Efficiency in the U.S. Airline Industry

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The candidate confirms that the work submitted is his/her own and that appropriate credit has been given where reference has been made to the work of others.

I dedicate my thesis to my supervisor Dr Kevin T. Reilly (1955 – 2015)

Kevin was not only my teacher and mentor but also someone with whom I shared a connection based on friendship, trust and understanding. This is only possible when the individual has a true love and appreciation for the academic discipline and Kevin was a master at his craft. My research career is beginning just as his ended, but his influence will always be a component of my work. I will miss you and could not have done this without you.

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List of Abbreviations

AE	Allocative Efficiency
ALF	Average Load Factor
AOOE	All Other Operating Expenses
ATM	Available Ton Miles
BC92	Battese and Coelli 1992
BTS	Bureau of Transport Statistics
CE	Cost Efficiency
CPI	Consumer Price Index
CRS	Constant Returns to Scale
DEA	Data Envelopment Analysis
DHL	DHL Express
DMU	Decision-Making Unit
DOT	Department of Transportation
EOD	Economies of Density
EOS	Economies of Scale
EPA	Environmental Protection Agency (EPA)
FedEx	FedEx Corporation
FTE	Full-Time Equivalents
GHG	Green House Gas
IATA	International Air Transport Association
ICAO	International Civil Aviation Organization
LCC	Low Cost Carrier
NPS	Number of Points served
OECD	Organization for Economic Co-operation and Development
OLS	Ordinary Least Squares
PLF	Passenger Load Factor
PPI	Producer Price index
RPM	Revenue Passenger Miles

RTD	Returns to Density
RTM	Revenue Ton Miles
RTS	Returns to Scale
TAOE	Total Aircraft Operating Expenses
TC	Total Cost
TE	Technical Efficiency
TFP	Total Factor Productivity
TSA	Transportation Security Administration
SFA	Stochastic Frontier Analysis
UPS	United Parcel Service, Inc.
U.S.	United States
VRS	Variable Returns to Scale

1. Introduction

The first stage of the transformation of the airline industry appeared with the Airline Deregulation Act of 1978. Post-deregulation, new carriers have emerged and new routes have opened up which connected cities never previously linked by a direct flight. The performance of airline carriers is now a subject of central debate. With competition having increased in many airline markets across the world, and now being at an all-time high, demand for premium travel services (particularly first-class seating) has suffered a significant decline. In addition, the rapid expansion of low cost carriers (LCCs) has drastically altered the nature of competition within the traditional airline industry (Brueckner et al., 2013). This is particularly the case on shorter-haul routes and has caused regional airlines to react or (in some cases) to fail. Rising labour costs and fluctuating fuel prices impact all airlines. Fuel is now approximately 30-40% of airlines costs (Zou and Hansen, 2012), compared to 13% in 2001. The significant rise and ongoing volatility in jet fuel costs further complicates the situation where the strategic response can take many forms, but all involve improving cost efficiency. More than at any time in the past, this has made efficiency a top priority for airline management (Merkert and Hensher, 2011). While cost management has always been an important part of airline administration, in recent years it has become a crucial part of the airline survival strategy. In the decade following the September 11th attacks in 2001, U.S. airlines have shown considerable resilience (all of the legacy carriers have received government support and have undergone Chapter 11 restructuring); with most having recently been able to improve their financial position and return to profitability as a result of significant consolidation and capacity discipline (IATA, 2014). However, it remains too early to tell if more airlines have yet to face financial difficulties or will be forced into further merger and acquisition activity. While initiatives to reduce costs are not unusual in the course of economic recessions, the efforts carried out by the airline industry have been considered extreme. These efforts have included scaling back workforces, changes to service and wage reductions from employee groups. Furthermore, these airlines have had to restructure themselves considerably, financially as well as operationally, regardless of whether they pursued bankruptcy protection or not.

It is therefore important to understand what operational measures airlines should adopt in order to remain competitive in the market and to perform well under turbulent market conditions. One strategy has been to adopt the low cost carrier (LCC) model, by either setting up a subsidiary low cost operation (such as American Airlines which is a subsidiary of the AMR Corporation – now part of the American Airlines Group Inc.) or by adopting the no-frills model, which most aviation markets have experienced in the recent past. Another strategy seen in the industry is that of increasing market power by way of forming alliances, as well as growth through mergers and acquisitions (such as United/Continental in 2011). However, it could be the case that airlines can become too large to operate cost efficiently (Merkert and Morrell, 2012). Previous literature (Merkert and Hensher, 2011), Merkert and Williams (2013) suggests that operational factors have significant impacts on costs and efficiency of airline operations. For example, passenger load factor, aircraft size and stage length have a huge impact on airline costs, with larger and fuller aircraft being able to spread unit costs over longer routes

The past decade has also seen a great increase in the demand for door-to-door shipment of products and packages, rather than just airport-to-airport service as in the early years of airfreight transportation. In addition to the door-to-door shipments, there has been an increase in the demand for fast, overnight service. As a result, air cargo companies have developed (separately from passenger airlines) and expanded quickly while simultaneously strengthening their presence in the airline industry. In so doing, they have become very important to the airline industry (as it relates to airport operators and plane manufacturers). In a world where time pressures are increasing value, the share of air cargo is steadily increasing commensurately.

The four largest air freight integrators in the world today are FedEx, UPS, TNT Express NV, and DHL Express (DHL). Integrators carry the majority of the market share of U.S. freight, with DHL, FedEx and UPS holding around 62% of enplaned revenue-tons of freight (Bureau of Transportation Statistics 2010). FedEx is undeniably the largest cargo carrier in the world, with 2014 revenues at the corporation totalling $45.6 billion US$[1].

Despite the high level of concentration, the integrated air freight industry is highly competitive in a number of aspects, such as delivery speed, service dependability and service convenience.

1.1. Contribution of the thesis

Most of the literature related to the measurement of airline efficiency has based its analysis either on parametric or non-parametric frontier methods from a production function perspective. Both the SFA and DEA methods are estimating the same underlying efficiency values but they can give different efficiency estimates for the

[1] Bloomsburg weekly: http://investing.businessweek.com/research/stocks/earnings/earnings.asp?ticker=FDX

units under analysis. This is due to the differences between the underlying assumptions. Although the two approaches are traditionally thought to be competing, there is no consensus as to which is the most appropriate technique; each has its own strengths and weaknesses (Coli et al, 2007). The main strength of DEA is that it is able to incorporate multiple inputs and outputs, and provides a scalar measure of relative efficiency by comparing the efficiency achieved by a decision-making unit (DMU) with the efficiency obtained by similar DMUs. The method therefore allows for a well-defined relation between inputs and outputs to be determined. In the case of multiple outputs this relation can be defined as an efficiency production possibility frontier. As this frontier is derived from an observed data set (empirical observations), it measures the relative efficiency of DMUs that can be obtained with the existing technology, fleet strategy or managerial strategy. The first drawback of DEA, is that it assumes all deviations from the efficient frontier are due to inefficiency (any statistical noise, measurement errors, omitted variables and other mis-specifications). Another critical drawback of DEA is the assumption of no random error in the data. As it is a nonparametric technique, statistical hypothesis tests are difficult.

The SFA technique in contrast, assumes that deviations from the efficient frontier can either be a result of inefficiency or a random shock. The main advantage of SFA is that there are a number of well-developed statistical tests to examine the validity of the model specification. Another benefit of SFA is that if an irrelevant variable is included, it will have a very small or possibly even a zero weighting in the calculation of the efficiency scores, allowing its impact to be insignificant. Finally, it allows for the decomposition of deviations from efficient levels between noise and pure inefficiency.

