robustness is a measure of how suitable an airline is for emulation. This was achieved by determining how often an efficient airline appeared in a reference set. Based on these scores the efficient airlines were categorised as highly robust, moderately robust and not robust. This is covered in detail in chapter four.

The PIM 3-0 software provides input and output targets as a byproduct of a model run. These targets are the values that would result in a 100 per cent efficiency score if they were the actual input and output values of each airline. In order to validate the software these target values were substituted for the actual values with the expectation that each airline would then score 100 per cent. On completion of the software validation, a one-at-a-time sensitivity analysis was carried out in order to assess the models sensitivity to input and out variable changes. This is covered in detail in chapter five.

In order to facilitate further analysis the airlines were divided into three categories based on their efficiency score; those that scored 100 per cent efficiency and those that scored above average and those that scored below average. Again this categorisation was applied to all three DEA models. These categories were aggregated which resulted in the identification of three airlines that scored 100 per cent in all three DEA models (Ryanair, Flybe and Estonian Air), two airlines that scored above average in all three models (Croatia Airlines and easyJet) and one airline that scored below average in all three models (KLM). One airline was selected from each group and for each selected airline the annual reports for the year 2011 were reviewed. Strategic, financial and operational data common to all three was extracted for further analysis and comparison across a range of headings.

3.2.7 Step 7 – Prepare and Present the Findings

This study consists of a Data Envelopment Analysis of European airlines. All three DEA models (CCR, CRS and Pure Scale) are performed and further analysis, primarily in the form of a comparative case study, is carried out based on the results. An evaluation of the robustness of each efficient airlines efficiency score is also carried out in order to ascertain which airlines are suitable role models for the less efficient airlines. The data is taken solely from primary sources i.e. annual reports. The results and findings are presented in chapters four, five and six below. The basic DEA model results are presented primarily in tabular and graphical format as this provides a clear and concise overview of the model outputs.

Chapter Four Results and Discussion

Introduction

This chapter presents the results of the three Data Envelopment Analyses that were performed. The results of each DEA model are presented in the following format:

1) A graph of efficiency scores and rankings is presented.
2) A table presenting the output targets of each airline. These figures represent the targets that each airline would need to attain (whilst maintaining their current input levels) in order to achieve a 100 per cent efficiency score.

The raw results from the three DEA models are then examined in greater depth. In doing so the best and worst performing airlines from the data set are identified and further analysed from various strategic, financial and operational perspectives.

The airlines are divided into the following three groups for each DEA model:

1) Those airlines that achieve 100 per cent efficiency score within each model.
2) Those airlines that achieve above average efficiency scores within each model.
3) Those airlines that achieve below average efficiency scores within each model.

One airline common to each group across all three models is selected for further analysis in order to confirm that the data envelopment analyses are valid.

4.1 Model Validation

One feature of Data Envelopment Analysis is the calculation of target variables. These targets are what each company needs to accomplish in order to achieve 100 per cent efficiency. For example, in table 4 which presents the results of the CCR model validation run, easyJet achieves an efficiency score of 84.44 per cent with an EBIT of €393.3 and 54.50 million passengers carried. Table 4 also presents target values for easyJet of; EBIT €511.69 and passengers carried 64.54 million. These are the specific targets that easyJet need to achieve in order to score 100 per cent efficiency. In order to validate the models, each model was run with the target variables substituted in place of the actual variables.

This resulted in 51 model validation runs the results of which are presented in tables 4, 5 and 6 below. Table 5 presents the results for the CCR validation model runs. Table 5 presents the results for the BCC model runs and Table 6 presents the results for the pure scale model runs. In each of the 51 model runs the substituted variables return an efficiency score of 100 per cent as expected. These results validate both the models and target variables.

Model Run	Airline	No. Employees (Actual)	Fuel Costs €M (Actual)	Staff Costs €M (Actual)	EBIT €M (Actual)	Passengers Carried Million (Actual)	CCR Model % Result (Actual)	EBIT €M (Target)	Passengers Carried Million (Target)	CCR Model % Validation Result
1	Ryanair	8063	1226.7	371.5	491.9	72.00	100.00	491.90	72.00	100
2	Flybe	2949	127.5	89.6	191.9	7.60	100.00	191.90	7.60	100
3	Estonian Air	283	24.8	10.0	57.5	0.68	100.00	57.50	0.68	100
4	Croatia Airlines	1136	44.0	31.0	69.2	1.90	88.47	78.22	2.15	100
5	easyJet	8288	1098.6	517.5	393.3	54.50	84.44	511.69	64.54	100
6	Aer Lingus	3491	288.7	260.6	243.8	9.50	66.86	364.64	14.21	100
7	Aegean	1615	184.0	86.0	40.3	6.50	60.06	100.83	10.82	100
8	Air Berlin	9113	1000.0	475.0	1.0	35.30	60.00	570.39	58.83	100
9	Meridiana Fly	2011	197.0	114.0	174.0	4.40	55.59	312.98	7.91	100
10	Air Astana	3358	132.0	62.6	121.9	3.00	53.34	228.52	5.62	100
11	Icelandair	1179	138.6	143.6	100.6	1.75	46.06	218.42	3.80	100
12	Turkish Airlines	18489	1632.0	677.3	666.3	33.00	38.68	1722.59	85.32	100
13	Finnair	7467	555.0	477.0	10.1	8.00	24.40	477.23	32.79	100
14	TAP Air Portugal	8661	717.0	524.0	89.1	9.75	23.05	550.81	42.30	100
15	British Airways	40000	3594.0	2515.8	779.0	34.25	18.96	4108.84	180.65	100
16	KLM	33918	2700.0	2100.0	343.0	19.70	13.10	2617.42	150.33	100
17	Lufthansa	115335	30000.0	6700.0	805.0	100.60	10.17	7917.41	989.43	100

Table 5. CCR Model Software Validation Results

Model Run	Airline	No. Employees (Actual)	Fuel Costs €M (Actual)	Staff Costs €M (Actual)	EBIT €M (Actual)	Passengers Carried Million (Actual)	BCC Model per cent Result (Actual)	EBIT €M (Target)	Passengers Carried Million (Target)	BCC Model per cent Validation Result
18	Ryanair	8063	1226.7	371.5	491.9	72.00	100.00	491.90	72.00	100
19	Flybe	2949	127.5	89.6	191.9	7.60	100.00	191.90	7.60	100
20	Aer Lingus	3491	288.7	260.6	243.8	9.50	100.00	243.80	9.50	100
21	British Airways	40000	3594	2515.8	779.0	34.25	100.00	779.00	34.25	100
22	Estonian Air	283	24.8	10.0	57.5.0	0.68	100.00	57.50	0.68	100
23	Lufthansa	115335	30000.0	6700.0	805.0	100.60	100.00	805.00	100.60	100
24	Meridiana Fly	2011	197.0	114.0	174.0	4.40	100.00	174.00	4.40	100
25	Turkish Airlines	18489	1632.0	677.3	666.3	33.00	100.00	666.30	33.00	100
26	Croatia Airlines	1136	44.0	31.0	69.2	1.90	96.31	82.63	1.97	100
27	easyJet	8288	1098.6	517.5	393.3	54.50	85.87	458.01	63.47	100
28	Icelandair	1179	138.6	143.6	100.6	1.75	85.32	117.91	2.61	100
29	Air Astana	3358	132.0	62.6	121.9	3.00	83.32	146.31	5.25	100
30	Aegean	1615	184.0	86.0	40.3	6.50	63.41	40.03	10.25	100
31	Air Berlin	9113	1000.0	475.0	1.0	35.30	60.12	430.03	58.72	100
32	KLM	33918	2700.0	2100.0	343.0	19.70	48.86	702.08	40.32	100
33	TAP Air Portugal	8661	717.0	524.0	89.1	9.75	25.02	356.11	38.97	100
34	Finnair	7467	555.0	477.0	10.1	8.00	24.51	308.58	32.65	100

Table 6. BCC Model Software Validation Results

Model Run	Airline	No. Employees (Actual)	Fuel Costs €M (Actual)	Staff Costs €M (Actual)	EBIT €M (Actual)	Passengers Carried Million (Actual)	Pure Scale Model % Result (Actual)	EBIT €M (Target)	Passengers Carried Million (Target)	Pure Scale Model % Validation Result
35	Ryanair	8063	1226.7	371.5	491.9	72.00	100.00	491.90	72.00	100
36	Flybe	2949	127.5	89.6	191.9	7.60	100.00	191.90	7.60	100
37	Estonian Air	283	24.8	10.0	57.5	0.68	100.00	57.50	0.68	100
38	Air Berlin	9113	1000.0	475.0	1.0	35.30	99.80	429.37	35.37	100
39	Finnair	7467	555.0	477.0	10.1	8.00	99.57	277.50	8.03	100
40	easyJet	8288	1098.6	517.5	393.3	54.50	98.34	399.95	55.42	100
41	Aegean	1615	184.0	86.0	40.3	6.50	94.72	108.69	6.86	100
42	TAP Air Portugal	8661	717.0	524.0	89.1	9.75	92.12	96.72	10.58	100
43	Croatia Airlines	1136	44.0	31.0	69.2	1.90	91.87	86.10	2.07	100
44	Aer Lingus	3491	288.7	260.6	243.8	9.50	66.86	364.64	14.21	100
45	Air Astana	3358	132.0	62.6	121.9	3.00	64.03	190.39	6.34	100
46	Meridiana Fly	2011	197.0	114.0	174.0	4.40	55.59	312.98	7.91	100
47	Icelandair	1179	138.6	143.6	100.6	1.75	53.98	186.36	3.80	100
48	Turkish Airlines	18489	1632.0	677.3	666.3	33.00	38.68	1722.59	85.32	100
49	KLM	33918	2700.0	2100.0	343.0	19.70	26.82	1278.74	73.44	100
50	British Airways	40000	3594.0	2515.8	779.0	34.25	18.96	4108.84	180.65	100
51	Lufthansa	115335	30000.0	6700.0	805.0	100.60	10.17	7917.41	989.43	100

Table 7. Pure Scale Model Software Validation Results

4.2 Results

On initial examination of the results it is clear that there is a certain level of consistency across the best performing airlines with three of them achieving 100 per cent efficiency across all three models. This implies that these airlines are performing well across the board, in terms of overall, technical and pure scale efficiency.

There is less consistency at the lower end of the scale in each model with a greater number of airlines changing position within the rankings. There is also greater movement across the three models with respect to airlines scoring above and below average. For example, Air Astana scores above average in the BCC model but below average in the CCR and CCR/BCC models. This implies that poorer performing airlines are less uniform in their performance and don't score as consistently as the better performers.

For a recap on the concepts of overall, technical and pure scale efficiency the reader is referred to Figure 3 on page 58. The Charnes, Cooper and Rhodes (CCR) model assumes constant returns to scale and is a measure of overall efficiency. The Banker, Charnes and Cooper (BCC) model assumes variable returns to scale and is a measure of pure technical (or managerial) efficiency. The ratio of overall efficiency score/pure technical score provides a measure of pure scale efficiency.

4.2.1 The Charnes, Cooper and Rhodes (CCR) Model – Overall Efficiency

Figure 10 is a graph presenting the efficiency scores and rankings according to the CCR model. The CCR model is a measure of overall technical efficiency. This model takes into account pure technical efficiency (a measure of management efficiency) and pure scale efficiency (a measure of whether or not the airline is operating optimally for its size). An airline is assumed to operate under constant returns to scale if an increase in inputs results in a proportionate increase in the outputs, i.e. if the inputs are doubled, then the outputs are also expected to double. As such it is a good indicator of general efficiency. However, any improvements made under this model may still leave inefficiency in the system. These underlying inefficiencies may be identified more explicitly by using the Banker, Charnes and Cooper (BCC) model to identify pure technical inefficiencies and the CCR/BCC ratio to identify pure scale inefficiencies as will be demonstrated.

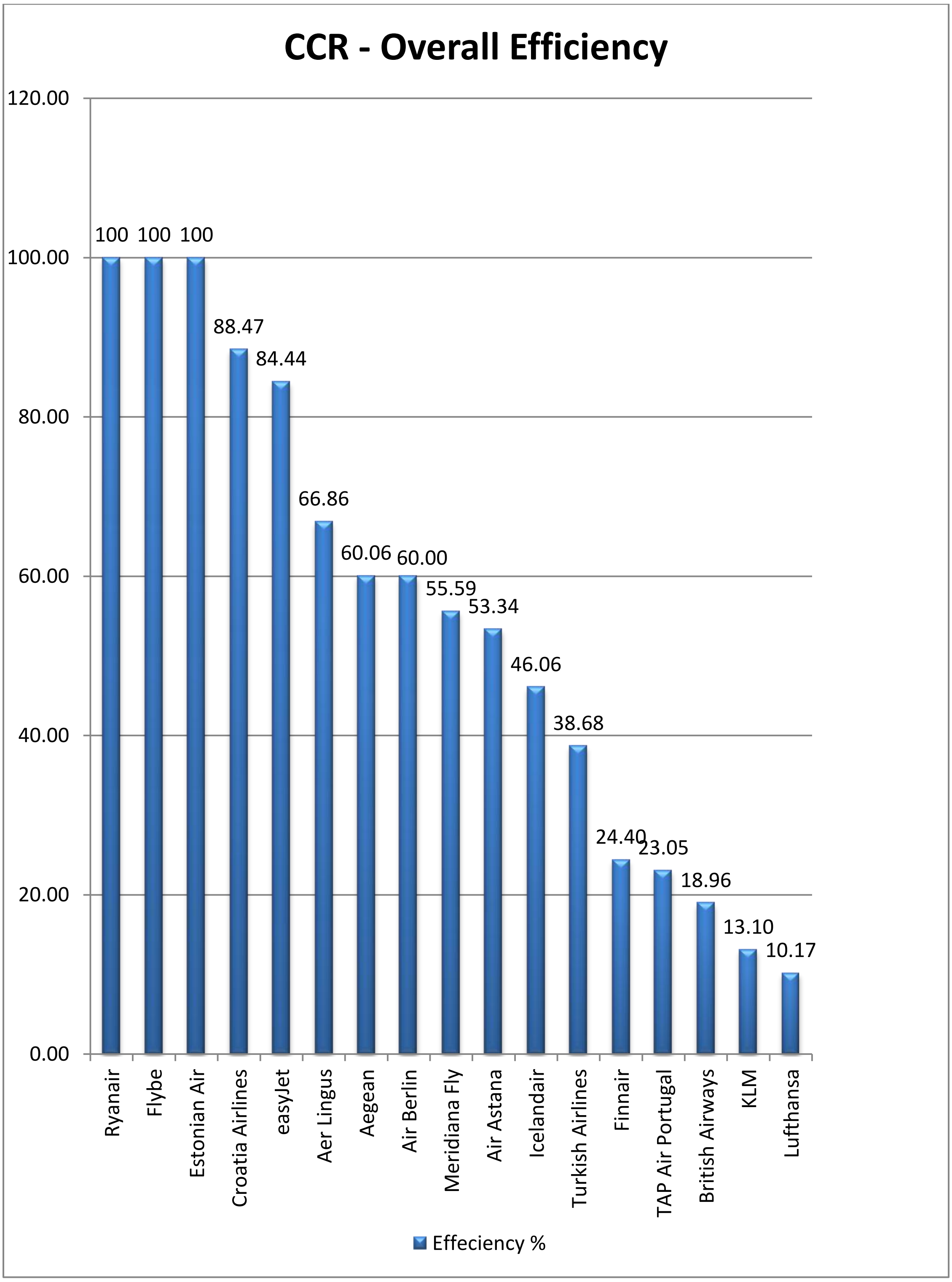

Figure 10. Overall Efficiency Scores and Rankings of Airlines

The above graph presents the overall efficiency scores and rankings for the 17 airlines examined according to the CCR model. From the graph it can be seen that three airlines Ryanair, Flybe and Estonian Air are operating at 100 per cent relative efficiency. It is important to remember that these efficiency scores are relative and not absolute. This is to say they are the most efficient airlines within the group of 17 airlines examined. The lowest scoring airline Lufthansa achieved an efficiency score of 10.17 per cent. This represents a spread of 89.83 per cent efficiency between the best and worst performing airlines. This is a significant differential across the group and implies that there are substantial efficiencies to be achieved within Lufthansa and other low scoring airlines.

On initial examination of the graph there appears to be a relatively clear division into three groups. This is as a result of two relatively large differentials in scores. The first large differential is 17.58 per cent between easyJet (84.44 per cent) and Aer Lingus (66.86 per cent). Therefore easyJet and airlines scoring above it were classified as the high scoring group. The second large differential is 14.28 per cent between Turkish Airlines (38.68 per cent) and Finnair (24.40 per cent). Therefore Finnair and the airlines scoring below it form the low scoring group. The remaining airlines form the mid-range group. The high scoring group consists of Ryanair, Flybe, Estonian Air, Croatia Airlines and easyJet. The mid-range scoring group consists of Aer Lingus, Aegean, Air Berlin, Meridiana Fly, Air Astana, Icelandair and Turkish Airlines. Finally, the low scoring group consists of Finnair, TAP Air Portugal, British Airways, KLM and Lufthansa.

The highly efficient group consists of three privately owned low cost carriers and two state owned flag carriers. The presence of the two flag carriers in this group is interesting as generally speaking flag carriers are found in the lowest scoring group. In fact the lowest scoring group consists exclusively of flag carrier airlines. Estonian Air and Croatian Airlines are different from the other flag carriers in that they are relatively small airlines. Also, they were founded in 1991 and 1989 respectively meaning that they came into existence during the period of time that the European airline market was being deregulated. Consequently they were free of many of the legacy issues that affected the existing flag carriers.

The least efficient group consists exclusively of national flag carriers all of which were founded prior to deregulation. As a result they were saddled with the myriad issues associated with traditional flag carriers of this era. These issues include a heavily entrenched and unionised workforce, political interference, resistance to change and an unreasonable expectation of service from the public (Flottau, 2012; Sparaco, 2012). As a result it is often extremely difficult if not impossible for these airlines to realise efficiency improvements. This may explain why this group attains such low efficiency scores when compared to the privately owned, non unionised post deregulation airlines in the highly efficient group.

The mid-range group consists of primarily flag carriers such as Turkish Airlines and Aer Lingus with only two privately owned carriers, Meridiana Fly and Air Berlin. It may be the case that these carriers are to some extent overcoming the issues that hinder the low scoring group. Consider the case of Aer Lingus which in recent years have made no secret of their intention to move towards a more low cost model (Carey, 2008). They are clearly having some success as a result of this strategy as the graph shows them to be the highest scorer in the mid-range group and just behind easyJet overall. This is despite the various encumbrances endured by the flag carriers.

Table 8 is a table presenting efficiency scores and output targets for each airline based on the output oriented CCR model.