There is a lack of information on cost efficiency over a longer, more recent time scale, and that it is required for a larger number of airlines. This thesis seeks to fill this gap in a number of ways. First, it extends the limited literature available on Stochastic Frontier Analysis of airline efficiency in more recent years. Second, it will be applying SFA to a much larger panel of passenger airlines over a longer time frame than has been previously studied. With a focus on a wider and more recent period, this provides a renewed efficiency valuation of the U.S. airline industry. In each analysis, the inclusion of environmental variables, which are not always included in previous frontier studies, is analysed. As noted by Lee and Worthington (2014), few studies of airline performance currently account for environmental variables. Therefore, findings should offer an updated and clear link between airline performance and industry characteristics during this time.

It is also important to understand what operational measures airlines should adopt in order to remain competitive in the market and to perform well under turbulent market conditions. The thesis further seeks to analyse the impact of fleet planning and strategic management decisions on airline efficiency comparing data envelopment analysis (DEA) and stochastic frontier analysis (SFA) results. In this way, both methods can be compared in terms of estimates and also robustness.

Finally, to the current day, the literature on cost structure, efficiency and economies of density/returns to scale of the air cargo industry remain sparse. Most of the literature on cargo airlines has been developed following studies that relate to the passenger airline literature. Research dedicated to cost structure analysis of the air cargo industry is limited due to the lack of structured data on cargo carriers, and more specifically, about integrators.

The thesis therefore seeks to address these issues above by focusing on efficiency in the air cargo industry as well as from the passenger industry from a stochastic frontier perspective.

In sum, the thesis contributes to our understanding of airline cost efficiency from a stochastic frontier analysis perspective. It further examines and measures the effects of airline characteristics on airline efficiency from a technical, allocative and cost perspective while also adding to the literature on data envelopment analysis. Moreover, in view of the air cargo industry's considerable growth in transported cargo and express services, the thesis investigates the efficiency and cost structure of the leading integrated carriers FedEx Corporation and United Parcel Service, Inc.

1.2. Structure of the thesis

The thesis is organised as follows:

Chapter 2 deepens the research on airline efficiency by employing a stochastic cost frontier (SFA) analysis, while taking an innovative approach to environmental factors and the modelling of September 11^{th}. A panel of twenty-four U.S. airlines observed quarterly from 1991-2012 is analysed, which is much larger than previous U.S. studies on cost and production efficiency. Results for average and firm-specific efficiency levels in the airline industry reveal that airlines were operating at 92.12% efficiency, ranging between 92.88% and 88.29%. This suggests that to operate efficiently, airlines can reduce their input costs by an average of 7.88%, holding their output constant. Total factor productivity is shown to have deteriorated quite substantially over the period by 50.7%. Similar results have been found in earlier studies, which suggest that perhaps deregulation of the airline industry has delivered productivity gains, which have since been lost. However, reasons for this still remain somewhat unclear. For the first time in SFA, effects of September 11th and bankruptcies have been accounted for. Results on environmental variables are consistent with the previous literature, but results are quite distinctive in the effects of September 11th. The immediate impacts of the terrorist attacks had a small but significant increase on airline costs, whereas those in the long run resulted in a small but significant decrease on costs.

Chapter 3 measures the effects of airline characteristics on airline efficiency from a technical, allocative and cost perspective. This is done by applying a two-stage Data Envelopment Analysis (DEA) approach, with partially bootstrapped random effects Tobit regressions in the second-stage to a sample of twenty-two U.S. airlines from 2006-2012. A Stochastic Frontier Analysis (SFA) is then performed in order to compare to results of the DEA analysis. Measures of cost efficiency are obtained, which have been adjusted to account for characteristic influences such as stage length, aircraft size, fleet age and fleet mix. Results suggest that the effects of route optimisation, in terms of average stage length, apply to all three aspects of efficiency. It is shown that DEA results for size and age are comparable to previous literature, while fleet mix (i.e. number of aircraft families) is found to be insignificant. Results from the SFA analysis are similar to the results found in the DEA Tobit regressions, but it is observed that the SFA is more robust in terms of significance.

Chapter 4 measures and compares the efficiency of U.S. air cargo integrators FedEx Corporation (FedEx) and United Parcel Service, Inc (UPS). A translog total cost model is estimated for the two carriers using quarterly data on costs from 1993Q3-2014Q4. An analysis of the cost structure of the air cargo business is undertaken. Efficiency scores are then measured by estimating a stochastic cost frontier model. This is the first study to offer a stochastic frontier perspective on cargo airlines and extends the knowledge on the currently minimal amount of information on the air cargo industry. Stochastic frontier analysis (SFA) reveals that UPS is most competitive in the U.S. market and has a slightly higher efficiency score, averaging over all years (97.8%) than FedEx (94.8%). The cost characteristics calculated at the sample means for both FedEx and UPS show that both integrators exhibit economies of density and economies of scale.

Chapter 5 summarises the empirical findings and concludes with the original contribution of the thesis, as well as considerations for future research.

2. Chapter 2: Efficiency in the U.S. Airline Industry from 1991-2012: A Stochastic Frontier Approach

2.1. Introduction

The U.S. air transport industry has undergone considerable change following the Airline Deregulation Act of 1978. Post-deregulation, new carriers have emerged and new routes have opened up which connected cities never before accessible from a direct flight. Fares dropped as competition and customer demand increased. The Gulf War, and the subsequent recession of the early 1990s saw a number of carriers' disappear completely or file for Chapter 11 bankruptcy. Those that survived were able to return to profitability toward the end of the 1990s. The industry faced its second economic downturn in 2001, with an increase in labour and fuel costs and a decrease in business travel. Following the terrorist attacks on September 11th 2001, the airline industry saw an even more critical decline in travel demand and faced significantly higher operating costs. These losses continued until 2006, after which a relatively stable period developed. In the past few years however, the U.S. Department of Transportation has been concerned with the treatment of passengers in terms of service quality and flight delays. Furthermore, the concerns over greenhouse gas (GHG) emissions due to air travel continue to mount. For the United States, it has been ruled by the Supreme Court that the Environmental Protection Agency (EPA) has the right and the duty to regulate GHG emissions under the Clean Air Act[2], which encompasses CO_2 emissions arising from transportation sectors. This could have huge cost implications as airlines might be expected to pay for their emissions in the future.

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[2] Massachusetts et. al. v. Environmental Protection Agency, (Argued November 29, 2006—Decided April 2, 2007).

As other countries aim to reduce their carbon levels in numerous different industries and sectors, there will be increased pressure for the airline industry to follow suit. As the travel industry is one of the most important industries in the U.S., it is crucial that we develop a better understanding on the evaluation of airline operation efficiency.

The number of empirical studies estimating different aspects of efficiency is substantial. The majority of the applications within the airline industry focus on technical inefficiency around the time of deregulation, from a production function perspective using either parametric (stochastic frontier analysis; SFA) or non-parametric (e.g. data envelopment analysis; DEA) approaches. Examples include Gillen and Lall (1997), Coelli et al. (1999), Alam and Sickles (2000), Chiou and Chen (2006), Sjögren and Söderberg (2011), Kutlu and Sickles (2012), Barros et al. (2013), among others. Some consider European airlines only in their analysis, such as those done by Assaf and Josiassen (2011) and Merkert and Williams (2013). Efficiency and productivity are fundamental to the success of the commercial aviation industry, and thus models that measure efficiency can be extremely valuable.

Both the SFA and DEA methods are estimating the same underlying efficiency measures but they can give different efficiency estimates for the units under analysis. This is due to the differences between the underlying assumptions. Although the two approaches are traditionally thought to be competing there is no consensus as to which is the most appropriate technique; each has its own strengths and weaknesses (Coli et al, 2007). However, Hu et al. (2010) note that SFA performs better than DEA in most cases. Data Envelopment Analysis (DEA) was first proposed by Charnes, Cooper and Rhodes (Charnes et al., 1978) and does not require the specification of the functional form relating inputs to outputs or the setting of weights for various factors. DEA methodology has frequently been applied in the air transport field, for example Good et al. (1995), Gillen and Lall (1997), Alam and Sickles (1998) and Adler and Golany (2001). The advantage of DEA method is its ability to accommodate a multiplicity of inputs and outputs. As it is a nonparametric technique, statistical hypothesis tests are not possible. Despite the growing interest in traditional DEA models, its drawback is that it assumes all deviations from the efficient frontier are due to inefficiency (any statistical noise, measurement errors, omitted variables and other mis-specifications are therefore (wrongly) badged as inefficiency).

The SFA technique in contrast, assumes that deviations from the efficient frontier can either be a result of inefficiency or a random shock. The main advantage of SFA is that there are a number of well-developed statistical tests to examine the validity of the model specification. Another benefit of SFA is that if an irrelevant variable is included, it will have a very small or possibly even a zero weighting in the calculation of the efficiency scores, allowing its impact to be insignificant.

Although the area of allocative and overall economic efficiency is not new in the literature of firms' performance, in terms of studies specific to the airline industry, these are not as prevalent (Abdullah et al., 2013). In addition, many do not adopt the use of a stochastic cost frontier function. The few exceptions include Inglada et al. (2006), who estimate two stochastic frontiers, one for a cost function and the other for a production function in order to compare the economic and technical efficiency of international airlines during the period 1996-2000. They find that the Asian airlines are economically the most efficient, with American carriers exhibiting scores which are quite low by comparison. Kumbhakar (1991) considers a translog cost function, which incorporates both technical and allocative inefficiencies using data on ten U.S. airlines observed over 1970-1980. Based on the results obtained, he argues that these airlines were allocatively efficient during the time period under observation. Atkinson and Cornwell (1994) consider both technical and allocative efficiency for a panel of 13 U.S. airlines over 1970-1981. They determine that allocative inefficiency is substantially more important than technical efficiency in raising costs and altering input usage. Good et al. (1995) apply both SFA and DEA in order to compare the efficiency differences of European and US airlines during the period 1976-1986. They conclude that European carriers were not as productively efficient (during the time of deregulation) as American carriers. Their work includes environmental variables for passenger load factor and stage length using a Cobb-Douglas function.

It thus becomes clear that there is a lack of information on cost efficiency over a longer and more recent time scale, and that it is required for a larger number of airlines. This chapter seeks to fill this gap in a number of ways. First, it considerably extends the limited literature available on Stochastic Frontier Analysis of airline efficiency to include more recent years (up to 2012). Second, it applies SFA to a panel of twenty-four U.S. airlines over the time period 1991Q1-2012Q3. With a focus on a wider and more recent period, this provides a more up to date and comprehensive efficiency valuation of the U.S. airline industry. The estimation of technical change or total factor productivity (TFP) is introduced by way of a cubic time trend. This cubic time trend is found to be an appropriate way to represent the business cycle. Finally, the inclusion of environmental variables, which are not always included in previous frontier studies is analysed as well as dummy variables for the effects of September 11^{th} and Chapter 11. As noted by Lee and Worthington (2014), few studies of airline performance currently account for environmental variables. Therefore, the findings of this study should offer an updated and clear link between airline performance and industry characteristics during this time.

The chapter is organised as follows: The methodology is discussed in Section 2.2. In Section 2.4, the data are presented. In Section 3, the results are shown, with a discussion found in Section 3.1. Finally, in Section 3.3, the conclusions are given and the contributions and limitations of the present research are set out.

2.2. Methodology: The Stochastic Cost Frontier Approach

The fundamental idea of efficiency goes back to Farrell (1957). He defined the different ways in which a productive unit can be inefficient, either (i) by failing to produce the maximum possible output available from a determined group of inputs (technically efficient), or (ii) by selecting sub-optimal input amounts, given the prices and marginal productivities (allocatively inefficient). Given the value of technical efficiency, the overall cost efficiency (CE) can be written as a product of technical and allocative efficiency values, assuming constant returns to scale (Coelli et al., 2005):

$$CE = TE \times AE \tag{2.1}$$

The concept of econometric estimation of efficiency however, is more recent and was developed simultaneously by Aigner et al. (1977), Meeusen and Broeck (1977) and Battese and Corra (1977). Their model not only incorporated the efficiency term into the analysis (as do the deterministic approaches) but was also able to capture the effects of exogenous shocks beyond the control of the productive units. It further incorporates errors in the observations and in the measurement of outputs.

For the Cobb-Douglas case, in logarithmic terms the stochastic frontier for a single output (Y_i), with n inputs (X_{ni}) can be expressed as:

$$lnY_{i=}\ \beta_o + \sum_{n=1}^{N} \beta_n lnX_{ni} + v_i - u_i \tag{2.2}$$

The term $v_i - u_i$ is a composite error term with v_i representing statistical noise (or randomness) and u_i expressing technical (cost) inefficiency. The error component for statistical noise is assumed to be independently and identically distributed, with zero mean and constant variance. The inefficiency component has similar properties except that it has a non-zero mean (because $u_i \geq 0$) . Here, β represents a technological parameter vector to be estimated.

The cost frontier is defined by Forsund et al. (1980) as the minimum cost for a particular level of output, given the technology and the prices of the inputs used. Following the methodology developed by Schmidt and Sickles (1984) using panel data; this study sets out to calculate the overall economic efficiency. Schmidt and Sickles (1984) present a single equation production function which is easily changed into a cost function by reversing the sign of the one sided error. The stochastic cost frontier function for panel data, for the i^{th} airline (*i*=1,2,…,N) during the t^{th} period (*t*=1,2,..,T) can thus be defined as:

$$C_{it} = \alpha + C(P_{it}, Y_{it},; \beta) + \ v_{it} + u_i \tag{2.3}$$

Here *C* is the observed cost; α is the constant; P is the input price vector and Y is the output. The residual v_{it} represents random noise with the same properties as described in (i). The term u_i in this case is the inefficiency of cost for the ith airline company with properties,$u_i \approx iidN^{+}\left(0, \sigma_\mu^2\right)$. It then follows that $u_i \geq 0$ for all i, and that it is identically distributed with mean μ and variance σ_μ^2 and is independent of v_{it}.

The term u_i has no time specification, which can be interpreted as economic efficiency varying between companies and not over time[3].

When dealing with a cost frontier, firms which lie on the stochastic frontier are efficient, with firms above the frontier being inefficient. The most cost efficient firms will be directly on the frontier and so it is not possible to be below the frontier. When obtaining efficiency estimates from frontier models, values closest to 1 represents more efficient firm and values closer to zero represent those firms which are less efficient. Therefore, a value between 0 and 1, represents the degree to which an airline succeeds in minimizing cost given input and output prices. For the purpose of this chapter, cost efficiency (the ratio of minimum cost to observed cost) can be written as follows:

$$CE_{it} = \exp(-u_{it}) \tag{2.4}$$

2.3. Model specification

In the econometric estimation of cost frontiers, a functional form must first be specified. A number of functional forms have been applied in empirical studies of airline costs. For examples of the classical cost model[4] see those of Caves et al. (1984), Gillen et al. (1990) Good et al. (1995), Oum and Yu (1998), Hansen et al. (2001), Wei and Hansen (2003), Zou and Hansen (2012), and Martín et al. (2013). The two most commonly used are the Cobb-Douglas function, or the translog function. The translog

3 As Schmidt and Sickles (1984) point out, for T=1 (pure cross Section of N firms), the model in (1) is simply the stochastic frontier of Aigner et al. (1977). For T > 1, it is a simplification of that model which precisely fits the typical framework in the panel-data literature with a firm effect but no time effect.