Airlines	Efficiency %	EBIT (€million)	EBIT Target (€million)	Passengers Carried (million)	Passengers Carried Target (million)
Ryanair	100.00	491.9	491.90	72.00	72.00
Flybe	100.00	191.9	191.90	7.60	7.60
Estonian Air	100.00	57.5	57.50	0.68	0.68
Croatia Airlines	88.47	69.2	78.22	1.90	2.15
easyJet	84.44	393.3	511.69	54.50	64.54
Aer Lingus	66.86	243.8	364.64	9.50	14.21
Aegean	60.06	40.3	100.83	6.50	10.82
Air Berlin	60.00	1.0	570.39	35.30	58.83
Meridiana Fly	55.59	174.0	312.98	4.40	7.91
Air Astana	53.34	121.9	228.52	3.00	5.62
Icelandair	46.06	100.6	218.42	1.75	3.80
Turkish Airlines	38.68	666.3	1722.59	33.00	85.32
Finnair	24.40	10.1	477.23	8.00	32.79
TAP Air Portugal	23.05	89.1	550.81	9.75	42.30
British Airways	18.96	779.0	4108.84	34.25	180.65
KLM	13.10	343.0	2617.42	19.70	150.33
Lufthansa	10.17	805.0	7917.41	100.60	989.43

Table 8. CCR Efficiency Scores & Output Targets

The target figures in the above table represent the number of passengers carried and EBIT that each airline would need to achieve without any increase in inputs (i.e. total number of staff, fuel costs or staff costs) in order to reach 100 per cent efficiency. Those airlines that score 100 per cent efficiency do not need to make any increases as they are already on the efficient frontier. Essentially, the difference between the reported figures and the target figures in the table represents the shortfall in each airlines potential output.

To take an example in percentage terms: Tap Air Portugal carried 9.75 million passengers and reported an EBIT of €89.1 million. In order to reach 100 per cent efficiency Tap Air Portugal needs a gain of 333.86 per cent in the number of passengers carried and a gain of 518.19 per cent in EBIT reported with no increase in any of the inputs i.e. total number of staff, fuel costs or staff costs.

As expected the airlines with the lowest efficiency scores have the largest shortfalls, with Lufthansa requiring an almost 10 fold increase in passengers carried. These are capacity shortfalls and in many cases such as this one, the increases required in order to reach the efficiency frontier are practically impossible. Conversely Croatia Airlines with an 88.47 per cent efficiency score only requires a 13.15 per cent increase in its passengers carried figure in order to begin moving towards the efficiency frontier.

4.2.2 The Banker, Charnes and Cooper (BCC) Model – Technical Efficiency

Figure 11 is a graph presenting the efficiency scores and rankings according to the BCC model. The BCC model is a measure of pure technical efficiency (a measure of management efficiency) only. This model differs from the CCR model in that it allows for variable returns to scale meaning that an increase in inputs will not necessarily result in a proportionate increase in outputs. As such it is considered a good indicator of managerial efficiency. Improvements made under this model alone may still leave inefficiency in the system. Any remaining scale related inefficiencies may be identified using the CCR/BCC (pure scale) models as will be demonstrated.

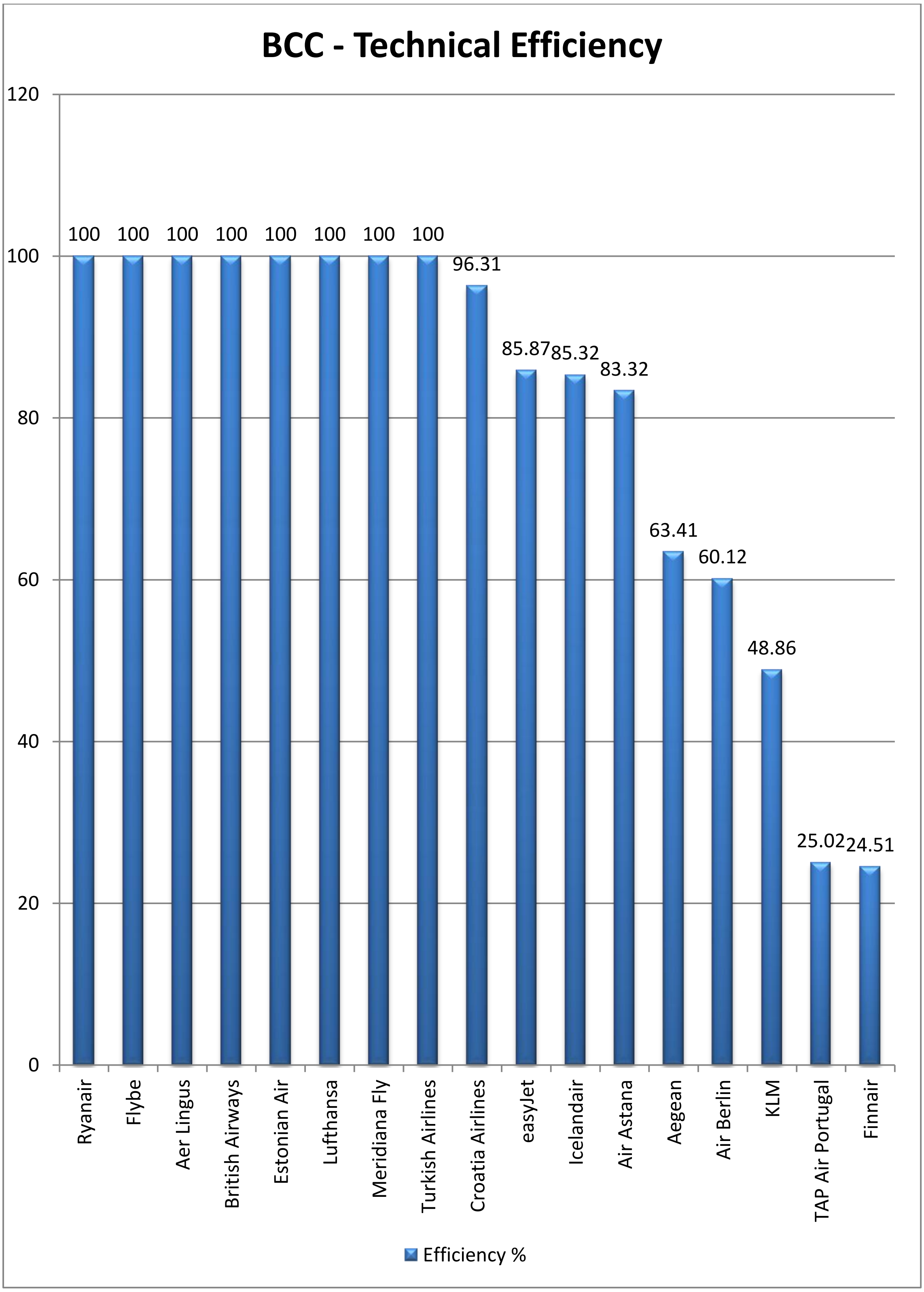

Figure 11. Technical Efficiency Scores & Rankings of Airlines

The above graph presents the technical efficiency scores and rankings for the 17 airlines examined according to the BCC model. In this case the graph shows that eight airlines are operating at 100 per cent relative efficiency compared to three for the CCR model. These airlines are Ryanair, Flybe, Estonian Air, Aer Lingus, British Airways, Lufthansa, Meridiana Fly and Turkish Airlines. Again, it is important to remember that these efficiency scores are relative and not absolute.

The lowest scoring airline Finnair achieved an efficiency score of 24.51 per cent. This represents a spread of 75.49 per cent efficiency between the best and worst performing airlines. This is also a significant differential across the group and although less so than for the CCR model it still implies that there are substantial efficiencies to be achieved within Finnair and other low scoring airlines.

This model is a specific measure of managerial efficiency. It shows that from this perspective the majority of the airlines examined are performing reasonably well overall. The efficiency scores are higher across the board with an average efficiency score of 80.75 per cent compared to 55.47 per cent for the CCR model. This demonstrates that the managerial teams appear to be having a positive impact on the overall efficiency of their airlines. The implication of this is that there are greater efficiencies to be realised in other areas i.e. scale efficiencies.

Whereas the CCR graph presented a clear division into three groups the BCC appears to show four distinct groups. This is as a result of three relatively large differentials in scores. The first large differential is 10.44 per cent between Croatia Airlines (96.31 per cent) and easyJet (85.87 per cent). Therefore Croatia Airlines and airlines scoring above it were classified as the high scoring group. The second large differential is 19.91 per cent between Air Astana (83.32 per cent) and Aegean (63.41 per cent). Therefore Air Astana and the airlines scoring above it but below Croatia Airlines form the high to mid-range scoring group. The third differential is 23.84 per cent between KLM (48.86 per cent) and TAP Air Portugal (25.02 per cent). Therefore KLM and the airlines scoring above it but below Air Astana form the low mid-range scoring group. The remaining airlines form the low range group. The high scoring group consists of the eight 100 per cent efficient airlines listed above and Croatia Air. There is an upper mid-range consisting of easyJet, Icelandair and Air Astana. The lower mid-range consists of Aegean, Air Berlin and KLM. Finally the lowest ranked airlines are TAP Air Portugal and Finnair.

When comparing the results of this model with the previous model there are several clear differences in the positioning of a number of the airlines. The three airlines that scored 100 per cent in the previous CCR model do so again here. They are joined at the top by five more airlines including British Airways and Lufthansa both of which had scored in the lowest ranking group previously. This implies that their issues lie in the scale of their operations as opposed to management efficacy. Finnair and TAP Air Portugal remain in the lowest scoring group across both models. This implies poor managerial performance.

The distribution of flag carriers also differs from the previous CCR model. In this case there are four flag carriers in the top tier as opposed to 1. This gives a 1:1 spilt of flag carriers to private entities compared to 1:2 previously. This may be indicative of a more level playing field in this area. Flag carriers are no longer necessarily being run by government departments but by independent management teams who are answerable to shareholders as opposed to government.

Table 9 is a table presenting efficiency scores and output targets for each airline based on the output oriented BCC model.

Airlines	Efficiency per cent	EBIT (€million)	EBIT Target (€million)	Passengers Carried (million)	Passengers Carried Target (million)
Ryanair	100.00	491.9	491.90	72.00	72.00
Flybe	100.00	191.9	191.90	7.60	7.60
Aer Lingus	100.00	243.8	243.80	9.50	9.50
British Airways	100.00	779.0	779.00	34.25	34.25
Estonian Air	100.00	57.5	57.50	0.68	0.68
Lufthansa	100.00	805.0	805.00	100.60	100.60
Meridiana Fly	100.00	174.0	174.00	4.40	4.40
Turkish Airlines	100.00	666.3	666.30	33.00	33.00
Croatia Airlines	96.31	69.2	82.63	1.90	1.97
easyJet	85.87	393.3	458.01	54.50	63.47
Icelandair	85.32	100.6	117.91	1.75	2.61
Air Astana	83.32	121.9	146.31	3.00	5.25
Aegean	63.41	40.3	129.69	6.50	10.25
Air Berlin	60.12	1.0	430.03	35.30	58.72
KLM	48.86	343.0	702.08	19.70	40.32
TAP Air Portugal	25.02	89.1	356.11	9.75	38.97
Finnair	24.51	10.1	308.58	8.00	32.65

Table 9. BCC Efficiency Scores & Output Targets

The target figures in the above table represent the number of passengers carried and EBIT that each airline would need to achieve without any increase in inputs (i.e. total number of staff) in order to reach 100 per cent efficiency. Those airlines that score 100 per cent efficiency do not need to make these increases as they are already on the frontier.

To take an example in percentage terms: Icelandair carried 1.75 million passengers and reported an EBIT of €100.6 million. In order to reach 100 per cent efficiency Icelandair needs a gain of 17.2 per cent in the number of passengers carried and a gain of 49.14 per cent in EBIT reported with no increase in inputs i.e. total number of staff.

As with the previous CCR model the airlines with the lowest efficiency scores also report the largest shortfall when it comes to capacity. However the BCC model differs in that it focuses specifically on managerial efficacy in an effort to explain the shortfalls. In direct opposition to the CCR model Lufthansa has a 100 per cent efficiency score and need not make any increases in its outputs. This implies that Lufthansa is employing effective managerial strategies and that any potential performance improvements lie in the area of scale efficiencies.

Once again the lowest performing airlines have the largest shortfalls with Finnair requiring a massive 30 fold increase in passengers carried and a four fold increase in EBIT in order to reach the efficient frontier. These figures clearly point to inefficiencies beyond that of management efficacy.

4.2.3 The Pure Scale Model - Pure Scale Efficiency

Figure 12 is a graph presenting the efficiency scores and rankings according to the Pure Scale model. This model is a measure of pure scale efficiency only. An airline is considered to be scale efficient when the size of its operation is optimal and any change to its size will result in a reduction in efficiency (Merkert & Morrell, 2012). Again, improvements made under this model alone may still leave inefficiency in the system due to managerial inefficiency.

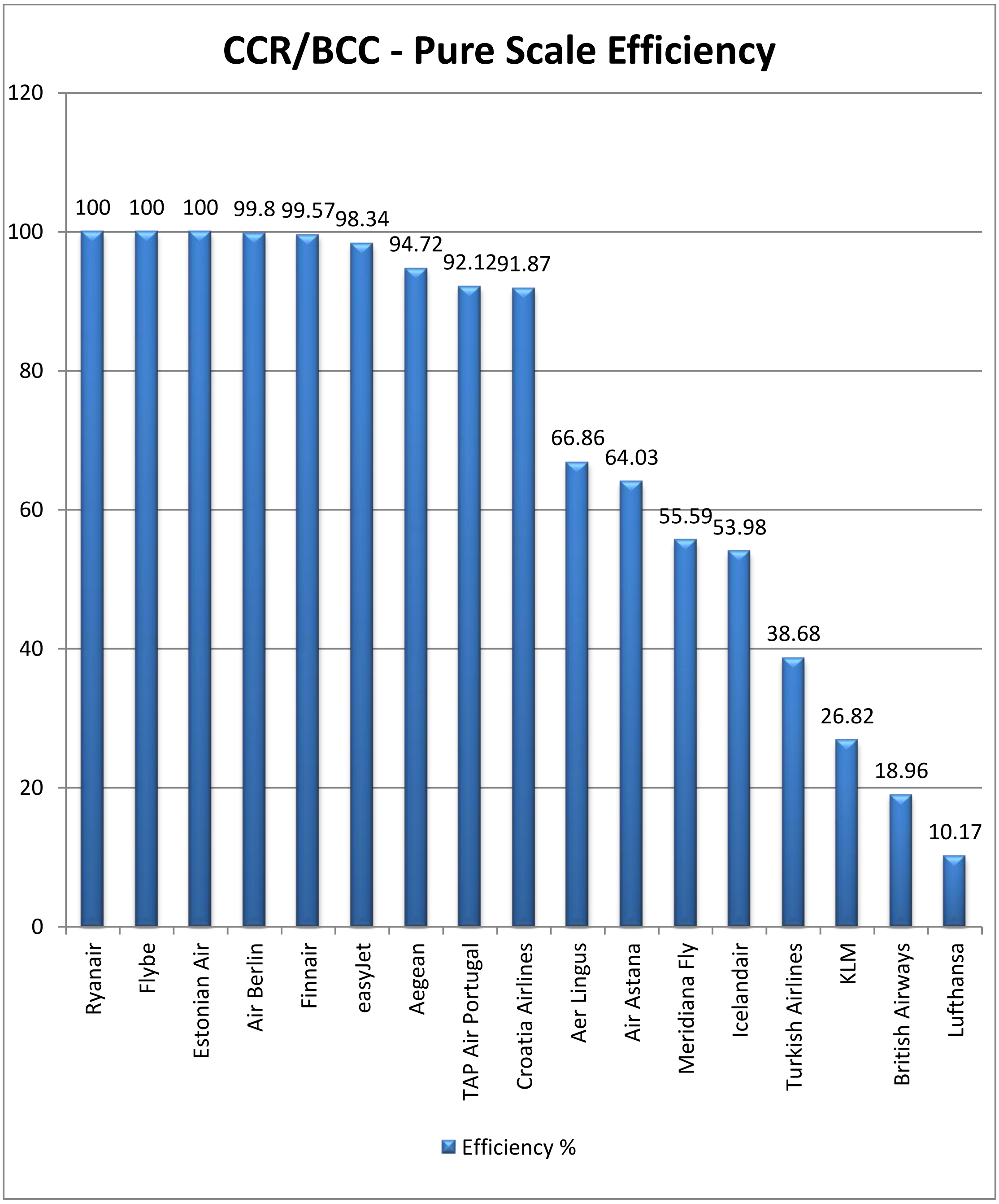

Figure 12. Pure Scale Efficiency Scores and Rankings of Airlines

The graph in figure 12 presents the pure scale efficiency scores and rankings for the 17 airlines examined according to the CCR/BCC model. Given the fact that the results for this model are derived from dividing the CCR results by the BCC results it to be expected that the scores would be similar to the CCR model. This is especially the case with airlines that score 100 per cent in both models. In this case the graph shows that three airlines are operating at 100 per cent relative efficiency. These are the same three airlines that scored 100 per cent in the CCR model i.e. Ryanair, Flybe and Estonian Air. Again similar to the CCR model the lowest scoring airline was Lufthansa which achieved a CCR/BCC efficiency score of 10.17 per cent. This represents a spread of 89.83 per cent efficiency between the best and worst performing airlines. This is an equivalent result to the CCR model. The average efficiency score for this model is 70.66 per cent which is higher than the CCR average but lower than the BCC model average. The graph once again lends itself to a three way split. This is as a result of two relatively large differentials in scores. The first large differential is 25.01 per cent between Croatia Airlines (91.87 per cent) and Aer Lingus (66.86 per cent). Therefore Croatia Airlines and airlines scoring above it were classified as the high scoring group. The second large differential is 15.3 per cent between Icelandair (53.98 per cent) and Turkish Airlines (38.68 per cent). Therefore Turkish Airlines and the airlines scoring below it form the low scoring group. The remaining airlines form the mid-range group. The high scoring group consists of Ryanair, Flybe, Estonian Air, Air Berlin, Finnair, easyJet, Aegean, TAP Air Portugal and Croatia Airlines. The mid-range group consists of Aer Lingus, Air Astana, Meridiana Fly and Icelandair. Finally Turkish Airlines, KLM, British Airways and Lufthansa form the low scoring group. There is very little spread within the high scoring group with only 8.13 per cent between the highest and lowest scores.

This results in a higher average score than the CCR model as reported above despite the overall spread of 89.83 per cent.

In this case the high scoring group consists of four flag carriers and five privately operated airlines. This gives a 1:1.25 ratio as opposed to the 1:1 ratio of the CCR model and the 1:2 ratio for the BCC model. The most anomalous score is that of Finnair. This airline scored in the lowest group for both CCR and BCC models. In the pure scale model it appears in the highest scoring group with a score of 99.57 per cent. This implies that Finnairs issues are not related to the scale of its operation and its efficiency scores are being lowered by a lack of managerial efficacy.

Given that this model is a measure of pure scale efficiency there is an interesting dichotomy between several of the airlines. Depending on the measure used i.e. passengers carried, aircraft operated, routes operated or profits KLM, British Airways, Lufthansa and Ryanair all rank either at, or very close to the top of the world’s largest airlines. Yet, Ryanair is the highest scoring airline in this category while KLM, British Airways and Lufthansa are the three worst performers. This indicates that these three airlines are not taking advantage of their size in order to drive efficiencies in their operations. Table 10 is a table presenting efficiency scores and output targets for each airline based on the output oriented pure scale model.