4 An average response function rather than a frontier.

is a flexible functional form in the sense of providing a second-order approximation to an unknown cost function. The Cobb-Douglas function can be considered to be a first-order approximation. The most widely used flexible functional form in a cost minimizing framework is the translog cost function.

In order to calculate the economic efficiency of the individual airline companies in this study, it is first required that a cost frontier function is estimated. This analysis presents results for the translog specification. A Cobb-Douglas functional form was also tested but will not be presented in this chapter as the translog model performed better (higher log-likelihood). However, Table A1 in the appendix summarises the estimation results obtained for the Cobb-Douglas stochastic frontier approach. The translog total cost function is defined as follows:

$$lnTC_{it} = \alpha \quad + \alpha_T t + \ \alpha_T t^2 + \alpha_T t^3 + \beta ln(Y_{it}) \ + \sum_j \gamma_j \ln(P_{jit}) + \sum_j \delta_j \ln(Z_{jit})$$

$$+ \frac{1}{2}\eta_{YY}[\ln(Y_{it})]^2 + \frac{1}{2}\sum_j \sum_k \phi_{jk} \ln(P_{jit}) \ln(P_{kit}) + \sum_k \theta_{Yk} \ln(Y_{it}) \ln(P_{kit}) + v_{it} + u_{it} \qquad (2.5)$$

where $lnTC_{it}$ is the total cost for airline i in time period t. On the right hand side, the first line contains all first order terms; second-order terms appear in the remaining lines. A cubic time trend t, t^2, t^3, is included; Y_{it} is the quantity of the output for airline i in time period t; P_{jit} the j^{th} input price for airline i in time period t; Z_{jit} the value of the j^{th} environemental characteristic for airline i in time period t.
The estimated coefficients are $\alpha's$, α_T , β, $\gamma's$, $\delta's$, η, $\phi's$, $\theta's$.

The symmetry of coefficients in the above function requires $\phi_{jk} = \phi_{kj}$ for all j and k. In addition, Christensen et al. (1973) state that a translog cost function must satisfy certain regulatory conditions. These ensure that a cost function is consistent with cost minimisation. A cost function must be linearly homogeneous in the input prices, requiring the following restrictions are imposed:

$$\sum_j \gamma_j = 1 \qquad \sum_j \phi_{jk} = 0(\forall k) \qquad \sum_k \theta_{Yk} = 0 \tag{2.6}$$

where subscripts k refers to, respectively, the k^{th} input in the translog equation (2.5).

Equations (2.6) ensure that a proportional increase in all input prices results in a proportionate increase in total costs. To illustrate, a 10% increase in all input prices leads to a 10% increase in total costs. The first of the three equations in (2.6) states that the first order coefficients for the input prices sum to one. Together with the following two equations in (2.6) that the second order coefficients involving input price must add to zero, scaling input prices by n will lead to a proportional increase in total costs.

As panel data is available, the model can be completed with the time variable in order to account for technological change in the industry (Stevenson, 1980). Among the explanatory variables, the cubic time trend t, t^2, t^3 (1 for the first period, 2 for the second period and so on) is included in order to appropriately model the business cycle (Evans and Kessides, 1993).

Equation (2.5) specifies the stochastic cost frontier function. The data sources and characteristics of the variables in these models are described in sections 2.5 and 2.6.

2.4. Data

2.4.1. Data sources

In order to estimate the cost frontier in (2.5), panel data from the U.S. Department of Transportation (DOT) Form 41 are sourced. Form 41 provides quarterly financial cost data and operating statistics per airline and per aircraft type. The individual panels for airline and aircraft types were combined in order to get quarterly fleet specific data for each airline. The dataset includes a large set of explanatory variables for the time period of 1991Q1-2012Q3. Data for twenty-four airlines during the study period were collected. The dependent and independent variables are presented in Table 2.1, and procedures for calculating these variables are discussed below. The inputs and outputs will be briefly outlined first, with further emphasis on the additional environmental and dummy variables.

All data has been constructed by the author following similar methods discussed in Tretheway and Windle (1983) and Sickles et al. (1986). The airlines included in this study are listed in Table A2 of the appendix. Several individual airline observations contain fewer quarters due to the fact that those airlines were not in existence over the whole sample period, or have not reported for the whole period. In addition, all nominal variables are transformed into real variables in 2012Q3 prices using the CPI index taken from the Bureau of Labour Statistics.

Table 2.1: Descriptive statistics of variables in cost model

Variable (ln)	**Variable Description**	**Mean**	**Standard deviation**	**Minimum**	**Maximum**
TC	Total cost (USD$; x$10^{7}$)	0.426	0.475	0.031	5.710
KM price	Price of capital-materials measured in dividing the sum of both categories by the number of revenue departures performed.	1562.825	1849.615	49.802	34943.700
Labour price	Price of labour calculated by dividing total labour expenses by the number of equivalent employees.	4791.016	1101.249	202.376	16597.080
Fuel price	Price of fuel which is the ratio of the amount spent on fuel to the reported amount consumed in gallons.	0.788	0.586	0.004	12.799
PLF	Passenger load factors taken as revenue passenger miles divided by available passenger miles.	1562.825	1849.605	49.802	34943.700
ASL	Average stage length taken as revenue aircraft miles divided by revenue number of departures.	822.822	452.019	140.388	3887.829
RTM	Revenue ton miles, measure of airline output which includes passenger and cargo of passengers (USD$; x 10^{10}).	0.884	1.030	0.000	4.890

2.4.2. Variables

The cost frontier function used has three inputs and one output. The three inputs are labour, fuel and capital-materials. These variables are all present in the major literature on airline costs, as set out in Section 2.1. For simplicity, the capital and materials are combined into one single variable. Unfortunately, there is no conclusive study to guide the selection of inputs and outputs in airline applications of efficiency measurements (Nissi and Rapposelli, 2008). However, it should be noted that the nature of performance measurement is greatly influenced by the input/output set identified in the airline production/cost process (Oum and Yu, 1998). The output is revenue ton kilometres. As this data set is a disaggregate account of a number of categories for each input, these must first be summed accordingly.

- Labour is the sum of pilots, co-pilots and all related employee expenses.
- Fuel is based on the total cost of aircraft fuel only (not including oil expenses).
- Capital and Materials is arrived at by summing both categories (capital costs include insurance, maintenance, depreciation and amortization. Materials costs include costs of other services the cost of all other components not previously included).

2.4.3. Environmental variables

In the airline cost literature, it has long been acknowledged that costs will be dependent upon the nature and quality of the airlines output as well as the quantity. As these vary over time and across carriers, the specification of the airline cost function in (2.8) needs to take these into account. Variables of this kind that typically often appear in the literature include a measure of the size of the airline's network (the number of points served), average aircraft capacity, passenger load factor and the average stage length. The introduction of number of points served was proposed by Caves et al. (1984) in order to identify economies of scale due to network characteristics. The use of number of points served is appropriate when making a distinction between returns to traffic density (the variation in unit costs as output increases in a fixed network size) and returns to scale or firm/network size (the variation in unit costs with respect to proportional changes in both network size and output; Gillen et al., 1990). The variables for passenger load factor and average stage length, measure how full the planes fly and how long the trips are on average, respectively. The omission of these two variables would cause an airline flying short distance markets to appear to be producing at a higher cost per ton-mile relative to those airlines serving longer-haul markets.