Airlines	Efficiency per cent	EBIT (€million)	EBIT Target (€million)	Passengers Carried (million)	Passengers Carried Target (million)
Ryanair	100.00	491.9	491.90	72.00	72.00
Flybe	100.00	191.9	191.90	7.60	7.60
Estonian Air	100.00	57.5	57.50	0.68	0.68
Air Berlin	99.80	1.0	429.37	35.30	35.37
Finnair	99.57	10.1	277.50	8.00	8.03
easyJet	98.34	393.3	399.95	54.50	55.42
Aegean	94.72	40.3	108.69	6.50	6.86
TAP Air Portugal	92.12	89.1	96.72	9.75	10.58
Croatia Airlines	91.87	69.2	86.10	1.90	2.07
Aer Lingus	66.86	243.8	364.64	9.50	14.21
Air Astana	64.03	121.9	190.39	3.00	6.34
Meridiana Fly	55.59	174.0	312.98	4.40	7.91
Icelandair	53.98	100.6	186.36	1.75	3.80
Turkish Airlines	38.68	666.3	1722.59	33.00	85.32
KLM	26.82	343.0	1278.74	19.70	73.44
British Airways	18.96	779.0	4108.84	34.25	180.65
Lufthansa	10.17	805.0	7917.41	100.60	989.43

Table 10. Pure Scale Efficiency Scores & Output Targets

Again in order to reach 100 per cent efficiency, the EBIT and Passengers Carried target figures in the above table are what each airline would need to achieve without increasing inputs (i.e. total number of staff). Airlines that score 100 per cent efficiency do not need to make these increases as they are already on the frontier.

To take an example in percentage terms;

Croatia Airlines carried 1.9 million passengers and reported an EBIT of €69.2 million. In order to reach 100 per cent efficiency Croatia Airlines needs a gain of 8.9 per cent in the number of passengers carried and a gain of 32.8 per cent in EBIT reported with no increase in inputs i.e. total number of staff.

In some cases the output targets are many multiples of the actual outputs being achieved which makes them unfeasible. However it may be argued that this is only the case for the lowest scoring eight airlines. Of the other nine airlines the lowest efficiency score is Croatia Airlines with 91.87 per cent. While it is no mean feat to increase passengers carried by 8.9 per cent and EBIT by 32.8 per cent it is not necessarily unrealistic or unobtainable. This is further highlighted when compared to Lufthansa which has a requirement to increase EBIT by 983.53 per cent in order to reach optimal efficiency and this is before passengers carried is considered.

4.3 Robustness Categories

Chen (1997) and Chen & Yeh (1998) proposed a method whereby the frequency of the reference set could be used to measure the robustness of an efficient airline relative to its efficient peers. The reference set is the set of efficient units that dominate a given inefficient unit on all axes. In other words, the more frequently an efficient airline is identified as a role model for inefficient airlines, the more robust it is. These airlines which appear frequently in the reference set of the inefficient airlines are likely to be efficient across a range of factors making them good examples to emulate.

Conversely, efficient airlines which appear infrequently in the reference set of the inefficient airlines are not as robust and therefore not suitable for emulation. This means that they are highly sensitive to small changes in their input and output variables and therefore their position on the frontier is tenuous.

Each airlines efficiency score is calculated relative only to the efficient airlines that dominate it on both the X and the Y axis. These dominant airlines constitute the reference set of the inefficient airline. This is demonstrated in figure 13 below.

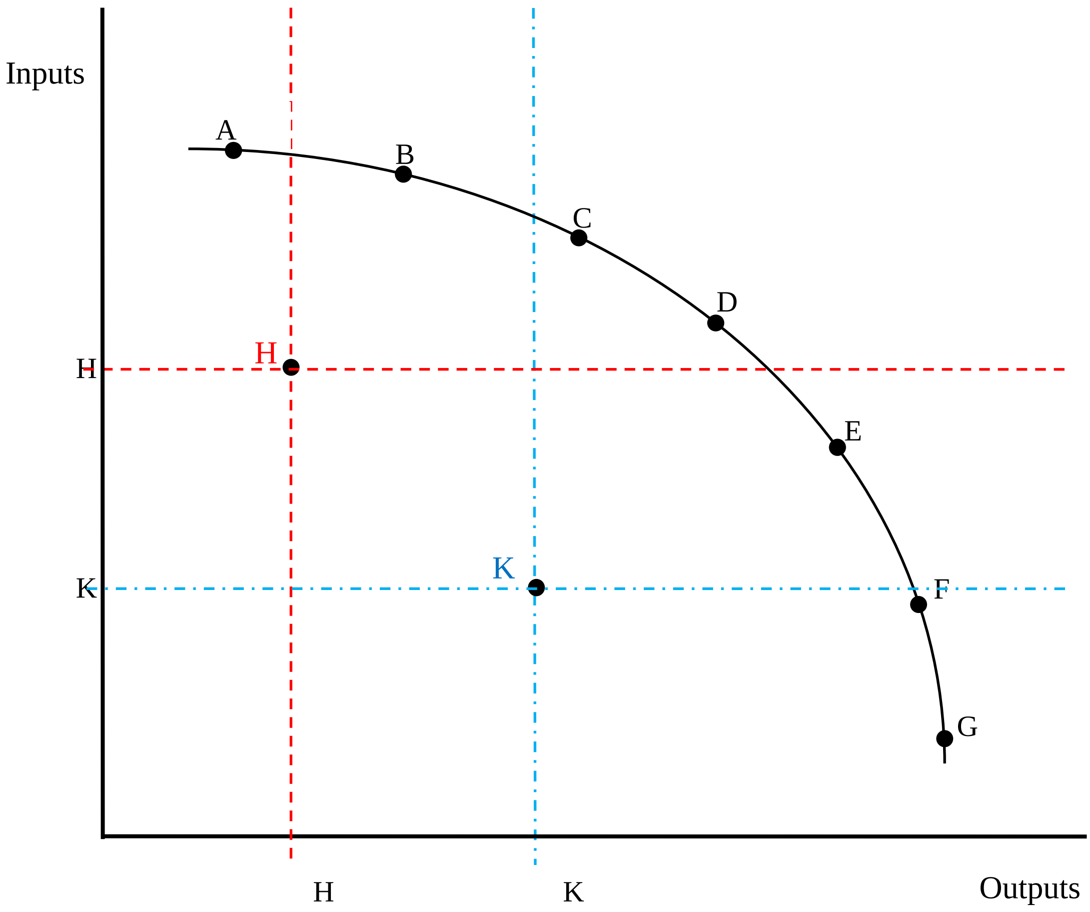

Figure 13. Pure Scale Efficiency Scores & Output Targets

In this example the reference set for DMU H consists of DMUs B, C and D because they are situated on the frontier and dominate DMU H on both the X and Y axis. The reference set for DMU K consists of DMUs C, D and E because they are situated on the frontier and dominate DMU K on both the X and Y axis.

In this study each efficient airline has the potential to appear 17 times in a reference set. An airline that appears 17 times is considered the most robust whilst an airline which does not appear in a reference set is not considered to be robust. In order to ascertain levels of robustness the range 0 to 17 is divided into three equal divisions.

- Highly Robust: 12 to 17
- Moderately Robust: 7 to 11
- Not Robust: 0 to 6

4.3.1 Reference Sets for Each Model (CCR, CRS and Pure Scale)

This section will examine the robustness of the airlines positioned on the efficient frontier for all three models; CCR, CRS and Pure Scale. The number of times an efficient airline appears in a reference set is calculated. This provides robustness scores for each efficient airline. The efficient airlines are then grouped into highly robust, moderately robust and not robust categories depending on how many times they appear in a reference set. This process identifies how "secure" each efficient airlines position is on the frontier.

4.3.2 Robustness - Charnes, Cooper and Rhodes (CCR)

The CCR model of DEA is a measure of overall efficiency. From another perspective, it is a measure of inefficiencies due to both managerial performance (pure technical efficiency) and company size (pure scale efficiency) combined.

In this case, three of the 17 airlines examined are situated on the efficiency frontier. In other words three of the airlines were 100 per cent efficient. This means that 14 out of 17 or 82.35 per cent of airlines examined were inefficient. Furthermore, there was a significant spread between the most and least efficient airlines of 89.83 per cent implying that the poorer performers were performing significantly worse than their efficient peers. The average efficiency score for this group is 55.47 per cent meaning that the inefficient airlines would have to increase their outputs, i.e. passengers carried and EBIT by 44.53 per cent on average to achieve 100 per cent efficiency.

Table 11 below shows a table displaying each of the airlines that appear on the efficient frontier (Ryanair, Flybe and Estonian Air) and the frequency with which they appear in the reference sets of each of the 17 airlines examined. For demonstration purposes consider Ryanair and Air Astana. Ryanair dominates (or is equalled) on all axes. Neither Flybe nor Estonian Air dominates Ryanair on all axes hence the reference set for Ryanair consists of one airline, Ryanair. Air Astana is dominated on all axes by Ryanair, Flybe and Estonian Air hence its reference set consists of Ryanair Flybe and Estonian Air.

Name	Ryanair	Flybe	Estonian Air
Ryanair	✓		
easyJet	✓	✓	
Flybe		✓	
Aegean	✓	✓	
Aer Lingus	✓	✓	✓
Air Berlin	✓	✓	
British Airways	✓	✓	✓
Croatia Airlines		✓	✓
Estonian Air			✓
Finnair	✓	✓	
Icelandair	✓		✓
KLM	✓	✓	✓
Lufthansa	✓		✓
Meridiana Fly	✓	✓	✓
TAP Air Portugal	✓	✓	
Turkish Airlines	✓	✓	✓
Air Astana	✓	✓	✓
Frequencies	14	13	10

Table 11. Table of CCR Model Reference Sets

Based on the above table Ryanair and Flybe are highly robust. These airlines may consequently be considered to be “well-rounded” performers or class leaders, making them suitable for emulation. Estonian Air is moderately robust, making it less suitable for emulation.

In order to facilitate further analysis, the results were divided into three groups:

- Airlines that scored 100 per cent efficiency

- Airlines that scored above average (55.47 per cent) but below 100 per cent
- Airlines that scored below average (55.47 per cent)

Airlines with 100% Score	Airlines with Above Average Score	Airlines with Below Average Score
Ryanair	Croatia Airlines	Air Astana
Flybe	easyJet	Icelandair
Estonian Air	Aer Lingus	Turkish Airlines
	Aegean	Finnair
	Air Berlin	TAP Air Portugal
	Meridiana Fly	British Airways
		KLM
		Lufthansa

Table 12. 100% Efficiency, Above Average & Below Average Scoring Groups within CCR

4.3.3 Robustness - Banker, Charnes and Cooper (BCC)

The BCC model of DEA is a measure of managerial performance. In this case eight of the 17 airlines examined are situated on the efficiency frontier. This means that nine out of 17 or 52.94 per cent of airlines examined were inefficient from a managerial performance perspective. Again there was a sizeable spread between the most and least efficient airlines of 75.49 per cent although not as significant as the previous model it still demonstrates a broad variance of managerial performance. The average efficiency score for this group is 80.75 per cent meaning that the inefficient airlines would have to increase their outputs, i.e. passengers carried and EBIT by 19.25 per cent on average to achieve 100 per cent efficiency.

Table 13 below shows each of the airlines that appear on the efficient frontier and the frequency with which they appear in the reference set as explained in the previous section.

Name	Ryanair	Flybe	Aer Lingus	British Airways	Estonian Air	Lufthansa	Meridiana Fly	Turkish Airlines
Ryanair	✓							
easyJet	✓	✓	✓					
Flybe		✓						
Aegean	✓	✓			✓			
Aer Lingus			✓					
Air Berlin	✓	✓						
British Airways				✓				
Croatia Airlines		✓			✓			
Estonian Air					✓			
Finnair	✓	✓						
Icelandair					✓		✓	
KLM	✓			✓				✓
Lufthansa						✓		
Meridiana Fly							✓	
TAP Air Portugal	✓	✓	✓					
Turkish Airlines								✓
Air Astana		✓			✓			
Freq:	7	8	3	2	5	1	2	2

Table 13. Table of BCC Model Reference Sets

Based on the above table none of the airlines are highly robust. Ryanair and Flybe are moderately robust, making them suitable for emulation, but not ideal. Estonian Air, Aer Lingus, British Airways, Lufthansa, Meridiana Fly and Turkish Airlines are not robust making them unsuitable for emulation as their position on the frontier is tenuous.

In order to facilitate further analysis, the results were divided into three groups:

- Airlines that scored 100 per cent efficiency
- Airlines that scored above average (80.75 per cent) but below 100 per cent
- Airlines that scored below average (80.75 per cent)

Airlines with 100 % Score	Airlines with Above Average Score	Airlines with Below Average Score
Ryanair	Croatia Airlines	Agean
Flybe	easyJet	Air Berlin
Aer Lingus	Iceland Air	KLM
British Airways	Air Astana	TAP Air Protugal
Estonian Air		Finnair
Lufthansa		
Meridiana Fly		
Turkish Airlines		

Table 14. 100% Efficiency, Above Average & Below Average Scoring Groups within BCC

4.3.4 Robustness - Pure Scale (CCR/BCC)

The CCR/BCC model of DEA is a measure of pure scale efficiency. In this case four of the 17 airlines examined appear on the efficiency frontier. This means that four out of 17 or 23.53 per cent of airlines examined were efficient from a pure scale perspective. Again there was a sizeable spread between the most and least efficient airlines of 89.83 per cent which demonstrates a broad variance of pure scale efficiency. The average efficiency score for this group is 70.66 per cent meaning that the inefficient airlines would have to increase their outputs, i.e. passengers carried and EBIT by 29.34 per cent on average to achieve 100 per cent efficiency.

Table 15 below shows a table displaying each of the airlines that appear on the efficient frontier and the frequency with which they appear in the reference set as explained in the previous section.

Name	Ryanair	Flybe	Estonian Air
Ryanair	✓		
easyJet	✓	✓	
Flybe		✓	
Aegean	✓	✓	✓
Aer Lingus			
Air Berlin	✓	✓	
British Airways			
Croatia Airlines		✓	✓
Estonian Air			✓
Finnair	✓	✓	
Icelandair			✓
KLM	✓		
Lufthansa			
Meridiana Fly			
TAP Air Portugal	✓	✓	
Turkish Airlines			
Air Astana		✓	✓
Frequencies	7	8	5

Table 15. Table of Pure Scale Reference Sets

Based on the above table none of the airlines are highly robust. Ryanair and Flybe are moderately robust, making them suitable for emulation, but again not ideal. Estonian Air appears in the not robust category.

In order to facilitate further analysis, the results were divided into three groups:

- Airlines that scored 100 per cent efficiency
- Airlines that scored above average (80.75 per cent) but below 100 per cent
- Airlines that scored below average (80.75 per cent)

Airlines with 100% Score	Airlines with Above Average Score	Airlines with Below Average Score
Ryanair	Air Berlin	Aer Lingus
Flybe	Finnair	Air Astana
Estonian Air	easyJet	Meridiana Fly
	Aegean	Icelandair
	TAP Air Protugal	Turkish Airlines
	Croatia Airlines	KLM
		British Airways
		Lufthansa

Table 16. 100% Efficiency, Above Average & Below Average Scoring Groups within Pure Scale

4.4 Further Analysis

As previously mentioned, in order to facilitate further analysis the airlines were split into the following groups. Those airlines that scored 100 per cent efficiency and those that scored above average but below 100 per cent and those that scored below average. This process resulted in the following groupings (see table 17 below):

- Ryanair, Flybe and Estonian Air were the only airlines that achieved 100 per cent efficiency scores in each of the CCR, BCC and CCR/BCC models.
- Croatia Airlines and easyJet were the only airlines that achieved above average efficiency scores in each model.

- KLM was the only airline to achieve a below average efficiency score in all three models.

Airlines with 100 per cent Score in all models	Airlines with Above Average Score in all models	Airlines with Below Average Score in all models
Ryanair	Croatia Airlines	KLM
Flybe	easyJet	
Estonian Air		

Table 17. 100% Efficiency, Above Average & Below Average Scoring Groups across all DEA Models

As Ryanair is the top scorer across all three models as well as being highly robust, it was chosen from the 100 per cent efficiency group for further analysis. easyJet was chosen from the above average group as it is closest to Ryanair with regard to strategy and market i.e. a low cost carrier operating in Europe. Finally, KLM was the only airline to score below average across all three DEA models and so was chosen by default.

4.4.1 Airlines Chosen for Further Analysis

4.4.1.1 Ryanair

Ryanair is a low cost airline based in Ireland. It was founded in 1985 and has grown to become one of the largest airlines in Europe (depending on metric).
Its business model is loosely based on that of U.S. carrier Southwest Airlines i.e. it is a point to point no frills short haul operator. Ryanair does not have any interline agreements with any other airline meaning it does not offer connections.

Ryanair currently operates a single type fleet of 303 Boeing 737-800 aircraft across 1600 routes and 180 destinations (Ryanair.com figures for 2014). The average

age of a Ryanair aircraft is approximately three years making it one of the youngest fleets in Europe.

In 2011 Ryanair carried 72 million passengers and performed 85,709 million Revenue Passenger Kilometres (RPK's). The average load factor in 2011 was 83 per cent. Ryanair employed 8063 people which equates to 8930 passengers carried for each member of staff.

4.4.1.2 KLM

Koninklijke Luchtvaart Maatschappij N.V. (Royal Dutch Airlines) or KLM is the national airline of the Netherlands. It was originally founded in 1919 and, like Ryanair, has grown to become one of the largest airlines in Europe (depending on metric).

KLM operates a hub and spoke network of short, medium and long haul routes. Interline agreements are in place meaning that passengers may connect with the KLM network along with their baggage. In other words a passenger may fly from Dublin to Amsterdam with Aer Lingus and then on to New York with KLM but only needs to check in once in Dublin and is not required to collect and recheck their baggage in Amsterdam.

KLM currently operates a mixed fleet of 118 aircraft consisting of five different types to 136 destinations (KLM.com figures for 2014). The average age of a KLM aircraft is currently approximately nine years.

In 2011 KLM carried 19.7 million passengers and performed 65,218 million Revenue Passenger Kilometres (RPK's). The average load factor in 2011 was 85.6 per cent. KLM employed 33,918 people which equates to 2966 passengers carried for each member of staff.

4.4.1.3 easyJet

easyJet is a UK based low cost airline. It was founded in 1995 and has like Ryanair and KLM grown to become one of the largest airlines in Europe (depending on metric).

Its business model is loosely based on that of U.S. carrier Southwest Airlines i.e. it is a point to point no frills short haul operator. easyJet does not have any interline agreements with any other airline meaning it does not offer connections.

easyJet currently operates a fleet of 138 Airbus A319 and 61 Airbus A320 aircraft across to 134 destinations (easyJet.com figures for 2014). easyJet is currently the world's largest operator of the Airbus A319. The average age of an easyJet aircraft is approximately four years making it one of the youngest fleets in Europe alongside Ryanair.

In 2011 easyJet carried 54.5 million passengers and performed 61,374 million Revenue Passenger Kilometres (RPK's). The average load factor in 2011 was 87.33 per cent. easyJet employed 8288 people which equates to 6576 passengers carried for each member of staff.

The annual reports of each airline for the year 2011 were revisited and data (strategic financial and operational) common to all three airlines in addition to the original input / output variables was extracted for further analysis. This additional data is categorised as follows.

	Strategic	Financial	Operational
Bases	✓		
Routes	✓		
Route Network	✓		
Cargo/Freight	✓		
Airframe Maintenance	✓		
Engine Maintenance	✓		
Rewards Program	✓		
Subsidiaries	✓	✓	
Fleet Mix	✓		✓
Annual Labour Costs per Staff Member		✓	
CO2 Emissions		✓	✓
Passengers per Staff Member			✓
Revenue Passenger Kilometres (RPK)			✓
Fleet Number			✓
Average Age of Fleet			✓
Average Daily Flight Hours			✓
Block Hours			✓
Load Factor			✓

Table 18. Strategic, Financial and Operational Data

Given that Ryanair is highly robust and thus may be considered a role model or class leader which its peers should seek to emulate this section will examine the figures for easyJet and KLM in comparison to Ryanair.

This data is presented in tabular form in table 19 below.

	Ryanair	easyJet	KLM
Bases	45	19	1
Routes	1300	547	304
CO2 Emissions	Ranked No. 1	Ranked No. 3	Ranked No. 7
Passengers per Staff Member	8930	6576	2966
Annual Labour Costs per Staff Member	€46,075	€62,440	€61,914
Revenue Passenger Kilometres (RPK)	85,709 million	61,374 million	65,218 million
Route Network	Point to Point	Point to Point	Hub and Spoke
Fleet Number	272	167	128
Fleet Mix	One Aircraft Type	Two Aircraft Types	8 Aircraft Types
Average Age of Fleet	3 yrs	4 yrs	11.4 yrs
Cargo/Freight	No	No	Yes
Subsidiaries	0	0	16
Airframe Maintenance	In house	Outsourced	Both
Engine Maintenance	Outsourced	Outsourced	Both
Average Daily Flight Hours	8.36	11.3	13.12
Rewards Program	No	No	Yes
Block Hours	829,981	761,708	613,334
Load Factor	83 per cent	87.30 per cent	85.60 per cent

Table 19. Comparison of Strategic, Financial and Operational data for Ryanair, easyJet and KLM

Bases

The point-to-point network model lends itself to multiple bases more so than the hub-and-spoke network model. Multiple bases allow for more flexibility in route structure and mean less exposure to external factors such as natural disasters, industrial action or congestion.

For example KLM is extremely vulnerable to any issues that may arise at Schipol airport. Strategically, multiple bases allow for penetration into a greater number of markets. The route structure is not limited by either aircraft range or a preference for operating frequent short haul flights.

In addition many airports offer financial incentives to airlines willing to establish a base at their facility. These range from reduced or waived passenger handling fees to the provision of free facilities (The Economist, 2013). In many cases these inducements are dependent on the airline delivering a minimum number of passengers to the airport. Ryanair have been particularly partial to these arrangements in the past but recent clarifications on what does and does not constitute state subsidy has at least reduced the proliferation of such incentives (O'Halloran, 2005).

The fact that many of Ryanair's staff are contract staff as opposed to permanent employees allows for more mobility with regard to personnel. There is no need for Ryanair to become involved in each state's tax and employment laws as these issues are the responsibility of the individual contractor. This permits Ryanair to assign staff to any of their bases dynamically, without complication (for Ryanair) and most importantly at minimum cost.

Routes

There is a large differential between the airlines in the number of routes operated. This is to be expected given the different network models, but what is perhaps more interesting is the ratio of routes operated to the number of aircraft:

Ryanair = 4.8 routes per aircraft operated

easyJet = 3.3 routes per aircraft operated

KLM = 2.4 routes per aircraft operated

This certainly implies a lack of efficiency with regard to aircraft utilisation in the case of KLM. However, it may be the case that this ratio in fact points to a greater inefficiency on behalf of easyJet as their model is the same as Ryanair's i.e. short haul point to point. This model relies on an intensive utilisation of flight assets. It may be the case that easyJet are operating more aircraft than they need to. There are other factors pointing to a lack of efficiency with regard to aircraft utilisation on easyJets part which will be examined later.

$C0_2$ Emissions

Actual $C0_2$ emissions were not reported in all three annual reports but world rankings were (www.ryanair.com; www.easyJet.com; www.klm.com). Despite the highest number of block hours Ryanair scores number one for the lowest $C0_2$ emissions per passenger. This is as a direct result of operating a young fuel efficient fleet. This is also helped by Ryanair's preference for secondary airports which results in less holding time and thus lower overall fuel burn.

A secondary benefit to low CO_2 emissions is the potential cost savings should an emissions trading scheme and/or carbon cap be imposed on European airlines. An attempt to impose a carbon tax on European airlines was defeated in 2012 after strong opposition from the worldwide aviation industry (Szakonyi, 2012). However, the "threat" of such a tax is ever present. If such a tax is introduced the cost will ultimately be passed on to the consumer in the form of higher ticket prices. Therefore, the airline with the lowest exposure to this tax will have the least associated increase in ticket prices in comparison to its less environmentally friendly peers giving it a competitive edge in the marketplace.

Passengers per Staff Member

The staffing figure presented in table 19 points to substantial overstaffing in KLM. The passengers carried per staff member figures for each airline are as follows

Ryanair = 8930 passengers carried per staff member

easyJet = 6576 passengers carried per staff member

KLM = 581 passengers carried per staff member

This represents a massive gulf between the best and worst performing airlines in terms of staff productivity. Each member of staff at Ryanair handles over 15 times more passengers than their counterpart at KLM. Whether this is down to inefficient rostering, generous working conditions or some other reason is beyond the scope of this study but undoubtedly there is the capacity for substantial savings in this area for KLM.

This over staffing is also evident when the number of staff versus fleet ratio is examined.

Ryanair = 29.6 staff per aircraft

easyJet = 49.7 staff per aircraft

KLM = 265 staff per aircraft

KLM have just under nine times the number of staff per aircraft as Ryanair. This is due at least in part to the relatively complex fleet mix. Each type of aircraft operated requires its own specifically qualified pilots, engineers and cabin crew. Despite this, the staff:aircraft ratio is still extremely skewed and there is clearly scope for savings for KLM if they were to target staff cuts.

Annual Labour Costs per Staff Member

The differential in labour costs per staff member between the three airlines is certainly as a result of Ryanair‘s preference for contract staff over full time employees. easyJet also employs this hiring practice, but not to the same extent as Ryanair. This means that for the majority of its staff Ryanair is not obliged to pay any form of social insurance or employee taxes. Annual holidays are also taken at the contractors expense. Apart from the obvious savings that this brings about it also allows for a simplified payroll process which also results in cost savings. In addition, as operational Ryanair staff i.e. flight and cabin crew, are paid on a block hour basis they are not getting paid if a flight is delayed on the ground. This is not the case with either KLM or easyJet.

With regard to sundries, Ryanair staff pay for their own training, medicals, uniforms and even their identification cards. Again this is not the case for KLM or easyJet. In fact Ryanair are one of the few airlines who impose these costs on their staff. While these practices have their critics the cost savings achieved as a result of them are apparent.

Revenue Passenger Kilometres (RPK)

The RPK totals are derived from multiplying the total number of revenue paying passengers by the distance in kilometres that they travelled. Ryanairs RPKs are very high primarily due to the sheer volume of passengers carried. Again Ryanair substantially exceeds KLM and easyJet with regard to RPKs. In fact easyJet returned fewer RPKs despite higher block hours performed and slightly higher load factors. RPKs are essentially an airlines “product”. An airline can provide as many seat kilometres as they like but it is only when they are filled with revenue paying passengers that they produce income.

Route Network

Both Ryanair and easyJet operate a short haul point-to-point network while KLM operates a short, medium and long haul hub and spoke network.

A hub and spoke network is a necessity for any airline operating long haul flights from a single base. The purpose of this type of network is to feed the long haul network from satellite airports where the market for long haul flights may not exist. For example, in order to fly from Kerry to New York with Aer Lingus a passenger is “fed” into the Aer Lingus long haul network by means of a commuter flight between Kerry and Dublin. The advantage to the passenger is the need for only one ticket, the requirement to check in only once and to have their bags checked through for the whole journey. The disadvantage for Aer Lingus is the added complexity and thus expense that this requires.

This arrangement can also cause disruption to an airlines' operation as the long haul flight is, at least to some extent, at the mercy of any delays that the feeder flight may experience. Also, the feeder portion of the flight is often subsidised to some extent in order that the airline is not seen to be penalising passengers for not living close to their long haul base. An additional complexity is the fact that passenger taxes are applied at the point of origin. For example a British Airways flight from London to New York may have passengers who originated in Dublin, Amsterdam and Paris all of whom attract different passenger tax rates.

Interline arrangements also exist on hub and spoke networks. In these cases, to take KLM as an example, KLM may allow the transfer of passengers onto its long haul network from any number of feeder airlines. A KLM flight to New York originating at Schipol may be fed by a British Airways flight from London, an Aer Lingus flight from Dublin and an Air France Flight from Paris. It is clear to see the potential complexity and subsequent expense that these arrangements are capable of adding to an operation. The primary advantage of a point-to-point network is simplicity. There are no connections, no passenger or baggage transfers and in the case of Ryanair and easyJet no interline arrangements. This results in a very simple and linear process. Once a passenger has reached their destination and collected their bags the airline has no further responsibility to them.

Fleet

Ryanair operate a young (3 years average age) fleet of Boeing 737 aircraft. This provides for commonality of flight crew, cabin crew and engineers as well as ground handling equipment. easyJet operates a young (4 years average age) fleet of Airbus A319 and A320 aircraft. While these are technically different types they also allow for commonality across flight crew, cabin crew and engineers and any associated savings. However this particular mix of types also allows for some level of flexibility of capacity on routes which the Ryanair 1 fleet type model does not. KLM operates an older (average age 11.4 years) mixed fleet ranging from 70 seat Fokker 70 regional jets up to Boeing 747s, some of which are almost 22 years old. This complexity of fleet substantially adds to costs not only as a result of crew training and complexity of maintenance but the older aircraft in the fleet are ‘previous generation’ and therefore are significantly less fuel efficient.

Cargo/Freight

KLM is the only airline of the three to offer a cargo/freight service. Again this adds complexity and thus expense to their operation.

In order to operate a cargo service an airline is required to purchase and maintain specialised equipment. In addition to this additional trained staff are required. The airline is also required to fulfil additional auditing requirements in terms of security. Yield parameters have to be set as in some cases it may be more profitable to offload passengers or their baggage in favour of cargo.

There is no doubt that providing a freight service is, or at least has the potential to be, profitable otherwise no airline would do so. However, any airline offering a combined cargo and passenger service is exposing itself to two different markets, for which the service itself is expensive to provide.

Once again simplicity and its associated cost saving appears to be preferred strategy for the better performing airlines.

Subsidiaries

Ryanair and easyJet concentrate solely on the ‘core business’ of being an airline. They both provide ancillary services such as hotel rooms, car hire, insurance, bus tickets, etc., but these are operated by other companies. Thus they are revenue earning and can easily be disposed of should they become a liability. KLM is the sole shareholder in 12 separate companies and a substantial shareholder in four more. As such it is vulnerable to any economic shocks that these subsidiaries may suffer. It also results in less focus on the company's core business.

The importance of concentrating on the "core business" can be demonstrated by Aer Lingus' introduction of the "Cahill Plan" in 1993 (Donoghue, 1994). At that time Aer Lingus was in serious financial difficulty with losses of over IE£11 million. Bernie Cahill, the then Chairman of the Board, introduced the Cahill Plan which was credited with effectively saving Aer Lingus from financial ruin. One critical element of the Cahill Plan was the streamlining of the airline so that it could concentrate on its core business. This resulted in the disposal of a number of wholly owned subsidiaries including hotels, maintenance facilities and other airlines. This reform was the first step in turning Aer Lingus into the profitable airline that it is today.

Airframe Maintenance

Ryanair performs all of its airframe maintenance in house. easyJet outsources this activity while KLM only outsources heavier maintenance. For example "D checks". This is where the aircraft is practically broken down into its constituent parts and each part is thoroughly examined. The exterior paint is removed in order to inspect the metal underneath. A "D check" takes approximately two months and up to 50,000 man hours. Given the amount of time an aircraft will be out of the schedule D checks are often planned for years in advance by the airlines.

The decision to perform airframe maintenance in house or outsource it is ultimately a strategic "judgment call". This is especially the case when dealing with a single type fleet (practically speaking easyJet may be considered a single type fleet). In these cases the decision making process is reasonably straight forward.

When dealing with a complex fleet mix there certainly appears, from a high level perspective at least, to be a strong case to be made for outsourcing airframe maintenance. The number of staff, training costs, inventory, equipment and hanger space required for this type of maintenance operation are enormous. The scheduling requirements are highly complex which also adds to cost.

Given the mobility of aircraft there exists a very competitive global maintenance market and given the above complexities it is hard to see how carrying out an in house maintenance program on a mixed type fleet could be done cost effectively.

Engine Maintenance

Both Ryanair and easyJet outsource all of their engine maintenance while KLM both outsources and performs some maintenance in house.

As with airframe maintenance above the decision to outsource engine maintenance is ultimately a strategic "judgment call" which in this case is the approach both Ryanair and easyJet have chosen.

Again KLM have chosen a strategy of mixing outsourcing and in house maintenance programs. For similar reasons with regard to airframe maintenance it is hard to see how such complex maintenance programs could be carried out cost effectively.

Average Daily Flight Hours

This figure is derived from yearly block hours ÷ 365 ÷ number of aircraft to give the average daily utilisation per aircraft.

Ryanair reports the lowest average daily flight hours (8.36hrs per day). This may be indicative of a level of inefficiency on Ryanair's part in terms of aircraft utilisation. When compared to easyJets (11.3 hours per day) daily average flight hours it is clear that Ryanair is getting approximately 33 per cent fewer flight hours per day from its aircraft.

This is due in part to Ryanair operating so many bases from secondary airports. The intensity of operation from these bases is less than those operated from primary airports. For example, Ryanair currently operates approximately 40 flight per week between its Dublin base and London Stansted and approximately 15 flights per week between its Shannon Base and London Stansted.

Rewards Program

KLM is the only airline of the three to offer a rewards program. Both Ryanair and easyJet are on record as saying they believe rewards programs add complexity and thus cost. They both consider their low fares to be the best reward to offer their customers.

A rewards program is of greater value to an airline operating on a well served route with customers for whom price is not necessarily the greatest concern. In many cases the low cost carriers compete specifically on price point.

In order to have a rewards programme an airline must offer rewards. These rewards generally consist of free upgrades or flights, lounge access and complimentary drinks and meals. Ultimately these inducements have to be paid for and result in higher fares. They also carry their own cost such as administration which again ultimately gets passed on to the consumer in the form of higher fares.

Block Hours

Block hours are measured as the time elapsed between the aircraft moving under its own power with the intention of flight on departure and when the parking brakes are applied on arrival. Again Ryanair returns the highest yearly figure for block hours. This is not surprising given the number routes that they operate.

It is also indicative of the fast turnaround of the aircraft. The low cost carriers put great emphasis on turning an aircraft around as quickly as possible. In other words they try to get the arriving passengers disembarked and the departing passengers embarked as quickly as possible. This is in addition to any services the aircraft requires i.e. fuel, catering and hygiene services. The general consensus in the airline industry is that an aircraft makes no money sitting on the ground.

This allows for higher aircraft utilisation and is reflected in the routes operated per aircraft ratio reported previously. When this figure is taken in conjunction with the average daily flight hours it again shows the efficiency in Ryanairs operation as opposed to KLMs. Despite the lowest average daily flight hours Ryanair reports the highest average daily block hours. This essentially means that Ryanairs crews are on duty for fewer hours but are performing more flights per day. The reverse is the case for KLM.

Load Factor

At 87.3 per cent easyJet is the class leader with KLM a close second at 85.6 per cent Ryanair comes third at 83 per cent. These are all excellent load factors and in many ways highlight just how bloated and inefficient KLM is since its load factor is not substantially higher than Ryanair despite the resources used in achieving it.

There is however another consideration. Load factors are a better indicator of performance for low cost carries as they depend more on passenger volume than long haul operators who depend on business and first class passengers to subsidise the economy fares. With this in mind a better comparator in this case is passenger yield which is a measure of how much money a flight makes.

For example, suppose two airlines operate two flights with 100 seats available on each. Each flight costs €5000 to operate. Airline A sells 85 seats at €100 each resulting in a profit of €3500. Airline B sells 75 seats at €150 each resulting in a profit of €6250. So despite airline A returning a load factor of 85 per cent and airline B returning a load factor of 75 per cent airline B is actually making a higher profit. Load factors of 100 per cent are considered an indication of poor yield management as if all of the seats on a flight are sold then the fares were set too low.

The above are all areas where airline management can make tangible changes in order to improve their company's performance. Reducing staff numbers, scrapping aircraft and more efficient use of staff have all been identified as means by which airlines may address downturns (Morrell, 2011).

The key findings of this chapter are the efficiency rankings for the 17 airlines examined according to the CCR, BCC and Pure Scale models, robustness scores and further analysis. There is a certain level of consistency across the top and bottom ranked airlines across the three models. Ryanair is the top performer according to all three models meaning that it is efficient in terms of overall, technical and pure scale efficiencies. Conversely, KLM consistently scores in the bottom three airlines across all three models. There is reasonable fluidity amongst the mid ranking airlines with for example, Finnair scoring fifth from the bottom, bottom and fifth from the top according to the CCR, BCC and Pure Scale models respectively. This indicates that the high performers are doing most things well, the mid range performers are doing some things well and the lower performers could improve in most areas.

The robustness scores are an important extension of the DEA process as they allow for distinction between those airlines situated on the frontier. The process of determining the reference sets identifies those airlines that are most secure on the frontier and so are the most suitable for poorer performing airlines to model themselves upon. This makes these airlines more 'valuable' when seeking to identify best practice.

The further analysis section compared a number of strategic, financial and operational elements of three selected airlines and indicates tendencies towards certain practices. For example, lower labour costs, higher number of routes, not carrying freight, high passenger to staff ratio, not having a rewards program and higher block hours are all characteristics of more efficient airlines. There are no barriers to the implementation of any of these practices by the less efficient airlines.

Chapter Five Sensitivity Analysis

Sensitivity Analysis

5.1 Introduction

The purpose of sensitivity analysis is to examine how sensitive a model is to parameter changes that may be introduced. Sensitivity analyses are usually performed as a series of separate experiments during which each variable is changed in isolation by a set amount. This allows the researcher to investigate what effect these changes have on the model outcome. Small alterations to the variables should not result in large changes to the model outcome.

The parameter values of any model are subject to change and error. Sensitivity analysis, broadly defined, is the investigation of these potential changes and errors and their potential impact on any on any conclusions drawn from the model (Baird, 1989). Essentially, a sensitivity analysis answers the question "what, if any, effect will changes in parameter values have on model output?" Thus a sensitivity analysis may be useful for a number of purposes for example:

- Testing the robustness of an optimal solution
- Identifying critical parameters
- Making recommendations more credible
- Testing a model for validity or accuracy

This provides confidence in a model and its outputs and hence is valuable when making a decision or recommendation on that basis. Even if the parameter values are set, for example price or weight, there is no guarantee that they will remain constant over time (Pannell, 1997).