In this study, the use of average stage length and passenger load factor is employed for the reasons outlined above. While previous work on stochastic cost frontier analysis has not always included these variables[5], some have attempted but have either been unsuccessful due to insignificance or have only been able to include one (exceptions being Kumbhakar (1991) and Good et al. (1995) for example, who find both to be significant).

Stage length, defined as the ratio of total revenue aircraft miles performed to the total number of revenue aircraft departures, is a measure of the network size. This variable is expected to have a negative effect on cost, for a given ton-mile, and on inefficiency for two main reasons. First, flying short distances suggests that the aircraft will be unproductive for longer time periods. Second, airlines are expected to

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[5] It should be noted that the literature on airline cost functions only (not including frontier analysis) does include the passenger load factor and average stage length variables in most cases.

see some economies of scale, as their fixed costs are spread over a larger output of revenue ton-miles.

Passenger load factor is defined as the ratio of revenue passenger miles to the available passenger miles, and is considered as a measure of market demand. As a higher number of passengers indicate better utilisation of aircraft, a negative relationship is expected between load factor and inefficiency. In terms of the cost relationship, as load factor increases costs should be expected to decrease, other things equal.

The variables considered here as environmental factors are at the same time potentially under the control of the firm. While this can be argued, for the purpose of the model estimation they will be considered as exogenously determined, as has been assumed in many previous studies (Caves et al. 1984; Coelli et al. 1999; Ryerson and Hansen 2013).

In addition to the environmental variables, dummies for seasonality, Chapter 11 and September 11th were included. It is well known that the nature of the commercial airline industry is both seasonal and cyclical. Therefore, it is important in the analysis to effectively control for these unique factors which are known to impact on airline costs. To account for seasonality, dummies for each quarter were constructed based on Q1; first quarter from January 1-March 3; Q2; Quarter 2: April 1-June 30; Q3; Quarter 3: July 1-September 30 and Q4: Quarter 4: October 1-December 31.

The Chapter 11 dummy[6] takes on a value of 1 if the airline is in bankruptcy and 0 if they are not. During the reported time period of the panel, of the twenty-four

[6] All information was taken from Airlines for America (A4A). The A4A is the premier trade group of the principal U.S. airlines. A4A represents the collective interests of the airlines though they are not a governmental organization, nor an airline. This information was then cross-checked with news articles that I have found when relevant, for each filing to be sure that the information reported is accurate.

airlines, 11 have declared a bankruptcy at least once. The remaining 13, which have not declared bankruptcy, are Air Wisconsin, AirTran, Alaska, Allegiant, American Eagle, Horizon, JetBlue, Midwest, SkyWest, Southwest, Tower Air, USA Jet and Virgin America[7].

Two dummies for the terrorist attacks on September 11th 2001 were taken into consideration. The first dummy, (Dsep11) accounts for the initial and immediate effects of the attacks. Only the quarter during which the attack took place and the following quarter are included. Thus, it takes a value of 1 in the quarter of September 11th and the quarter subsequently following, or zero otherwise. The second dummy (DPsep11) is to investigate the permanent effect of September 11th and takes a value of 0 prior to the quarter of September 11th and a value of 1 in each time period on and after the attacks until the very end of the data time period.

2.4.4. Input prices

The prices of these inputs are obtained by dividing the reported costs of each by the corresponding quantity. The input prices and the dependent variable, total cost (TC), are collected from U.S. DOT Data in Form 41 Schedule P-5.2. This figure only reflects operating costs and excludes ownership costs related to depreciation and rentals.

Aircraft operating statistics are then taken from Form 41 Schedule PO5B. These statistics, collected for scheduled and non-scheduled service, include gallons of fuel consumed; available seat miles; revenue aircraft miles; departures performed and revenue ton-miles. From these prices and statistics, the unit price of fuel, labour and

[7] Both Tower and Allegiant Air have declared bankruptcy but this was outside of the time frame for which the panel data has been made available for from Form 41.

capital-materials as well as the average stage length and passenger load factor are derived.

Labour unit price is total expenditure on labour, divided by the total number of full-time employees taking part-time employees as full-time equivalents (FTE). The Bureau of Transport Statistics defines full-time equivalent employees as follows: FTE count two part-time employees as one full-time employee. While it would be more appropriate to assign a more precise definition to the number of part time employees, this was not possible due to lack of data. Fuel unit price, is total amount spent on fuel, divided by the total gallons of fuel consumed. This differs from other studies such as Inglada et al. (2006) who instead derive an "energy price" using energy cost divided by available capacity. The unit price of Capital-materials[8] is measured as the sum of expenses in these two categories divided by the number of revenue departures. Finally, similarly to Kumbhakar (1991) and Atkinson and Cornwell (1994), average stage length is calculated by taking revenue aircraft miles divided by revenue number of departures, and passenger load factor was derived by taking the number of revenue passenger miles divided by the available passenger miles.

With regards to the output variable of the model, revenue ton-miles (RTMs) represent the main outputs for a typical passenger focused airline in this dataset. The airlines in the data set are limited to passenger carriers only and all charter companies have been excluded. Only a minor portion of their traffic will undertake cargo, mail and other types of business. The total reported revenue ton miles is thus the only output used here, which on passenger flights include the weight of revenue passengers and their luggage as well as any revenue freight or mail carried (Durso, 2007). This also follows previous work by Oum and Yu (1995) and Zou and Hansen (2012b).

[8] The capital-materials was initially divided by the number of planes in the airline's fleet but this produced insignificant results.

Other studies have used Available Ton Miles (ATMs), which reflects available aircraft capacity, as output. This is a measure of potential output rather than actual output and has thus not been considered appropriate. Finally, some carriers have been omitted due to very limited reported data and/or missing data.

2.5. Results

Following the model specification, data and variable description, the results for the translog cost frontier estimation are reported in Table 2.2. A true fixed effects model was chosen (Greene 2005). In the traditional fixed effects models of Schmidt and Sickles (1984), and the random effects model, both assume that cost efficiency is time invariant. These models are also unable to separate inefficiency and firm heterogeneity. For a changing airline industry over a long panel, such an assumption of time invariance would be unconvincing. Furthermore, in these other models, the treatment of the "effect" as the inefficiency does not consider the prospect of other unmeasured heterogeneity that is unrelated to inefficiency. Any such heterogeneity that exists will show up in (or as) the inefficiency that is to be measured. A more reasonable assumption made by the true fixed effects model is to allow inefficiency to change over time. As the objective is to estimate the cost frontier for the individual airlines across the US, the true fixed effects model is preferred as it can separate out heterogeneity from inefficiency and allows cost inefficiency to vary over time.

The total cost and the regressors have all been transformed into logarithms. The data has been demeaned such that the dependent and independent variables, except dummies, PLF and ASL, are estimated about the mean values in the dataset (divided by their geometric mean). This allows for the first order coefficients to be interpreted as cost elasticities.

The coefficients of all first order terms are statistically significant at the 1% level and most of the remaining coefficients on second order terms are also significant at the 1% level. This indicates that the selection of inputs and outputs have been appropriate for the cost frontier estimation. In addition, both PLF and ASL were statistically significant. Further discussions of these results are presented in Section 3.1.