There is an array of sensitivity analysis techniques that may be applied to a particular model. These range from simple one-at-a-time analyses to standardised regression coefficients to structured tests based on partitioning of empirical input distribution (Hamby, 1994). In the context of this research three of the most relevant sensitivity analysis methods are:

5.2 One-at-a-time sensitivity analysis

This is the most straightforward means of performing a sensitivity analysis. This method consists of repeatedly changing one parameter value at a time while the remaining parameter values remain constant (O'Neill, Gardner & Mankin, 1980). Sensitivity rankings for each parameter may be derived by increasing and decreasing each parameter by a set percentage while the other parameter values remain constant. Any change in model output is then recorded and parameters may be ranked in order of sensitivity.

5.3 Factorial design

This method involves changing each parameter by a range of set amounts (i.e. +/- 10 per cent, +/- 20 per cent and +/-50 per cent) then running the model for every possible permutation of these changes (Box, Hunter & Hunter, 1978). The changes in parameter values may be predefined or may be chosen arbitrarily by the researcher. This technique results in enormous amounts of data. For example, a model with six parameters subject to the six percentage changes stated above requires 6^6 or 46,656 model runs. This makes analysis of the results difficult.

5.4 Subjective sensitivity analysis

The subjective sensitivity analysis is a subjective analysis of each individual parameter by a subject matter expert (Downing, Gardner & Hoffman, 1985). This method depends on the subject matter experts deciding before a model is run which parameters will have the least influence on the model outcome and hence may be discarded. This technique may be used to reduce the number of parameters for a given model in order to reduce the amount of data to manageable amount. It is a blunt instrument and due to its subjectivity lacks a scientific approach.

5.5 Method

This study will use the One-at-a-time method of sensitivity analysis. This technique was chosen on the following basis: it is uncomplicated and requires no subject matter expert knowledge; it produces a manageable amount of data and as a result of its scientific approach it is replicable and verifiable. It is also one of the most commonly used sensitivity analysis techniques (Eschenbach & Gimpel, 1990). In order to keep the data levels manageable Ryanair, easyJet and KLM were chosen to be analysed with regard to sensitivity. These three airlines were chosen on the basis of their DEA scores which are discussed in chapter six.

Each model (CCR, BCC and Pure Scale) was re- run for each of the three airlines with the following changes to the input and output variables. This resulted in 270 separate model runs in total, the results of which are tabulated and presented in Appendix C.

5.5.1 Input Changes

Each input variable (number of employees, fuel costs and staff costs) was increased and decreased separately by 10 per cent, 20 per cent and then 50 per cent. No other variables were altered and a model run was executed after each variable change. This action was carried out for each of the three airlines Ryanair, easyJet and KLM and across each of the three models, BCC, CCR and Pure Scale. This resulted in 162 separate model runs the results of which are presented in tabular form an Appendix C.

5.5.2 Output Changes

Each output variable (EBIT and passengers carried) was increased and decreased separately by 10 per cent, 20 per cent and then 50 per cent. No other variables were altered and a model run was executed after each variable change. This action was carried out for each of the three airlines Ryanair, easyJet and KLM across each of the three models, BCC, CCR and Pure Scale. This resulted in 108 separate model runs the results of which are presented in tabular form an Appendix C.

5.5.3 Sensitivity Index

Parameter sensitivity may be ranked according to a sensitivity index. A sensitivity index may be calculated using a number of methods which results in a value that reflects the relative sensitivity of the model parameters to the model output. Hamby (1994) identified 14 potential sensitivity indices including relative deviation and partial rank correlation coefficient. These methods are highly complex and when subsequently compared by Hamby (1995) none were found to perform as well as a simple index proposed by Hoffman & Gardner (1983);

$$SI = (D_{max} – D_{min}) / D_{max}$$

SI = sensitivity index

D_{max} = output when parameter set to maximum value

D_{min} = output when parameter set to minimum value

Pannell (1997) suggested that the following simpler sensitivity index is satisfactory and maybe even preferable to the Hoffman & Gardner approach;

$$SI = (D_{max} – D_{min})$$

This is the sensitivity index used to calculate the sensitivity rankings of the parameters in this study. In this study D_{max} is defined as (Parameter + 50 per cent) and D_{min} is defined as (Parameter - 50 per cent).

5.5.4 Charnes, Cooper & Rhodes Model Sensitivity Indices

The sensitivity indices for the parameters for the CCR model are as follows in tables 20, 21 and 22:

Ryanair

Parameter	D_{max}	D_{min}	SI ($D_{max} - D_{min}$)
No. Employees	100	100.00	0.00
Fuel Costs	100	100.00	0.00
Staff Costs	100	100.00	0.00
EBIT	100	100.00	0.00
Passengers Carried	100	96.23	3.77

Table 20. CCR Model Sensitivity Indices for Ryanair

easyJet

Parameter	D_{max}	D_{min}	SI ($D_{max} - D_{min}$)
No. Employees	84.15	100.00	-15.85
Fuel Costs	74.63	100.00	-25.37
Staff Costs	84.44	100.00	-15.56
EBIT	88.63	84.44	4.19
Passengers Carried	100.00	46.99	53.01

Table 21. CCR Model Sensitivity Indices for easyJet

KLM

Parameter	D_{max}	D_{min}	SI ($D_{max} - D_{min}$)
No. Employees	12.29	17.82	-5.53
Fuel Costs	9.46	24.48	-15.02
Staff Costs	13.10	13.68	-0.58
EBIT	14.79	12.36	2.43
Passengers Carried	18.57	8.26	10.31

Table 22. CCR Model Sensitivity Indices for KLM

It should be noted that sensitivity indices are dimensionless (Eckhardt, 2012). This means that they are pure numbers and as such their "sign" is irrelevant. For example, a sensitivity index value of +10 or -10 has the same absolute value i.e. 10.

Ryanair CCR

From table 20 Ryanair's parameters in order of sensitivity (descending) are; 1. Passengers carried 2. All other parameters scored 0. Ryanair CCR model outputs do not drop below 100 per cent efficiency when any one parameter, with the exception of passengers carried, is either increased or decreased by up to 50 per cent. This further demonstrates how solid Ryanair's position is on the efficient frontier. The airline can absorb a loss of at least 50 per cent in EBIT without impacting on its efficiency score. A 50 per cent drop in passengers carried only results in a 3.77 per cent drop in efficiency. In terms of inputs a 50 per cent increase in any one input still results in an efficiency score of 100 per cent. This points to highly efficient use of inputs. This insulates Ryanair to a large extent from various factors the most significant of which is fuels costs.

easyJet CCR

From table 21 above, easyJet's CCR model parameters in order of sensitivity (descending) are; 1. Passengers carried 2. Fuel costs 3. Number of employees 4. Staff costs and 5. EBIT. The most critical parameter for easyJet is passengers carried. An examination of the results presented in Appendix C indicates that an increase of 20 per cent in the number of passengers carried will result in an efficiency score of 100 per cent. Given that passengers carried has the highest sensitivity index this is the parameter that has the greatest effect on the efficiency score and so should be prioritised by decision makers when considering strategies for improving efficiency. A 20 per cent change in fuel costs or staff costs will also result in an efficiency score of 100 per cent. Since these parameters have lower sensitivity indices they should not be given the same priority as passengers carried. EBIT has the lowest sensitivity index so despite being a critical element of business performance, in this scenario it makes the least contribution to efficiency score.

KLM CCR

KLMs CCR model parameters in order of sensitivity (descending) are as follows from table 22; 1. Fuel costs 2. Passengers carried 3. Number of employees 4. EBIT 5. Staff costs. The most critical parameter for KLM is fuel costs. An examination of the results presented in Appendix C indicates that a decrease of 50 per cent in fuel costs will result in an efficiency score of 24.48 per cent. Despite resulting in a marginal improvement in efficiency, fuel costs has the highest sensitivity index and is the parameter that has the greatest effect on the efficiency score and provides a starting point for decision makers when considering strategies for improving efficiency. A 50 per cent change in passengers carried, number of employees or EBIT also result in marginal increases in efficiency. The parameter with the lowest sensitivity index, staff costs, when reduced by 50 per cent results in an improvement of 0.58 per cent in the efficiency score. The largest increase in efficiency score for any parameter is 11.38 per cent where fuel costs are reduced by 50 per cent (CCR efficiency score when fuel costs are reduced by 50 per cent 24.48 per cent - original CCR efficiency score 13.1 per cent = 11.38 per cent change (See model run 192 in Table 42 Appendix C)) this is indicative of the high level of inefficiencies present in KLM.

5.5.5 Banker, Charnes & Cooper Sensitivity Indices

The sensitivity indices for the BCC model are as follows in tables 23, 24 and 25:

Ryanair

Parameter	D_{max}	D_{min}	SI ($D_{max} - D_{min}$)
No. Employees	100	100	0
Fuel Costs	100	100	0
Staff Costs	100	100	0
EBIT	100	100	0
Passengers Carried	100	100	0

Table 23. BCC Model Sensitivity Indices for Ryanair

easyJet

Parameter	D_{max}	D_{min}	SI ($D_{max} - D_{min}$)
No. Employees	85.87	100.00	-14.13
Fuel Costs	79.35	100.00	-20.65
Staff Costs	85.87	100.00	-14.13
EBIT	100.00	84.50	15.50
Passengers Carried	100.00	84.62	15.38

Table 24. BCC Model Sensitivity Indices for easyJet

KLM

Parameter	D_{max}	D_{min}	SI ($D_{max} - D_{min}$)
No. Employees	48.86	53.53	-4.67
Fuel Costs	47.41	59.89	-12.48
Staff Costs	48.86	51.25	-2.39
EBIT	70.84	30.39	40.45
Passengers Carried	54.31	47.14	7.17

Table 25. BCC Model Sensitivity Indices for KLM

Ryanair BCC

As shown in table 23, Ryanairs parameters in order of sensitivity (descending) are; 1. All parameters scored 0. Ryanairs BCC model outputs do not drop below 100 per cent efficiency when any one parameter is either increased or decreased by up to 50 per cent. This again demonstrates how solid Ryanair's position is on the efficient frontier. The airline can absorb a minimum change of 20 per cent in all parameters without reducing its efficiency score. This indicates a highly efficient use of inputs.

easyJet BCC

easyJets parameters presented in table 24, in order of sensitivity (descending) are; 1. Fuel costs 2. EBIT 3. Staff costs 4. Number of employees and 5. Passengers carried. The most critical BCC model parameter for easyJet is fuel costs. An examination of the results presented in Appendix C indicates that a decrease of 20 per cent in fuel costs will result in an efficiency score of 100 per cent. Given that fuel costs has the highest sensitivity index this is the parameter that has the greatest effect on the efficiency score and so should be prioritised by decision makers when considering strategies for improving efficiency. A 50 per cent change in number of employees or 20 per cent change in staff costs, EBIT or passengers carried will also result in an efficiency score of 100 per cent. Since these parameters have lower sensitivity indices they should not be given the same priority as passengers carried. Passengers carried has the lowest sensitivity index so should be given the least priority when targeting inefficiencies.

KLM BCC

From table 25, KLM parameters in order of sensitivity (descending) are; 1. EBIT 2. Fuel costs 3. Passengers carried 4. Number of employees and 5. Staff costs. The most critical BCC model parameter for KLM is EBIT. An examination of the results presented in Appendix C indicates that an increase of 50 per cent in EBIT will result in an efficiency score of 70.84 per cent. This is a relatively significant improvement in efficiency of 21.98 per cent considering that the parameter with the lowest sensitivity index (passengers carried) results in a 5.45 per cent improvement when increased by 50 per cent. The largest increase in efficiency score for any parameter is 21.98 per cent (EBIT +50 per cent) which is again indicative of the high level of inefficiencies present in KLM.

5.5.6 Pure Scale Sensitivity Indices

The sensitivity indices for the Pure Scale ratio are below in tables 26, 27 and 28:

Ryanair

Parameter	D_{max}	D_{min}	SI ($D_{max} - D_{min}$)
No. Employees	100	100.00	0.00
Fuel Costs	100	100.00	0.00
Staff Costs	100	100.00	0.00
EBIT	100	100.00	0.00
Passengers Carried	100	96.23	3.77

Table 26. Pure Scale Model Sensitivity Indices for Ryanair

easyJet

Parameter	D_{max}	D_{min}	SI ($D_{max} - D_{min}$)
No. Employees	97.99	100.00	-2.01
Fuel Costs	94.05	100.00	-5.95
Staff Costs	98.34	100.00	-1.66
EBIT	88.63	99.93	-11.30
Passengers Carried	100.00	55.53	44.47

Table 27. Pure Scale Model Sensitivity Indices for easyJet

KLM

Parameter	D_{max}	D_{min}	SI ($D_{max} - D_{min}$)
No. Employees	25.15	33.29	-8.14
Fuel Costs	19.96	40.87	-20.91
Staff Costs	26.82	26.70	0.12
EBIT	20.88	40.67	-19.79
Passengers Carried	34.20	17.52	16.68

Table 28. Pure Scale Model Sensitivity Indices for KLM

Ryanair Pure Scale

Table 26 shows Ryanairs parameters in order of sensitivity (descending) are; 1. Passengers carried 2. All other parameters scored 0. Ryanair pure scale ratio outputs do not drop below 100 per cent efficiency when any one parameter, except passengers carried, is either increased or decreased by up to 50 per cent. This further demonstrates how solid Ryanairs position is on the efficient frontier. A 50 per cent drop in passengers carried results in a 3.77 per cent drop in pure scale efficiency. In terms of inputs a 50 per cent increase in any one input still results in a pure scale efficiency score of 100 per cent. This points to Ryanair operating at an optimal level in terms of scale.

easyJet Pure Scale

easyJets parameters in table 27 in order of sensitivity (descending) are; 1. Passengers carried 2. EBIT 3. Fuel costs 4. Number of employees and 5. Staff costs. The most critical pure scale ratio parameter for easyJet is passengers carried. An examination of the results presented in Appendix C indicates that an increase of 20 per cent in passengers carried will result in an efficiency score of 100 per cent. Given that passengers carried has the highest sensitivity index this is the parameter that has the greatest effect on the efficiency score and so should be prioritised by decision makers when considering strategies for improving efficiency. A 50 per cent change in number of employees or 20 per cent change in fuel costs will also result in an efficiency score of 100 per cent. Since these parameters have lower sensitivity indices they should not be given the same priority as passengers carried. Staff costs has the lowest sensitivity index so should be given the least priority when targeting inefficiencies. Despite being second in terms of sensitivity index an increase in EBIT of 50 per cent results in a pure scale efficiency score of 88.63 per cent.

KLM Pure Scale

KLM parameters in table 28 in order of sensitivity (descending) are; 1. Fuel costs 2. EBIT 3. Passengers carried 4. Number of employees and 5. Staff costs

The most critical pure scale ratio parameter for KLM is fuel costs. An examination of the results presented in Appendix C indicates that a decrease of 50 per cent in fuel costs will result in a pure scale efficiency score of 40.87 per cent. This is an improvement in efficiency of 14.05 per cent. As with the previous models (CCR and BCC) KLM once again demonstrates high levels of inefficiency.

Chapter Six Conclusion

6.1 Conclusions Relevant to the Airline Industry

This thesis examined the overall, technical and scale efficiencies of a group of European airlines using publicly available data (annual reports) for the year 2011. The best and worst performers were identified and analysed in an attempt to explain why they performed as they did. In order to achieve this, three data envelopment analyses were carried out. This resulted in identification of their efficiency scores and the input and output targets which each airline would need to meet in order to achieve pareto optimisation. In addition the level of robustness of the efficient airlines was determined.

This investigation employed a funnel approach to input and output variable selection. Annual reports for each airline were examined and potential input and output variable were selected where sufficient information was available to provide an in depth comparison. This resulted in three inputs: number of staff, fuel costs and staff costs; and two outputs: EBIT and passengers carried.

The results indicated that in terms of overall efficiency the average efficiency score is 55.47 per cent. Three airlines scored 100 per cent efficiency and thus defined the efficiency frontier. On the basis of the frequency of their appearance in the reference set Flybe, Ryanair and Estonian Air were identified as highly robust.

In terms of managerial performance the average efficiency score is 80.75 per cent. Eight airlines scored 100 per cent efficiency and defined the efficiency frontier. No airlines were identified as highly robust. Ryanair, Flybe and Estonian Air were identified as moderately robust. In terms of pure scale the average efficiency score is 70.66 per cent. Three airlines scored 100 per cent efficiency and defined the efficiency frontier. Again no airlines were identified as highly robust. Ryanair, Flybe and Estonian Air were identified as moderately robust, making them suitable for emulation.

In order to facilitate further analysis three airlines were chosen, one from each performance group and further information common to all three extracted from their annual reports. This information pertained to their financial, operational and strategic positions. Ryanair having scored 100 per cent across all three models and being highly robust was chosen as the benchmark. easyJet and KLM were compared and it was found that with regard to the measures chosen generally speaking, the less the equivalence with Ryanair, the lower the performance score. This further analysis validated the results from the original data envelopment analyses. This proves that a valid company analysis is possible using publicly available and easily accessible data. However it should be noted that data availability is not consistent. This is important not only for the operators themselves in terms of benchmarking themselves against their peers, but also for external analysts or investors who may wish to identify the best performers from a given data set.

This research is an examination of the efficiency of 17 European airlines. Ultimately every airline produces the same basic product as its competitors i.e. a seat travelling from A to B. Service offerings beyond ‘the seat’ do differ with full service carriers providing ancillaries such as food and checked luggage as part of the ticket price. In order to sell this seat an airline must focus on differentiating itself from its competitors. It would appear from this study that the less successful airlines are the ones that focus on differentiating the product as opposed to how it is produced. The “full service” carriers such as KLM and Turkish Airlines have historically focused outwardly with regard to their product, pursuing ever higher service levels. The problem with this strategy is that once an innovative new service offering is successfully introduced it is immediately emulated by competitors. Thus, costs increase and any initial advantages are lost.

This study demonstrates that in the majority of cases it is the low cost carriers that achieve the highest efficiency scores. This is as a result of the airlines looking inwardly and differentiating themselves in terms of how they produce the product as opposed to the product itself. Thus they are able to distinguish their product in terms of price not service level. This is far more difficult to emulate.

In recent years there has been a paradigm shift with regard to airline business models. The market now demands low fares and the full service carriers are finding it difficult to compete on this front. This is not entirely the carriers own fault. It is not a simple matter of adopting the business model of a low cost carrier. As this research has demonstrated many of the elements required to operate a long haul service i.e. a hub and spoke network, a mixed fleet and operating from primary airports are not conducive to the low cost model. This represents a very real challenge for the industry.

6.2 Conclusions Relevant to the Research Approach Taken

This research came about as a result of the authors' desire to find a method where successful airlines could be identified and compared across financial and operational measures. After a review of the literature surrounding performance measurement Data Envelopment Analysis was identified as an appropriate method by which this comparison could be made. However, in a review of the literature surrounding DEA several gaps were identified and ultimately addressed by this study. In doing so this research makes the following contributions to the current body of knowledge:

This study builds on previous work by applying all three models of DEA to an airline focused study. Much of the previous work in this area (Zhu, 2011; Lu, Wang, Hung & Lu, 2012; Lee & Worthington, 2014; Joo & Fowler, 2014) has not made use of all three models. Merkert & Williams (2013) did apply all three models but did not report pure technical or pure scale results also their study was restricted to PSO (Public Service Obligation) airlines. Chang, Yu & Chen (2013) applied and reported results for all three models in their study which focused on Chinese airports. Thus the contribution made by this researchers study is the application and reporting of all three DEA models as applied to the airline industry.

6.3 Conclusions Relevant to the use of DEA as a Research Technique

An ongoing issue with DEA is the selection of input and output variables. Also, one of the assumptions of DEA is that all DMUs of interest are observed and all relevant inputs and outputs have been measured (Gajewski, Lee, Botti, Pramjariyakul & Taunton, 2009). These choices are made by the relevant researcher and in the majority of cases the input and output data were drawn from third party sources (Assaf & Jesiassen, 2011; Assaf; 2011; Lu, Wang, Hung & Lu, 2012; Lin, 2012; Steven, Dong & Dresner, 2012; Wanke, 2013; Arjomandi & Seufert, 2014). This results in an immediate constraint with regard to data availability. For example, Joo & Fowler (2014) in their paper “Exploring Comparative Efficiency and Determinants of Efficiency for Major World Airlines” drew their data from the “World Airline Report” who in turn appear to draw their data from IATA. This resulted in the omission of Ryanair (not an IATA member) which by a number of metrics is a major world airline. Lee & Worthington (2014) also specifically point out that their input and output selection was restricted by data availability. Their data sources were World Air Transport Statistics and ICAO. Squalli (2014) also commented on the restricted data availability from IATA and ICAO. In a small number of cases (Strycekova, 2011; Ismail & Jenatabadi, 2014) no meaningful information on data collection is provided.

In an attempt to overcome the data availability issues this researcher undertook an extensive investigation in order to establish what data was actually available from primary sources so as not to be constrained by what data a third party has chosen to report. The data gathered using this process was only constrained by whether or not it was provided by the primary source (i.e. airline annual report). For example, Cyprus Airways do not provide information on load factors in their Annual Reports therefore this data was literally unavailable as opposed to being meta-constrained as a result of a third party's reporting rules.

Researcher subjectivity is an issue with DEA and Parkin & Hollingsworth (1997) found that no guidance is provided on input/output selection. It is too easy for the decision maker to skew the results of a DEA analysis by including favourable input or output variables. Conversely, unfavourable input or output variables may be excluded in order to influence the results. As such input and output selection needs to be as objective as possible. Meaningful and objective data are often difficult to obtain due to commercial sensitivities. In many of the existing DEA studies this is not an issue as they are focusing on the DEA process itself as opposed to the actual subject matter (i.e. the comparison of airlines) and as such the input and output variable selection is of lesser consequence. In the cases where the objective is the analysis of the subject matter the majority of studies source their input and output variable from pre existing sources. For example, Kumar & Gulati (2008) obtain their input/output variables from amalgamated publications consisting of pre collated data. Similarly, Barbott, Costa & Sochirca (2008) used data for their airline based DEA study which was previously collated and published by the UK Civil Aviation Authority. This approach to data collection results in a pre-emptive constraining of the data set.

In this research the 77 DMUs initially selected for analysis were chosen with no knowledge of what data were available. This approach was designed to examine the feasibility of applying DEA to a set of DMUs for which the availability of input/output data was unknown. In essence the airlines to be examined were selected on the basis of interest as opposed to the availability of pre collated data. This approach resulted in the exclusion of 60 airlines from the analysis due to a lack of suitable data. While the analysis itself returned valid results it is clear that there are questions surrounding the suitability of DEA for analysis of a specific entity without prior knowledge of data availability relative to its peers. This is undoubtedly a limitation of the DEA process as its applicability is dependent on very specific data availability.

6.4 Conclusions Relating to Sensitivity, Robustness and Further Analysis

A sensitivity analysis was performed in order to ascertain how sensitive the three DEA models used in this study were. None of the empirical work on DEA reviewed by the researcher included any type of sensitivity analysis thus this study builds on the previous work in this area. The purpose of a sensitivity analysis is to investigate what effect changes in parameter values have on model output (Baird, 1989). Thus a sensitivity analysis can be useful for several purposes such as; testing the robustness of an optimal solution, identifying critical parameters, making recommendations more credible or testing a model for validity or accuracy. The method of sensitivity analysis employed by this study was the one-at-a-time method (Downing, Gardner & Hoffman, 1985) and although it is one of the most commonly used sensitivity analysis methods (Eschenbach & Gimpel, 1990) the researcher found no record of its use in a DEA study. The results of the sensitivity analysis are presented in Appendix C and demonstrate that the models employed are not excessively sensitive to input/output parameter changes.

Taking this work a step further, the individual input/output parameters were analysed in terms of sensitivity. This analysis builds on all of the previous DEA studies reviewed by the researcher. Hamby (1994) identified fourteen potential sensitivity indices and subsequently identified a relatively simple index as proposed by Hoffman & Gardner (1983) as the best performer in terms of ranking parameter sensitivity (Hamby, 1995). The results of this analysis are presented in Chapter 5 and provide sensitivity rankings for each input/output parameter according to each DEA model. Each input/output parameter, when altered resulted in a change of efficiency score for KLM and easyJet. However, the most significant result was the identification of 'Passengers Carried' as Ryanair's only sensitive parameter according to the CCR and Pure Scale models of DEA. This parameter sensitivity analysis is remarkable as it demonstrates just how far ahead of the other airlines examined Ryanair is in terms of efficiency and its ability to cope with dramatic changes in its input and output parameters. This goes beyond the calculation of efficiency scores and provides a means by which an airline can identify which of its input/output parameters have the greatest effect on its relative efficiency.

If several DMU's are positioned on the efficiency frontier they cannot be ranked relative to each other as they have all scored 100 per cent and thus are considered equal (Martin & Roman, 2006). A method was proposed by Chen (1997) and Chen & Yeh (1998) whereby the frequency of the reference set could be used to measure the robustness of an efficient airline relative to its efficient peers. Using this method robustness scores were determined for each airline within each DEA model the results of which are presented in Chapter 4. The application of this method to a DEA study provides a means whereby DMU's situated on the efficient frontier can be ranked relative to each other. This additional ranking process is particularly valuable in situations where a large proportion of DMU's are situated on the frontier. For example,

Figure 11 shows the efficiency scores of the seventeen airlines examined in this study according to the BCC model. Eight of the airlines that achieved a 100 per cent efficiency score are situated on the frontier and hence considered equal. Measuring the robustness of these eight airlines allows for them to be ranked relative to each other (see Table 13). Although this additional ranking is not in terms of efficiency but rather 'suitability for emulation' it is still a significant development within the field of DEA as demonstrated by this study.

All of the models in this study were output oriented. This is traditionally the orientation used in DEA studies as it was originally developed as a measure of production efficiency. This gives a measure of how far short an entity is falling from its potential maximum output. An analysis using this orientation is valid in terms of absolute results. This is sufficient for academic or research purposes. However, given the massive shortfalls in outputs found during the course of this study (almost 1000 per cent in some cases) it is clear that these would be unreasonable targets in a "real world" setting. If DEA were to be used in a practical sense input oriented models would provide more targeted controllable results. For example, given the outputs used in this study, EBIT and passengers carried, increasing these values would be beneficial but clearly achieving these increases would not be a straightforward task. Conversely, a reduction in the input values i.e. staff numbers, fuel costs and labour costs while not necessarily straightforward is much more attainable.

This research set out to examine European airlines in an attempt to identify those who are leading the field in terms of company performance. This objective was achieved and in doing so the airlines examined were benchmarked and their financial, operational and strategic activities were compared and best practices or common characteristics that may be emulated by the poorer performing airlines were identified.

Value was added to the Data Envelopment Analyses through the addition of sensitivity analyses on not only the models themselves but on the individual parameters. The analyses were further developed through the application of robustness measures to the results. Overall this work adds to the body of knowledge not only through the results of the actual analyses themselves but by the identification and application of additional methodologies which allow for the expansion of the DEA process.

6.5 Limitations

One of the greatest limitations of any DEA analysis is that of data availability. Given that a comparison is being made the same data must be available for all DMUs being examined. This was certainly the case in this study. This becomes even more problematic if the research is attempting to focus on a particular airline for which the required data may not be available. Depending on the scenario this data may not be available due to any number of reasons from commercial sensitivity to the fact that it's just not recorded. This limits the "open" application of DEA as the researcher is very much constrained by the availability of data. This results in the very real danger of "measuring what you can and not what you should".

There were issues surrounding the data used with respect to Lufthansa. The data were taken from the Lufthansa Group annual report and as such were "Group Level" data. The Lufthansa Group report provides data on the Lufthansa Group, the Lufthansa Airline Group and Lufthansa the airline. However, the inputs and outputs required were only available at the group level. Despite that it was decided to use the Lufthansa group data on the basis that the higher number of DMU's used the better the quality of the results. This was not the case in this instance. The results returned in the case of Lufthansa were flawed on account of the data being the only data that were Group Level. Other airlines such as SAS and Singapore Airlines also report their figures in this manner and serious consideration should be given when using this data in similar analyses. In hindsight the author would not have included the Lufthansa Group data.

DEA is a non parametric model. While this can be advantageous it does have drawbacks. Non parametric methods are generally employed in hypothesis testing as opposed to estimating or measuring effects. This combined with the fact that the data from annual reports is already a year or two old means that results tend to be “lagging”.

A recurring limitation of DEA is that of subjectivity regarding the selection of inputs and outputs and this study is no different. While attempts were made to identify and use the most commonly used inputs and outputs data availability forced the researcher into choosing suitable alternatives. In one instance EBIT was chosen as an alternative to Tonne KMs as cargo figures were not included. The researcher felt that EBIT was a better measure of “production” but other variables such as load factor were also available and just as valid, it was rejected on grounds that there was little variation in the values with most airlines reporting loads between 65 per cent and 75 per cent. Another researcher may have chosen load factor with entirely different results.

6.6 Further Research

This study would benefit from a longitudinal approach. This would allow for the tracking of changes in efficiency scores over time. This combined with any adjustments to the factors in the further analysis section such as number of bases, fleet or passengers per staff member would allow for the identification of any correlations that may exist between these adjustments and efficiency scores. Such correlations would provide great assistance in strategic decision making and planning. This approach could also be expanded to include comparisons of efficiency scores with more “traditional” financial performance measures. If correlation was identified this could provide extremely targeted identification low and high performing areas of the business.

There is potential to make further use of a two stage approach to DEA similar to that identified by Zhu (2011). This works by taking sets of airlines grouped under headings such as European, American, Asian and African. These airlines may be low cost, long haul or regional. A data envelopment analysis is performed and the top performer from each group is identified. A second analysis is then performed using only these top performers. This results in the identification of a worldwide industry leader. The potential for a two stage approach is practically endless given the enormous variability of the process.

Given the importance of ancillary revenue to airline profitability it would be worthwhile to analyse each revenue stream on its own individual merits. Revenue could be broken down into ticket sales, onboard sales, insurance sales, hotels and car rental for example. Each value could then be used as an output variable in either a single or two stage analysis in order to identify areas which are falling short of their full potential.

One avenue that was considered by this researcher but discounted on grounds of time constraints was the inclusion of qualitative passenger data. This could include passenger perception of safety, on time performance, customer service or price. This aspect of performance measurement was notably missing from any literature on airline performance. Passengers are the end product of an airline and it seems remiss that their input is missing from any attempts to measure and compare airline performance with a view to improvement.

There is some scope for a collaborative study from both an academic and practitioner perspective. DEA is unusual as it requires one individual to be familiar not only with the relatively complex mathematics of the process (usually an academic) but also with the elemental aspects of the airline industry (usually a practitioner). One possible outcome of such collaboration may be overcoming the subjectivity issues surrounding input and output selection. This has the potential to result in a more standardised model of DEA applicable specifically to the airline industry.

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Appendix A Input and Output Usage

Author	Inputs	Outputs
Zhu (2011)	Two Stage Approach: Stage 1 Inputs • Cost per available seat mile • Salaries per available seat mile • Wages per available seat mile • Benefits per available seat mile • Fuel expenses per available seat mile	Stage 1 Outputs • Load Factor • Fleet Size Stage 2 Outputs • Revenue passenger miles • Passenger revenue
Chiou & Chen (2006)	• Fuel costs • Personnel costs • Aircraft cost – including maintenance, depreciation and interest (12 months)	• No of flights • Seat mile • Passenger miles • Embarkation passengers
Greer (2006)	• Labour • Aircraft fuel • Fleet wide aircraft seating capacity	• Available seat miles
Sheraga (2004)	• Available ton KMs • Operating cost • Non flight assets	• Revenue passenger KMs • Non passenger revenue ton-KMs
Adler & Galany (2001)	• Total lending related charges • Total passenger charges paid to airport • Airline station costs including ground staff salaries • Airline operating costs including fuel and crew salaries	• Profit • Revenue • Total no of passengers carried • Average load factors *Two outputs suggested but not used:* • Average delay in minutes at each hub airport • Minimum connecting times at hub airport.

Charnes & Gallages and Li (1996)	• Seat KMs available • Cargo ton KMs available • Fuel • Labour	• Passenger KMs performed
Sengupta (1999)	• Available ton KMs • Total operating cost net of depreciation and amortization costs • Total non flight assets defined as total assets minus flight equipment at cost net of depreciation and amortization	• Revenue passenger KMs • Non passenger revenue
Schefczyk (1993)	• Available ton KMs • Operating Cost • Non flight Assets	• Revenue passenger KMs • Non passenger revenue
Assaf & Josiassen (2012)	• Labour • Capital • Fuel • Other operating inputs (total assets)	• Revenue passenger KMs • Incidental revenues
Schmidt & Sickles (1984)	• Labour index • Materials • Energy • Capital Expenses	• Tonne KMs performed
Barla & Perelman (1989)	• Labour • Aircraft Capacity	• Tonne KMs performed
Cornwall, Schmidt & Sickles (1990)	• Labour index • Materials • Energy • Capital Expenses	• Tonne KMs performed
Distexhe & Perelman (1994)	• Labour • Aircraft Capacity	• Tonne KMs performed. Passengers and Freight

Good, Röller & Sickles (1995)	• Labour • Materials • No. of aircraft	• Revenues
Oum & Yu (1995)	• Labour • Fuel • Materials • Flight Equipment	• Revenue passenger KMs • Revenue tonne KMs • Ancillary output
Baltagi, Griffen & Rich (1995)	• Capital • Labour	• Tonne KMs performed
Ahn, Good & Sickles (1997)	• Labour • Materials • Fuel	• Revenues
Coelli, Perelman & Romano (1999)	• Labour • Capital	• Tonne KMs performed
Barbott , Costa & Sochirca (2008)	• No of employees • No of aircraft • Fuel (Gallons consumed)	• Revenue passenger KMs • Revenue tonne KMs • Ancillary output
Barros & Peypoch (2009)	• No of employees • Operational costs • No of aircraft	• EBIT • Revenue passenger KMs

Appendix B European IATA Member Airlines (2011)

Continent	Company	Country Base	Annual Report Available
Europe	Aegean Airlines	Greece	Y
Europe	Adria Airlines	Slovenia	N
Europe	Aer Lingus	Ireland	Y
Europe	Aerosuit Airlines	Ukraine	N
Europe	Aigle Azur	France	N
Europe	Air Astana	Kazakhstan	Y
Europe	Air Austral	France	N
Europe	Air Baltic	Latvia	N
Europe	Air Berlin	Germany	Y
Europe	Air Corsica	France	N
Europe	Air Europa	Spain	N
Europe	Air France	France	Y
Europe	Air Malta	Malta	Y
Europe	Air Moldova	Molodva	N
Europe	Air Nostrum	Spain	N
Europe	Air One S.p.A.	Italy	N
Europe	Alitalia	Italy	N
Europe	Atlasjet Airlines	Turkey	N
Europe	Austrain	Austria	N
Europe	B & H Airlines	Bosnia & Herzogovina	N
Europe	Belavia	Belarus	N
Europe	Belle Air	Albania	N
Europe	Blue Panorama	Italy	N
Europe	Blue 1	Finland	N
Europe	BMI	UK	N
Europe	BMI Regional	UK	N
Europe	British Airways	UK	Y
Europe	Brussels Airlines	Belgium	N
Europe	Bulgaria Air	Bulgaria	N
Europe	Cargolux Airlines International S.A.	Luxembourg	N
Europe	Carpatair	Romania	N
Europe	CityJet	Ireland	N
Europe	Condor	Germany	N
Europe	Corsair International	France	N
Europe	Croatia Airlines	Croatia	Y
Europe	Cyprus Airways	Cyprus	Y
Europe	Czech Airlines	Czech Republic	N
Europe	Estonian Air	Estonia	Y
Europe	Euroatlantic Airways	Portugal	N
Europe	European Air Transport	Belgium	N
Europe	Eurowings	Germany	N
Europe	Finnair	Finland	Y

Europe	Flybe	UK	Y
Europe	Freebird Airlines	Turkey	N
Europe	Iberia	Spain	Y
Europe	Icelandair	Iceland	Y
Europe	Intersky	Austria	N
Europe	Jat Airways	Serbia	N
Europe	KLM	Netherlands	Y
Europe	LOT Polish Airlines	Poland	N
Europe	Lufthansa	Germany	Y
Europe	Lufthansa CityLine	Germany	N
Europe	Luxair	Luxembourg	N
Europe	Malmo Aviation	Sweden	N
Europe	Meridiana Fly	Italy	Y
Europe	NIKI	Germany	N
Europe	Olympic Air	Greece	N
Europe	Onier Air	Turkey	N
Europe	Pegasus Airlines	Turkey	N
Europe	PGA - Portugalia Airlines	Portugal	N
Europe	SAS	Sweden	Y
Europe	SATA AirAcores	Portugal	N
Europe	SATA Internacional	Portugal	N
Europe	Sky Airlines	Turkey	N
Europe	SunExpress	Turkey	N
Europe	Swiss	Switzerland	Y
Europe	TAP Air Portugal	Portugal	Y
Europe	Tarom SA	Romania	N
Europe	THY Turkish Airlines	Turkey	Y
Europe	TNT Airways SA	Belgium	N
Europe	TUIfly	Germany	N
Europe	Ukraine International Airlines	Ukraine	N
Europe	Virgin Atlantic	UK	N
Europe	White Coloured By You	Portugal	N
Europe	Wideroe	Norway	N

Table 29. Table of IATA Member Airlines (2011)