In addition to the true fixed effects model presented in this chapter, a number of other models were evaluated. First, a likelihood-ratio test was performed on the inclusion or exclusion of the characteristic variables lnALS, lnALF, DCh11, Dsep11, and DPsep11 for the true fixed effects model. Results indicate a Chi squared value of 837.51 with Probability > chi2 = 0.0000. This result confirms that the inclusion of characteristic variables together, results in a statistically significant improvement in model fit. A likelihood-ratio test was also performed comparing the true fixed effects model with the random effects model. The random effects model was dropped in favour of the true fixed effects with a likelihood-ratio of 189.18 and critical value of 2.706[9] (one degree of freedom). This indicated that a time-invariant model does not perform as well as the time-varying model presented here.

Finally, both a true random effects and random effects model were also estimated. These both failed to converge (iterations did not run), indicating they were not an appropriate model and were therefore dropped.

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[9] The random effects model had a lower log likelihood of 1126.0788

Table 2.2: Parameter estimates of the translog cost function

Variable	**Coefficient**	**t-statistic**
lnRTM	0.956	68.60***
lnKM	0.306	20.25***
lnL	0.229	14.18***
lnF	0.464	41.65***
.5*lnRTM2	-0.014	-2.510**
.5*lnKM2	0.107	12.39***
.5*lnL2	0.115	5.36***
.5*lnF2	-0.027	-1.55
lnRTMlnKM	-0.007	-1.66*
lnRTMlnL	-0.019	-3.00***
lnRTMlnF	0.040	8.00***
lnKMlnL	-0.125	-11.86***
lnKMlnF	0.017	1.90*
lnLlnF	0.010	0.55
lnPLF	-1.150	-20.82***
lnASL	-0.610	-19.76***
Q1	-0.017	-2.08**
Q2	0.018	2.12**
Q3	0.024	-2.81***
DCh11	-0.028	-2.26***
Dsep11	0.094	4.48***
DPsep11	-0.091	-5.28**
Productivity measure		
t	0.041	5.56***
t2	-0.001	-1.63*
t3	0.000	2.01**
σ_u^2	0.010	8.43***
σ_v^2	0.008	21.03***
$\lambda = \frac{\sigma_u^2}{\sigma_u^2 + \sigma_v^2}$	0.527	68.63***
Total number of observations	1518	

Log-likelihood: 1220.6680
*Variables are significant at the 10% level.
**Variables are significant at the 5% level.
***Variables are significant at the 1% level.

Table 2.3: Parameter estimates of translog cost function literature

Authors	Variables	Coefficient
Bauer (1990)	Output (Revenue passenger ton miles/revenue cargo ton miles)	0.856/0.140***
	Average stage length	-0.293***
	Average Load factor	-0.663***
	Labour price	0.469***
	Energy price	0.232***
	Capital price	0.100***
	Material price	0.199***
Caves et al. (1984)	Output (four summed categories: revenue passenger miles of scheduled service, revenue passenger miles of charter service, revenue ton miles of mail, revenue ton miles of all other freight)	0.804
	Average stage length	-0.148
	Load factor	-0.264
	Labour price	0.356
	Fuel price	0.166
	Material/capital price	0.478
		*All coefficients are highly significant
Gillen et al. (1990)	Output (scheduled revenue passenger kilometers; scheduled revenue freight kilometers; non-scheduled (charter) revenue ton kilometers passenger/freight)	0.971 (sample mean)
	Average stage length	-0.181
	Load factor	0.734
	Labour price	0.322
	Fuel price	0.199
	Material/capital price	0.478
Oum and Zhang (1991)	Returns to Scale (derived)	0.906
	Average stage length	-0.241
	Labour price	0.372
	Fuel price	0.254

	Material price Capital price	0.374 0.162 *All coefficients are highly significant
Atkinson and Cornwell (1994)	Output (capacity ton miles) Average stage length Labour Energy Materials	0.227 1.477** 0.750** -0.433** 0.521**
Inglada et al. (2006)	Output (available ton kilometers) Labour price Energy price Material/other services price Capital price	0.679** 0.106** 0.231** 0.373** 0.291**
Ryerson and Hansen (2013)	Average stage length Labour Fuel Materials	0.803*** 0.296*** 0.408*** 0.302***
Zou and Hansen (2012)	Output (revenue ton miles) Average stage length Materials Capital	0.485*** -0.1873** 0.413*** -0.0543***

*Variables are significant at the 10% level.
**Variables are significant at the 5% level.
***Variables are significant at the 1% level.

2.9. Discussion

Table 2.2 contains estimation results for the translog cost frontier estimation. The first order coefficient with respect to the output variable, revenue ton-miles, 0.956, is positive and statistically significant. Its value of effectively 1 indicates constant returns to scale. This confirms neither economies nor diseconomies of scale exits, or in other words costs go up proportionally with a change in output. It is typical in the literature to find constant returns or mild increasing returns to scale (see for example Caves et al. (1984), Gillen et al. (1990), Oum and Zhang (1991), Bauer (2000) and additionally Jara-Díaz et al. (2013)). Some previous results are found in Table 2.3 for comparison purposes. One element that could explain the diversity of the results obtained by the literature is the different specification of the variables representing output. A number of different variables are used in these models but the majority chose a revenue ton kilometre or an available ton kilometre measure. The greatest disadvantage of the available kilometre measurement previously noted, is that it measures a potential output rather than an actual output, so was not appropriate for this analysis.

The first order coefficient of fuel price, 0.464, implies that at the sample mean, a 10% increase in fuel price would increase the airlines total cost by 4.6%. Similarly, first order coefficient for capital-materials, 0.306, and labour, 0.229, implies that at the sample mean, a 10% increase in either input would increase the airlines total cost by 3.0% and 2.3% respectively. All coefficients for capital-materials, fuel and labour show expected signs and are within acceptable ranges of previous literature. These elasticities can also all be interpreted as cost shares of labour, fuel and capital-materials. For example, it can be concluded that the share of total cost attributed to fuel is 46.0%. Furthermore, these results are thought to be reasonable as they are within close range to the cost shares in the actual data, with labour at 31%, fuel at 43% and capital-materials at 25% of total costs.

Beyond the output variable and these three key input variables, environmental variables PLF and ASL show expected signs and magnitudes and both are found to be statistically significant. While some previous studies using frontier analysis have excluded either one of or both these variables, the model estimates show that the inclusion of these variables is justified by their significant effect. The coefficients on PLF and ASL imply a negative relationship between these variables and cost. It would be expected that a higher load factor would indicate better utilization of aircraft (i.e. one aircraft with high load factor vs. two aircraft with low load factor), thus an increase in load factor would be expected to decrease costs and indicate a more efficient airline. In particular, 10% increase in the passenger load factor will generate a decrease of 11.5% in costs. Similarly, a 10% increase in the variable representing average stage length of the airline decreases costs by 6.1%. As described in Caves et al. (1984), airlines unit costs decrease considerably as average stage length increase. They also note that costs vary inversely with average load factor. Similar results for PLF and ASL are found in Bauer (1990) for example. Further comparisons can be found in Table 2.3

The dummy for Chapter 11 shows a small but statistically significant negative effect (-0.03) of filing for bankruptcy on costs. This negative effect on costs was also found by Barla and Koo (1999) who empirically examine the effects of bankruptcy protection (Chapter 11) on an airline and its rivals' pricing strategies. Their main results indicate that once Chapter 11 has been filed, the airline is able to reduce its operating costs by approximately 4.2%. This is partially reflected in lower prices after declaring bankruptcy (-2.3%). A reason they suggest for this is that Chapter 11 airlines may be able to cut costs in ways that the non-bankrupt firms cannot (see also Barla and Koo 1999; Borenstein and Rose 1995). A firm operating in Chapter 11 is given the right to postpone all repayments of capital and interest until reorganisation has been finalised[10]. It is also able to reject any contracts which they believe are not in the

10 Termed "automatic stay" (Bankruptcy Code section 362 a,b).

best interest of the firm, such as collective bargaining agreements[11]. Thus, a firm undergoing bankruptcy protection is given flexibility and bargaining power to renegotiate contracts, which could result in cost reductions and subsequently lower fares. Two examples of airlines, which have been able to do these types of renegotiations, are Continental Airlines and American West.