Appendix C Sensitivity Analysis

Model Run	Airline	No. Employees (Actual)	Fuel Costs €M (Actual)	Staff Costs €M (Actual)	EBIT €M (Actual)	Passengers Carried Million (Actual)	CCR Model % Result (Actual)	Input Change %	CCR Model % Sensitivity Result
1	Ryanair	8063	1226.7	371.5	491.9	72	100	Employees + 10% (8869)	100
2	Ryanair	8063	1226.7	371.5	491.9	72	100	Employees + 20% (9676)	100
3	Ryanair	8063	1226.7	371.5	491.9	72	100	Employees + 50% (12095)	100
4	Ryanair	8063	1226.7	371.5	491.9	72	100	Employees - 10% (7257)	100
5	Ryanair	8063	1226.7	371.5	491.9	72	100	Employees - 20% (6451)	100
6	Ryanair	8063	1226.7	371.5	491.9	72	100	Employees - 50% (4032)	100
7	Ryanair	8063	1226.7	371.5	491.9	72	100	Fuel Cost + 10% (1349.4)	100
8	Ryanair	8063	1226.7	371.5	491.9	72	100	Fuel Cost + 20% (1472.0)	100
9	Ryanair	8063	1226.7	371.5	491.9	72	100	Fuel Cost + 50% (1840.1)	100
10	Ryanair	8063	1226.7	371.5	491.9	72	100	Fuel Cost - 10% (1104.0)	100
11	Ryanair	8063	1226.7	371.5	491.9	72	100	Fuel Cost - 20% (981.4)	100
12	Ryanair	8063	1226.7	371.5	491.9	72	100	Fuel Cost - 50% (613.4)	100
13	Ryanair	8063	1226.7	371.5	491.9	72	100	Staff + 10% (408.7)	100
14	Ryanair	8063	1226.7	371.5	491.9	72	100	Staff + 20% (445.8)	100
15	Ryanair	8063	1226.7	371.5	491.9	72	100	Staff + 50% (557.3)	100
16	Ryanair	8063	1226.7	371.5	491.9	72	100	Staff - 10% (334.4)	100
17	Ryanair	8063	1226.7	371.5	491.9	72	100	Staff - 20% (297.2)	100
18	Ryanair	8063	1226.7	371.5	491.9	72	100	Staff - 50% (185.8)	100

Table 30. Ryanair CCR Sensitivity Analysis for Input Parameters

Model Run	Airline	No. Employees (Actual)	Fuel Costs €M (Actual)	Staff Costs €M (Actual)	EBIT €M (Actual)	Passengers Carried Million (Actual)	BCC Model % Result (Actual)	Input Change %	BCC Model % Sensitivity Result
19	Ryanair	8063	1226.7	371.5	491.9	72	100	Employees + 10% (8869)	100
20	Ryanair	8063	1226.7	371.5	491.9	72	100	Employees + 20% (9676)	100
21	Ryanair	8063	1226.7	371.5	491.9	72	100	Employees + 50% (12095)	100
22	Ryanair	8063	1226.7	371.5	491.9	72	100	Employees - 10% (7257)	100
23	Ryanair	8063	1226.7	371.5	491.9	72	100	Employees - 20% (6451)	100
24	Ryanair	8063	1226.7	371.5	491.9	72	100	Employees - 50% (4032)	100
25	Ryanair	8063	1226.7	371.5	491.9	72	100	Fuel Cost + 10% (1349.4)	100
26	Ryanair	8063	1226.7	371.5	491.9	72	100	Fuel Cost + 20% (1472.0)	100
27	Ryanair	8063	1226.7	371.5	491.9	72	100	Fuel Cost + 50% (1840.1)	100
28	Ryanair	8063	1226.7	371.5	491.9	72	100	Fuel Cost- 10% (1104.0)	100
29	Ryanair	8063	1226.7	371.5	491.9	72	100	Fuel Cost - 20% (981.4)	100
30	Ryanair	8063	1226.7	371.5	491.9	72	100	Fuel Cost - 50% (613.4)	100
31	Ryanair	8063	1226.7	371.5	491.9	72	100	Staff + 10% (408.7)	100
32	Ryanair	8063	1226.7	371.5	491.9	72	100	Staff + 20% (445.8)	100
33	Ryanair	8063	1226.7	371.5	491.9	72	100	Staff + 50% (557.3)	100
34	Ryanair	8063	1226.7	371.5	491.9	72	100	Staff - 10% (334.4)	100
35	Ryanair	8063	1226.7	371.5	491.9	72	100	Staff - 20% (297.2)	100
36	Ryanair	8063	1226.7	371.5	491.9	72	100	Staff - 50% (185.8)	100

Table 31. Ryanair BCC Sensitivity Analysis for Input Parameters

Model Run	Airline	No. Employees (Actual)	Fuel Costs €M (Actual)	Staff Costs €M (Actual)	EBIT €M (Actual)	Passengers Carried Million (Actual)	Pure Scale % Result (Actual)	Input Change %	Pure Scale % Sensitivity Result
37	Ryanair	8063	1226.7	371.5	491.9	72	100	Employees + 10% (8869)	100
38	Ryanair	8063	1226.7	371.5	491.9	72	100	Employees + 20% (9676)	100
39	Ryanair	8063	1226.7	371.5	491.9	72	100	Employees + 50% (12095)	100
40	Ryanair	8063	1226.7	371.5	491.9	72	100	Employees - 10% (7257)	100
41	Ryanair	8063	1226.7	371.5	491.9	72	100	Employees - 20% (6451)	100
42	Ryanair	8063	1226.7	371.5	491.9	72	100	Employees - 50% (4032)	100
43	Ryanair	8063	1226.7	371.5	491.9	72	100	Fuel Cost + 10% (1349.4)	100
44	Ryanair	8063	1226.7	371.5	491.9	72	100	Fuel Cost + 20% (1472.0)	100
45	Ryanair	8063	1226.7	371.5	491.9	72	100	Fuel Cost + 50% (1840.1)	100
46	Ryanair	8063	1226.7	371.5	491.9	72	100	Fuel Cost- 10% (1104.0)	100
47	Ryanair	8063	1226.7	371.5	491.9	72	100	Fuel Cost - 20% (981.4)	100
48	Ryanair	8063	1226.7	371.5	491.9	72	100	Fuel Cost - 50% (613.4)	100
49	Ryanair	8063	1226.7	371.5	491.9	72	100	Staff + 10% (408.7)	100
50	Ryanair	8063	1226.7	371.5	491.9	72	100	Staff + 20% (445.8)	100
51	Ryanair	8063	1226.7	371.5	491.9	72	100	Staff + 50% (557.3)	100
52	Ryanair	8063	1226.7	371.5	491.9	72	100	Staff - 10% (334.4)	100
53	Ryanair	8063	1226.7	371.5	491.9	72	100	Staff - 20% (297.2)	100
54	Ryanair	8063	1226.7	371.5	491.9	72	100	Staff - 50% (185.8)	100

Table 32. Ryanair Pure Scale Sensitivity Analysis for Input Parameters

Model Run	Airline	No. Employees (Actual)	Fuel Costs €M (Actual)	Staff Costs €M (Actual)	EBIT €M (Actual)	Passengers Carried Million (Actual)	CCR Model % Result (Actual)	Output Change %	CCR Model % Sensitivity Result
55	Ryanair	8063	1226.7	371.5	491.9	72	100	EBIT + 10% (541.1)	100.00
56	Ryanair	8063	1226.7	371.5	491.9	72	100	EBIT + 20% (590.3)	100.00
57	Ryanair	8063	1226.7	371.5	491.9	72	100	EBIT + 50% (737.9)	100.00
58	Ryanair	8063	1226.7	371.5	491.9	72	100	EBIT - 10% (442.7)	100.00
59	Ryanair	8063	1226.7	371.5	491.9	72	100	EBIT - 20% (393.5)	100.00
60	Ryanair	8063	1226.7	371.5	491.9	72	100	EBIT - 50% (246.0)	100.00
61	Ryanair	8063	1226.7	371.5	491.9	72	100	Pax Carried + 10% (79.2)	100.00
62	Ryanair	8063	1226.7	371.5	491.9	72	100	Pax Carried + 20% (86.4)	100.00
63	Ryanair	8063	1226.7	371.5	491.9	72	100	Pax Carried + 50% (108.0)	100.00
64	Ryanair	8063	1226.7	371.5	491.9	72	100	Pax Carried - 10% (64.8)	100.00
65	Ryanair	8063	1226.7	371.5	491.9	72	100	Pax Carried - 20% (57.6)	100.00
66	Ryanair	8063	1226.7	371.5	491.9	72	100	Pax Carried - 50% (36.0)	96.23

Table 33. Ryanair CCR Sensitivity Analysis for Output Parameters

Model Run	Airline	No. Employees (Actual)	Fuel Costs €M (Actual)	Staff Costs €M (Actual)	EBIT €M (Actual)	Passengers Carried Million (Actual)	BCC Model % Result (Actual)	Output Change %	BCC Model % Sensitivity Result
67	Ryanair	8063	1226.7	371.5	491.9	72	100	EBIT + 10% (541.1)	100
68	Ryanair	8063	1226.7	371.5	491.9	72	100	EBIT + 20% (590.3)	100
69	Ryanair	8063	1226.7	371.5	491.9	72	100	EBIT + 50% (737.9)	100
70	Ryanair	8063	1226.7	371.5	491.9	72	100	EBIT - 10% (442.7)	100
71	Ryanair	8063	1226.7	371.5	491.9	72	100	EBIT - 20% (393.5)	100
72	Ryanair	8063	1226.7	371.5	491.9	72	100	EBIT - 50% (246.0)	100
73	Ryanair	8063	1226.7	371.5	491.9	72	100	Pax Carried + 10% (79.2)	100
74	Ryanair	8063	1226.7	371.5	491.9	72	100	Pax Carried + 20% (86.4)	100
75	Ryanair	8063	1226.7	371.5	491.9	72	100	Pax Carried + 50% (108.0)	100
76	Ryanair	8063	1226.7	371.5	491.9	72	100	Pax Carried - 10% (64.8)	100
77	Ryanair	8063	1226.7	371.5	491.9	72	100	Pax Carried - 20% (57.6)	100
78	Ryanair	8063	1226.7	371.5	491.9	72	100	Pax Carried - 50% (36.0)	100

Table 34. Ryanair BCC Sensitivity Analysis for Output Parameters

Model Run	Airline	No. Employees (Actual)	Fuel Costs €M (Actual)	Staff Costs €M (Actual)	EBIT €M (Actual)	Passengers Carried Million (Actual)	Pure Scale % Result (Actual)	Output Change %	Pure Scale % Sensitivity Result
79	Ryanair	8063	1226.7	371.5	491.9	72	100	EBIT + 10% (541.1)	100.00
80	Ryanair	8063	1226.7	371.5	491.9	72	100	EBIT + 20% (590.3)	100.00
81	Ryanair	8063	1226.7	371.5	491.9	72	100	EBIT + 50% (737.9)	100.00
82	Ryanair	8063	1226.7	371.5	491.9	72	100	EBIT - 10% (442.7)	100.00
83	Ryanair	8063	1226.7	371.5	491.9	72	100	EBIT - 20% (393.5)	100.00
84	Ryanair	8063	1226.7	371.5	491.9	72	100	EBIT - 50% (246.0)	100.00
85	Ryanair	8063	1226.7	371.5	491.9	72	100	Pax Carried + 10% (79.2)	100.00
86	Ryanair	8063	1226.7	371.5	491.9	72	100	Pax Carried + 20% (86.4)	100.00
87	Ryanair	8063	1226.7	371.5	491.9	72	100	Pax Carried + 50% (108.0)	100.00
88	Ryanair	8063	1226.7	371.5	491.9	72	100	Pax Carried - 10% (64.8)	100.00
89	Ryanair	8063	1226.7	371.5	491.9	72	100	Pax Carried - 20% (57.6)	100.00
90	Ryanair	8063	1226.7	371.5	491.9	72	100	Pax Carried - 50% (36.0)	96.23

Table 35. Ryanair Pure Scale Sensitivity Analysis for Output Parameters

Model Run	Airline	No. Employees (Actual)	Fuel Costs €M (Actual)	Staff Costs €M (Actual)	EBIT €M (Actual)	Passengers Carried Million (Actual)	CCR Model % Result (Actual)	Input Change %	CCR Model % Sensitivity Result
91	easyJet	8288	1098.6	517.5	393.3	54.5	84.4	Employees + 10% (9117)	84.38
92	easyJet	8288	1098.6	517.5	393.3	54.5	84.4	Employees + 20% (9946)	84.32
93	easyJet	8288	1098.6	517.5	393.3	54.5	84.4	Employees + 50% (12432)	84.15
94	easyJet	8288	1098.6	517.5	393.3	54.5	84.4	Employees - 10% (7460)	84.71
95	easyJet	8288	1098.6	517.5	393.3	54.5	84.4	Employees - 20% (6630)	93.29
96	easyJet	8288	1098.6	517.5	393.3	54.5	84.4	Employees - 50% (4144)	100.00
97	easyJet	8288	1098.6	517.5	393.3	54.5	84.4	Fuel Cost + 10% (1208.5)	84.44
98	easyJet	8288	1098.6	517.5	393.3	54.5	84.4	Fuel Cost + 20% (1318.3)	74.63
99	easyJet	8288	1098.6	517.5	393.3	54.5	84.4	Fuel Cost + 50% (1647.9)	74.63
100	easyJet	8288	1098.6	517.5	393.3	54.5	84.4	Fuel Cost- 10% (988.7)	93.76
101	easyJet	8288	1098.6	517.5	393.3	54.5	84.4	Fuel Cost - 20% (878.9)	100.00
102	easyJet	8288	1098.6	517.5	393.3	54.5	84.4	Fuel Cost - 50% (549.3)	100.00
103	easyJet	8288	1098.6	517.5	393.3	54.5	84.4	Staff + 10% (568.7)	84.44
104	easyJet	8288	1098.6	517.5	393.3	54.5	84.4	Staff + 20% (621.0)	84.44
105	easyJet	8288	1098.6	517.5	393.3	54.5	84.4	Staff + 50% (776.3)	84.44
106	easyJet	8288	1098.6	517.5	393.3	54.5	84.4	Staff - 10% (465.8)	84.44
107	easyJet	8288	1098.6	517.5	393.3	54.5	84.4	Staff - 20% (414.0)	100.00
108	easyJet	8288	1098.6	517.5	393.3	54.5	84.4	Staff - 50% (258.8)	100.00

Table 36. easyJet CCR Sensitivity Analysis for Input Parameters

Model Run	Airline	No. Employees (Actual)	Fuel Costs €M (Actual)	Staff Costs €M (Actual)	EBIT €M (Actual)	Passengers Carried Million (Actual)	BCC Model % Result (Actual)	Input Change %	BCC Model % Sensitivity Result
109	easyJet	8288	1098.6	517.5	393.3	54.5	85.87	Employees + 10% (9117)	85.87
110	easyJet	8288	1098.6	517.5	393.3	54.5	85.87	Employees + 20% (9946)	85.87
111	easyJet	8288	1098.6	517.5	393.3	54.5	85.87	Employees + 50% (12432)	85.87
112	easyJet	8288	1098.6	517.5	393.3	54.5	85.87	Employees - 10% (7460)	85.87
113	easyJet	8288	1098.6	517.5	393.3	54.5	85.87	Employees - 20% (6630)	94.93
114	easyJet	8288	1098.6	517.5	393.3	54.5	85.87	Employees - 50% (4144)	100.00
115	easyJet	8288	1098.6	517.5	393.3	54.5	85.87	Fuel Cost + 10% (1208.5)	80.33
116	easyJet	8288	1098.6	517.5	393.3	54.5	85.87	Fuel Cost + 20% (1318.3)	79.35
117	easyJet	8288	1098.6	517.5	393.3	54.5	85.87	Fuel Cost + 50% (1647.9)	79.35
118	easyJet	8288	1098.6	517.5	393.3	54.5	85.87	Fuel Cost- 10% (988.7)	93.87
119	easyJet	8288	1098.6	517.5	393.3	54.5	85.87	Fuel Cost - 20% (878.9)	100.00
120	easyJet	8288	1098.6	517.5	393.3	54.5	85.87	Fuel Cost - 50% (549.3)	100.00
121	easyJet	8288	1098.6	517.5	393.3	54.5	85.87	Staff + 10% (568.7)	85.87
122	easyJet	8288	1098.6	517.5	393.3	54.5	85.87	Staff + 20% (621.0)	85.87
123	easyJet	8288	1098.6	517.5	393.3	54.5	85.87	Staff + 50% (776.3)	85.87
124	easyJet	8288	1098.6	517.5	393.3	54.5	85.87	Staff - 10% (465.8)	85.87
125	easyJet	8288	1098.6	517.5	393.3	54.5	85.87	Staff - 20% (414.0)	100.00
126	easyJet	8288	1098.6	517.5	393.3	54.5	85.87	Staff - 50% (258.8)	100.00

Table 37. easyJet BCC Sensitivity Analysis for Input Parameters

Model Run	Airline	No. Employees (Actual)	Fuel Costs €M (Actual)	Staff Costs €M (Actual)	EBIT €M (Actual)	Passengers Carried Million (Actual)	Pure Scale % Result (Actual)	Input Change %	Pure Scale % Sensitivity Result
127	easyJet	8288	1098.6	517.5	393.3	54.5	98.34	Employees + 10% (9117)	98.27
128	easyJet	8288	1098.6	517.5	393.3	54.5	98.34	Employees + 20% (9946)	98.20
129	easyJet	8288	1098.6	517.5	393.3	54.5	98.34	Employees + 50% (12432)	97.99
130	easyJet	8288	1098.6	517.5	393.3	54.5	98.34	Employees - 10% (7460)	98.27
131	easyJet	8288	1098.6	517.5	393.3	54.5	98.34	Employees - 20% (6630)	98.20
132	easyJet	8288	1098.6	517.5	393.3	54.5	98.34	Employees - 50% (4144)	100.00
133	easyJet	8288	1098.6	517.5	393.3	54.5	98.34	Fuel Cost + 10% (1208.5)	95.72
134	easyJet	8288	1098.6	517.5	393.3	54.5	98.34	Fuel Cost + 20% (1318.3)	94.05
135	easyJet	8288	1098.6	517.5	393.3	54.5	98.34	Fuel Cost + 50% (1647.9)	94.05
136	easyJet	8288	1098.6	517.5	393.3	54.5	98.34	Fuel Cost- 10% (988.7)	95.72
137	easyJet	8288	1098.6	517.5	393.3	54.5	98.34	Fuel Cost - 20% (878.9)	100.00
138	easyJet	8288	1098.6	517.5	393.3	54.5	98.34	Fuel Cost - 50% (549.3)	100.00
139	easyJet	8288	1098.6	517.5	393.3	54.5	98.34	Staff + 10% (568.7)	98.34
140	easyJet	8288	1098.6	517.5	393.3	54.5	98.34	Staff + 20% (621.0)	98.34
141	easyJet	8288	1098.6	517.5	393.3	54.5	98.34	Staff + 50% (776.3)	98.34
142	easyJet	8288	1098.6	517.5	393.3	54.5	98.34	Staff - 10% (465.8)	98.34
143	easyJet	8288	1098.6	517.5	393.3	54.5	98.34	Staff - 20% (414.0)	100.00
144	easyJet	8288	1098.6	517.5	393.3	54.5	98.34	Staff - 50% (258.8)	100.00