The dummy Dsept11, was 0.09 and significant at the 1% level. This indicates that the initial temporary effects of September 11th increased airline costs. In addition to directly causing a temporary but complete shutdown of the commercial aviation system, the attacks of September 11th had a negative impact on air travel demand in the short-run. This would have contributed to a rise in airlines costs at the time relative to output. Following the downturn in demand for domestic air travel as a result of September 11th, numerous airlines have experienced a financial crisis never before seen with many filing for bankruptcy. This seems counter intuitive to the results for the permanent effects of September 11th, which are discussed next.

The dummy DPsep11 is statistically significant at the 1% level, with a negative coefficient and value (-0.09). This suggests that a permanent, long run result of the attacks was a decrease in airline costs. One reason could be that with the increased number of bankruptcy filings after the attack many carriers have been engaging in dramatic cost-cutting programs (Ito and Lee, 2005). Another possibility is that the airlines were able to cut their security costs due to the implementation of the Aviation and Transportation Security Act[12]. Furthermore, this variable could be picking up the Chapter 11 effects better than the Ch11 variable itself. This could indicate a possible collinearity issue.

11 Bankruptcy Code Section 1113.

12 http://www.gpo.gov/fdsys/pkg/BILLS-107s1447enr/pdf/BILLS-107s1447enr.pdf

Developed as a direct result of the events of September 11th, the Aviation and Transportation Security Act was introduced on September 21st, 2001 (107th Congress, 2001-2002) and was enacted after being signed by President Bush on November 19th, 2001. The Act introduced new security measures and formed the Transportation Security Administration (TSA). It holds authority over the security of those travelling within the U.S. and the main purpose was to make airport security the responsibility of the federal government. This improved the way Americans viewed travel safety. Previous to the Act, airport security was the responsibility and thus cost burden of the airlines and the airport authorities. It could be that this shift in security costs has impacted the airlines in a positive way in terms of reducing costs.

Using this estimated frontier, it is possible to generate indices for cost efficiency (CE), calculated in accordance with 2.4. The distributional assumption for the inefficiency term was half-normal. These scores are presented in Table 2.4, which displays the average efficiency for each airline in each reporting year. The mean efficiency is 92.12%. This value indicates that, to operate efficiently, airlines could on average reduce their input costs by 7.88% without decreasing their outputs. The maximum score of airline efficiency was Trans World and Virgin America with 92.88% and 92.87% respectively over the whole period. The highest score in any one year was Horizon with 97.4% efficiency in 2005. Southwest, Alaska, America West, Delta and United were all a very close second at around the 92.8% mark. The lowest score was USA Jet Airlines with 88.3% over the whole period. They also received the lowest score in any one year of 79.6% in 2007. The median efficiency is 92.6% and the standard deviation is 1.05%. Finally, Table 2.5 summarises the total average efficiency scores of all airlines, for all years combined. Due to the data set incorporating a very large number of airlines, only a select few of these have been chosen for discussion based on stability.

Both Southwest and Virgin have managed to achieve a large degree of stability in efficiency scores over their reporting periods, highlighting their effective cost control. Interestingly, Southwest was able to use its relatively strong position to limit the effects of September 11th. It has also never filed for bankruptcy. U.S. Airways, in contrast, displays slightly more volatility in their cost efficiency trend. U.S. Airways emerged from bankruptcy protection in March 2003 and received $900 million in federal bailout money, with efficiency scores increasing slightly (from 94.3% in 2003 to 95.0% in 2004). Only two years since its first filing, they were again forced to return to the protection of the bankruptcy courts with efficiency scores falling, and then quickly improving again. The cost efficiency trend for Southwest is illustrated in Figure 3.1 and U.S. Airways in Figure 3.2. Interestingly, there is a drop in efficiency in 2008 across most firms. It was during this time that airlines faced huge increases in fuel price due to the oil crisis.

Table 2.4: Average cost efficiency rankings of U.S. airlines

Airline	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
Northwest	0.939	0.942	0.946	0.944	0.926	0.929	0.932	0.919	0.929	0.937	0.933	0.911	0.930	0.942	0.927	0.918	0.926	0.865	0.934			
Southwest	0.941	0.939	0.938	0.936	0.929	0.921	0.921	0.937	0.929	0.933	0.938	0.920	0.923	0.933	0.935	0.930	0.931	0.918	0.940	0.938	0.909	0.883
Horizon	0.822	0.830	0.849	0.846	0.854	0.856	0.872	0.916	0.910	0.908	0.900	0.919	0.930	0.967	0.974	0.960	0.958	0.940	0.966	0.969		
Hawaiian	0.820	0.869	0.936	0.941	0.958	0.953	0.954	0.961	0.835	0.937	0.935	0.934	0.921	0.921	0.919	0.905	0.903	0.882	0.944	0.940	0.911	0.913
Continental	0.946	0.943	0.934	0.941	0.916	0.908	0.910	0.896	0.896	0.933	0.935	0.924	0.929	0.941	0.934	0.929	0.927	0.901	0.951	0.955	0.917	
Delta	0.934	0.932	0.934	0.927	0.937	0.927	0.942	0.936	0.931	0.927	0.935	0.908	0.912	0.938	0.943	0.936	0.929	0.906	0.944	0.939	0.892	0.906
American	0.941	0.940	0.946	0.934	0.924	0.926	0.922	0.911	0.911	0.915	0.920	0.891	0.914	0.939	0.936	0.935	0.937	0.919	0.951	0.953	0.924	0.922
Alaska	0.917	0.919	0.927	0.934	0.936	0.931	0.934	0.928	0.933	0.930	0.919	0.912	0.924	0.936	0.930	0.925	0.932	0.904	0.952	0.951	0.922	0.925
United	0.933	0.932	0.935	0.922	0.926	0.930	0.936	0.935	0.932	0.934	0.924	0.894	0.939	0.936	0.927	0.930	0.936	0.909	0.952	0.947	0.909	0.896
America West	0.940	0.941	0.936	0.931	0.938	0.939	0.943	0.939	0.938	0.936	0.929	0.913	0.920	0.925	0.915	0.903	0.892					
Air Wisconsin	0.953	0.942	0.880	0.963	0.966	0.964	0.957	0.953	0.944	0.904	0.918	0.900	0.928	0.900	0.903	0.905	0.898	0.801	0.896	0.901	0.866	0.881
Tower Air	0.822	0.922	0.921	0.936	0.918	0.937	0.951	0.934	0.936													
Trans World	0.941	0.946	0.926	0.936	0.929	0.935	0.925	0.899	0.909	0.938	0.931											
SkyWest													0.894	0.896	0.885	0.868	0.924	0.943	0.954	0.940	0.941	0.949
ATA	0.944	0.944	0.947	0.948	0.935	0.924	0.922	0.931	0.931	0.914	0.919	0.921	0.933	0.941	0.916	0.873	0.910					
Midwest	0.918	0.917	0.923	0.931	0.932	0.933	0.926	0.933	0.937	0.912	0.889	0.913	0.930	0.955	0.953	0.940	0.939	0.905	0.902			
US Airways	0.918	0.916	0.911	0.898	0.909	0.908	0.906	0.907	0.907	0.903	0.933	0.922	0.943	0.950	0.946	0.948	0.944	0.911	0.952	0.958	0.930	0.938
Allegiant																0.942	0.898	0.850	0.949	0.930	0.882	0.889
Eagle				0.965	0.958	0.902	0.908	0.912	0.899	0.924	0.926	0.891	0.918	0.934	0.924	0.927	0.924	0.876	0.939	0.939	0.942	
JetBlue										0.933	0.962	0.947	0.945	0.939	0.915	0.909	0.915	0.873	0.937	0.933	0.881	0.893
Comair												0.971	0.961	0.966	0.926	0.888	0.864	0.829	0.912			
AirTran								0.894	0.932	0.884	0.908	0.918	0.924	0.928	0.926	0.928	0.932	0.900	0.949	0.949	0.940	0.944
USA Jet																	0.796	0.886	0.964		0.889	0.880
Virgin																			0.940	0.931	0.909	0.934