Table 38. easyJet Pure Scale Sensitivity Analysis for Input Parameters

Model Run	Airline	No. Employees (Actual)	Fuel Costs €M (Actual)	Staff Costs €M (Actual)	EBIT €M (Actual)	Passengers Carried Million (Actual)	CCR Model % Result (Actual)	Output Change %	CCR Model % Sensitivity Result
145	easyJet	8288	1098.6	517.5	393.3	54.5	84.4	EBIT + 10% (432.6)	84.46
146	easyJet	8288	1098.6	517.5	393.3	54.5	84.4	EBIT + 20% (471.9)	85.50
147	easyJet	8288	1098.6	517.5	393.3	54.5	84.4	EBIT + 50% (589.9)	88.63
148	easyJet	8288	1098.6	517.5	393.3	54.5	84.4	EBIT - 10% (353.9)	84.44
149	easyJet	8288	1098.6	517.5	393.3	54.5	84.4	EBIT - 20% (314.7)	84.44
150	easyJet	8288	1098.6	517.5	393.3	54.5	84.4	EBIT - 50% (196.7)	84.44
151	easyJet	8288	1098.6	517.5	393.3	54.5	84.4	Pax Carried + 10% (59.9)	92.81
152	easyJet	8288	1098.6	517.5	393.3	54.5	84.4	Pax Carried + 20% (65.4)	100.00
153	easyJet	8288	1098.6	517.5	393.3	54.5	84.4	Pax Carried + 50% (81.8)	100.00
154	easyJet	8288	1098.6	517.5	393.3	54.5	84.4	Pax Carried - 10% (49.1)	76.18
155	easyJet	8288	1098.6	517.5	393.3	54.5	84.4	Pax Carried - 20% (43.6)	68.82
156	easyJet	8288	1098.6	517.5	393.3	54.5	84.4	Pax Carried - 50% (27.3)	46.99

Table 39. easyJet CCR Sensitivity Analysis for Output Parameters

Model Run	Airline	No. Employees (Actual)	Fuel Costs €M (Actual)	Staff Costs €M (Actual)	EBIT €M (Actual)	Passengers Carried Million (Actual)	BCC Model % Result (Actual)	Output Change %	BCC Model % Sensitivity Result
157	easyJet	8288	1098.6	517.5	393.3	54.5	85.87	EBIT + 10% (432.6)	93.39
158	easyJet	8288	1098.6	517.5	393.3	54.5	85.87	EBIT + 20% (471.9)	100.00
159	easyJet	8288	1098.6	517.5	393.3	54.5	85.87	EBIT + 50% (589.9)	100.00
160	easyJet	8288	1098.6	517.5	393.3	54.5	85.87	EBIT - 10% (353.9)	84.50
161	easyJet	8288	1098.6	517.5	393.3	54.5	85.87	EBIT - 20% (314.7)	84.50
162	easyJet	8288	1098.6	517.5	393.3	54.5	85.87	EBIT - 50% (196.7)	84.50
163	easyJet	8288	1098.6	517.5	393.3	54.5	85.87	Pax Carried + 10% (59.9)	92.88
164	easyJet	8288	1098.6	517.5	393.3	54.5	85.87	Pax Carried + 20% (65.4)	100.00
165	easyJet	8288	1098.6	517.5	393.3	54.5	85.87	Pax Carried + 50% (81.8)	100.00
166	easyJet	8288	1098.6	517.5	393.3	54.5	85.87	Pax Carried - 10% (49.1)	84.82
167	easyJet	8288	1098.6	517.5	393.3	54.5	85.87	Pax Carried - 20% (43.6)	84.62
168	easyJet	8288	1098.6	517.5	393.3	54.5	85.87	Pax Carried - 50% (27.3)	84.62

Table 40. easyJet BCC Sensitivity Analysis for Output Parameters

Model Run	Airline	No. Employees (Actual)	Fuel Costs €M (Actual)	Staff Costs €M (Actual)	EBIT €M (Actual)	Passengers Carried Million (Actual)	Pure Scale % Result (Actual)	Output Change %	Pure Scale % Sensitivity Result
169	easyJet	8288	1098.6	517.5	393.3	54.5	98.34	EBIT + 10% (432.6)	90.43
170	easyJet	8288	1098.6	517.5	393.3	54.5	98.34	EBIT + 20% (471.9)	85.50
171	easyJet	8288	1098.6	517.5	393.3	54.5	98.34	EBIT + 50% (589.9)	88.63
172	easyJet	8288	1098.6	517.5	393.3	54.5	98.34	EBIT - 10% (353.9)	99.93
173	easyJet	8288	1098.6	517.5	393.3	54.5	98.34	EBIT - 20% (314.7)	99.93
174	easyJet	8288	1098.6	517.5	393.3	54.5	98.34	EBIT - 50% (196.7)	99.93
175	easyJet	8288	1098.6	517.5	393.3	54.5	98.34	Pax Carried + 10% (59.9)	99.93
176	easyJet	8288	1098.6	517.5	393.3	54.5	98.34	Pax Carried + 20% (65.4)	100.00
177	easyJet	8288	1098.6	517.5	393.3	54.5	98.34	Pax Carried + 50% (81.8)	100.00
178	easyJet	8288	1098.6	517.5	393.3	54.5	98.34	Pax Carried - 10% (49.1)	89.82
179	easyJet	8288	1098.6	517.5	393.3	54.5	98.34	Pax Carried - 20% (43.6)	81.32
180	easyJet	8288	1098.6	517.5	393.3	54.5	98.34	Pax Carried - 50% (27.3)	55.53

Table 41. easyJet Pure Scale Sensitivity Analysis for Output Parameters

Model Run	Airline	No. Employees (Actual)	Fuel Costs €M (Actual)	Staff Costs €M (Actual)	EBIT €M (Actual)	Passengers Carried Million (Actual)	CCR Model % Result (Actual)	Input Change %	CCR Model % Sensitivity Result
181	KLM	33918	2700	2100	343	19.7	13.1	Employees + 10% (37310)	12.81
182	KLM	33918	2700	2100	343	19.7	13.1	Employees + 20% (40702)	12.53
183	KLM	33918	2700	2100	343	19.7	13.1	Employees + 50% (50877)	12.29
184	KLM	33918	2700	2100	343	19.7	13.1	Employees - 10% (30526)	13.51
185	KLM	33918	2700	2100	343	19.7	13.1	Employees - 20% (27134)	13.74
186	KLM	33918	2700	2100	343	19.7	13.1	Employees - 50% (16959)	17.82
187	KLM	33918	2700	2100	343	19.7	13.1	Fuel Cost + 10% (2970)	12.17
188	KLM	33918	2700	2100	343	19.7	13.1	Fuel Cost + 20% (3240)	11.36
189	KLM	33918	2700	2100	343	19.7	13.1	Fuel Cost + 50% (4050)	9.46
190	KLM	33918	2700	2100	343	19.7	13.1	Fuel Cost- 10% (2160)	15.49
191	KLM	33918	2700	2100	343	19.7	13.1	Fuel Cost - 20% (2160)	15.49
192	KLM	33918	2700	2100	343	19.7	13.1	Fuel Cost - 50% (1350)	24.48
193	KLM	33918	2700	2100	343	19.7	13.1	Staff + 10% (2310)	13.10
194	KLM	33918	2700	2100	343	19.7	13.1	Staff + 20% (2520)	13.10
195	KLM	33918	2700	2100	343	19.7	13.1	Staff + 50% (3150)	13.10
196	KLM	33918	2700	2100	343	19.7	13.1	Staff - 10% (1890)	13.10
197	KLM	33918	2700	2100	343	19.7	13.1	Staff - 20% (1680)	13.10
198	KLM	33918	2700	2100	343	19.7	13.1	Staff - 50% (1050)	13.68

Table 42. KLM CCR Sensitivity Analysis for Input Parameters

Model Run	Airline	No. Employees (Actual)	Fuel Costs €M (Actual)	Staff Costs €M (Actual)	EBIT €M (Actual)	Passengers Carried Million (Actual)	BCC Model % Result (Actual)	Input Change %	BCC Model % Sensitivity Result
199	KLM	33918	2700	2100	343	19.7	48.86	Employees + 10% (37310)	48.86
200	KLM	33918	2700	2100	343	19.7	48.86	Employees + 20% (40702)	48.86
201	KLM	33918	2700	2100	343	19.7	48.86	Employees + 50% (50877)	48.86
202	KLM	33918	2700	2100	343	19.7	48.86	Employees - 10% (30526)	48.86
203	KLM	33918	2700	2100	343	19.7	48.86	Employees - 20% (27134)	49.52
204	KLM	33918	2700	2100	343	19.7	48.86	Employees - 50% (16959)	53.53
205	KLM	33918	2700	2100	343	19.7	48.86	Fuel Cost + 10% (2970)	47.95
206	KLM	33918	2700	2100	343	19.7	48.86	Fuel Cost + 20% (3240)	47.41
207	KLM	33918	2700	2100	343	19.7	48.86	Fuel Cost + 50% (4050)	47.41
208	KLM	33918	2700	2100	343	19.7	48.86	Fuel Cost- 10% (2160)	50.77
209	KLM	33918	2700	2100	343	19.7	48.86	Fuel Cost - 20% (2160)	50.77
210	KLM	33918	2700	2100	343	19.7	48.86	Fuel Cost - 50% (1350)	59.89
211	KLM	33918	2700	2100	343	19.7	48.86	Staff + 10% (2310)	48.86
212	KLM	33918	2700	2100	343	19.7	48.86	Staff + 20% (2520)	48.86
213	KLM	33918	2700	2100	343	19.7	48.86	Staff + 50% (3150)	48.86
214	KLM	33918	2700	2100	343	19.7	48.86	Staff - 10% (1890)	48.86
215	KLM	33918	2700	2100	343	19.7	48.86	Staff - 20% (1680)	48.89
216	KLM	33918	2700	2100	343	19.7	48.86	Staff - 50% (1050)	51.25

Table 43. KLM BCC Sensitivity Analysis for Input Parameters

Model Run	Airline	No. Employees (Actual)	Fuel Costs €M (Actual)	Staff Costs €M (Actual)	EBIT €M (Actual)	Passengers Carried Million (Actual)	Pure Scale % Result (Actual)	Input Change %	Pure Scale % Sensitivity Result
217	KLM	33918	2700	2100	343	19.7	26.82	Employees + 10% (37310)	26.22
218	KLM	33918	2700	2100	343	19.7	26.82	Employees + 20% (40702)	25.62
219	KLM	33918	2700	2100	343	19.7	26.82	Employees + 50% (50877)	25.15
220	KLM	33918	2700	2100	343	19.7	26.82	Employees - 10% (30526)	27.46
221	KLM	33918	2700	2100	343	19.7	26.82	Employees - 20% (27134)	27.74
222	KLM	33918	2700	2100	343	19.7	26.82	Employees - 50% (16959)	33.29
223	KLM	33918	2700	2100	343	19.7	26.82	Fuel Cost + 10% (2970)	25.38
224	KLM	33918	2700	2100	343	19.7	26.82	Fuel Cost + 20% (3240)	23.96
225	KLM	33918	2700	2100	343	19.7	26.82	Fuel Cost + 50% (4050)	19.96
226	KLM	33918	2700	2100	343	19.7	26.82	Fuel Cost- 10% (2160)	30.05
227	KLM	33918	2700	2100	343	19.7	26.82	Fuel Cost - 20% (2160)	30.50
228	KLM	33918	2700	2100	343	19.7	26.82	Fuel Cost - 50% (1350)	40.87
229	KLM	33918	2700	2100	343	19.7	26.82	Staff + 10% (2310)	26.82
230	KLM	33918	2700	2100	343	19.7	26.82	Staff + 20% (2520)	26.82
231	KLM	33918	2700	2100	343	19.7	26.82	Staff + 50% (3150)	26.82
232	KLM	33918	2700	2100	343	19.7	26.82	Staff - 10% (1890)	26.82
233	KLM	33918	2700	2100	343	19.7	26.82	Staff - 20% (1680)	26.80
234	KLM	33918	2700	2100	343	19.7	26.82	Staff - 50% (1050)	26.70

Table 44. Pure Scale Sensitivity Analysis for Input Parameters

Model Run	Airline	No. Employees (Actual)	Fuel Costs €M (Actual)	Staff Costs €M (Actual)	EBIT €M (Actual)	Passengers Carried Million (Actual)	CCR Model % Result (Actual)	Output Change %	CCR Model % Sensitivity Result
235	KLM	33918	2700	2100	343	19.7	13.1	EBIT + 10% (377.3)	13.44
236	KLM	33918	2700	2100	343	19.7	13.1	EBIT + 20% (411.6)	13.78
237	KLM	33918	2700	2100	343	19.7	13.1	EBIT + 50% (514.5)	14.79
238	KLM	33918	2700	2100	343	19.7	13.1	EBIT - 10% (308.7)	12.77
239	KLM	33918	2700	2100	343	19.7	13.1	EBIT - 20% (274.4)	12.43
240	KLM	33918	2700	2100	343	19.7	13.1	EBIT - 50% (171.5)	12.36
241	KLM	33918	2700	2100	343	19.7	13.1	Pax Carried + 10% (21.7)	14.09
242	KLM	33918	2700	2100	343	19.7	13.1	Pax Carried + 20% (23.6)	15.03
243	KLM	33918	2700	2100	343	19.7	13.1	Pax Carried + 50% (29.6)	18.57
244	KLM	33918	2700	2100	343	19.7	13.1	Pax Carried - 10% (17.7)	12.12
245	KLM	33918	2700	2100	343	19.7	13.1	Pax Carried - 20% (15.8)	11.80
246	KLM	33918	2700	2100	343	19.7	13.1	Pax Carried - 50% (9.9)	8.26

Table 45. CCR Sensitivity Analysis for Output Parameters

Model Run	Airline	No. Employees (Actual)	Fuel Costs €M (Actual)	Staff Costs €M (Actual)	EBIT €M (Actual)	Passengers Carried Million (Actual)	BCC Model % Result (Actual)	Output Change %	BCC Model % Sensitivity Result
247	KLM	33918	2700	2100	343	19.7	48.86	EBIT + 10% (377.3)	52.86
248	KLM	33918	2700	2100	343	19.7	48.86	EBIT + 20% (411.6)	56.86
249	KLM	33918	2700	2100	343	19.7	48.86	EBIT + 50% (514.5)	70.84
250	KLM	33918	2700	2100	343	19.7	48.86	EBIT - 10% (308.7)	44.85
251	KLM	33918	2700	2100	343	19.7	48.86	EBIT - 20% (274.4)	40.85
252	KLM	33918	2700	2100	343	19.7	48.86	EBIT - 50% (171.5)	30.39
253	KLM	33918	2700	2100	343	19.7	48.86	Pax Carried + 10% (21.7)	49.75
254	KLM	33918	2700	2100	343	19.7	48.86	Pax Carried + 20% (23.6)	50.61
255	KLM	33918	2700	2100	343	19.7	48.86	Pax Carried + 50% (29.6)	54.31
256	KLM	33918	2700	2100	343	19.7	48.86	Pax Carried - 10% (17.7)	47.96
257	KLM	33918	2700	2100	343	19.7	48.86	Pax Carried - 20% (15.8)	47.14
258	KLM	33918	2700	2100	343	19.7	48.86	Pax Carried - 50% (9.9)	47.14

Table 46. KLM BCC Sensitivity Analysis for Output Parameters

Model Run	Airline	No. Employees (Actual)	Fuel Costs €M (Actual)	Staff Costs €M (Actual)	EBIT €M (Actual)	Passengers Carried Million (Actual)	Pure Scale % Result (Actual)	Output Change %	Pure Scale % Sensitivity Result
259	KLM	33918	2700	2100	343	19.7	26.82	EBIT + 10% (377.3)	25.43
260	KLM	33918	2700	2100	343	19.7	26.82	EBIT + 20% (411.6)	24.43
261	KLM	33918	2700	2100	343	19.7	26.82	EBIT + 50% (514.5)	20.88
262	KLM	33918	2700	2100	343	19.7	26.82	EBIT - 10% (308.7)	28.47
263	KLM	33918	2700	2100	343	19.7	26.82	EBIT - 20% (274.4)	30.43
264	KLM	33918	2700	2100	343	19.7	26.82	EBIT - 50% (171.5)	40.67
265	KLM	33918	2700	2100	343	19.7	26.82	Pax Carried + 10% (21.7)	28.33
266	KLM	33918	2700	2100	343	19.7	26.82	Pax Carried + 20% (23.6)	29.71
267	KLM	33918	2700	2100	343	19.7	26.82	Pax Carried + 50% (29.6)	34.20
268	KLM	33918	2700	2100	343	19.7	26.82	Pax Carried - 10% (17.7)	25.26
269	KLM	33918	2700	2100	343	19.7	26.82	Pax Carried - 20% (15.8)	23.71
270	KLM	33918	2700	2100	343	19.7	26.82	Pax Carried - 50% (9.9)	17.52

Table 47. KLM Pure Scale Sensitivity Analysis for Output Parameters

Appendix D Data Collation and Normalisation

Airline	No. Employees	Currency of Original Data	Original Fuel Costs (Million)	Euro Value Fuel Costs (Million)	Original Staff Costs (Million)	Euro Value Staff Costs (Million)	Original EBIT (Million)	Euro Value EBIT (Million) + €71 Millon	Total No Passengers
Ryanair	8063	€	1226.7	1226.7	371.5	371.5	420.9	491.9	72.00M
Flybe	2949	£	106.4	127.5	74.8	89.6	100.9	191.9	7.60M
Aer Lingus	3491	€	3491.0	288.7	288.7	260.6	172.8	243.8	9.50M
British Airways	40000	£	3000.0	3594.0	2100.0	2515.8	591.0	779.0	34.25.00M
Estonian Air	283	€	24.8	24.8	10.0	10.0	-13.5	57.5	679000.00
Lufthansa	115335	€	30000.0	30000.0	6700.0	6700.0	734.0	805.0	100.60M
Meridiana Fly	2011	€	197.0	197.0	114.0	114.0	103.0	174.0	4.40M
Turkish Airlines	18489	TRY	4000.0	1632.0	1600.0	677.3	595.3	666.3	33.00M
Croatia Airlines	1136	HRK	337.0	44.0	234.5	31.0	-1.8	69.2	1.89M
easyJet	8288	£	917.0	1098.6	432.0	517.5	269.0	393.3	54.50M
Icelandair	1179	ISK	22000.0	138.6	228000.0	143.6	47000.0	100.6	1.75M
Air Astana	3358	€	132.0	132.0	62.6	62.6	50.9	121.9	3.00M
Aegean	1615	€	184.0	184.0	86.0	86.0	-30.7	40.3	6.50M
Air Berlin	9113	€	1000.0	1000.0	475.0	475.0	-70.0	1.0	35.30M
KLM	33918	€	2700.0	2700.0	2100.0	2100.0	272.0	343.0	19.70M
TAP Air Portugal	8661	€	717.0	717.0	524.0	524.0	18.1	89.1	9.75M
Finnair	7467	€	555.0	555.0	477.0	477.0	-60.9	10.1	8.00M

Table 48. Collated and Normalised Data from Airline Annual Reports