*Note that blank cells indicate the airline did not report in this year/quarter and thus data was not available for analysis.

Table 2.5: Total average efficiency scores per airline (all reported years)

Airline	**Average Efficiency %**
Trans World	92.88
Virgin	92.87
Southwest	92.83
Alaska	92.83
America West	92.82
Delta	92.80
United	92.80
Northwest	92.79
American	92.78
Continental	92.69
ATA	92.67
Midwest	92.57
US Airways	92.54
AirTran	92.38
Eagle	92.27
JetBlue	92.17
Tower Air	91.95
SkyWest	91.93
Hawaiian	91.78
Air Wisconsin	91.47
Comair	91.46
Horizon	90.73
Allegiant	90.57
USA Jet	88.29
Average (all airlines)	**92.12**

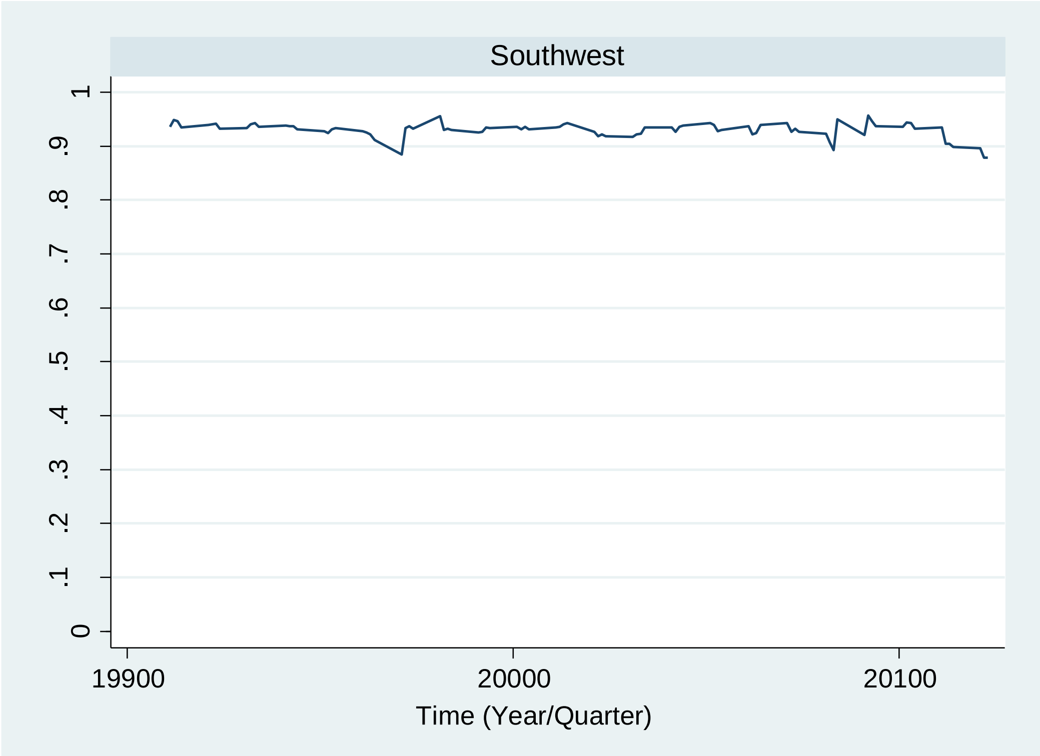

Figure 2.1: Southwest Airlines cost efficiency trend

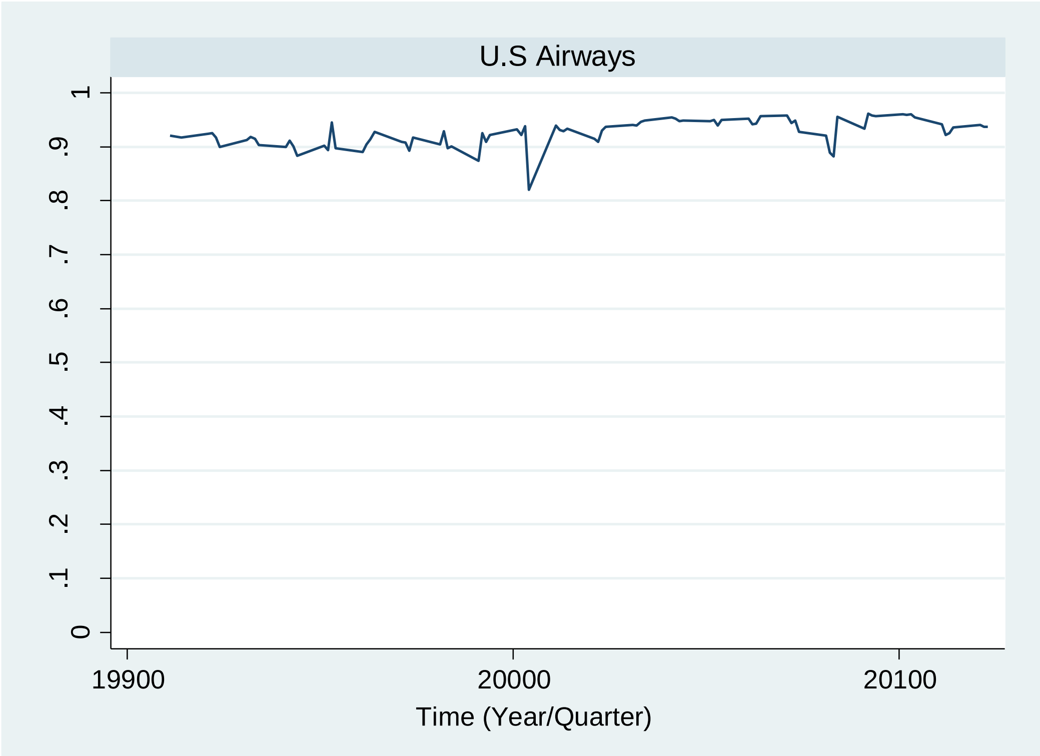

Figure 2.2: U.S. Airways cost efficiency trend

Most airlines show relatively steady efficiency scores, which improve over the sample period. One exception in particular is Horizon, who shows a strong positive trend in efficiency improvements going from 82.2% efficiency in 1991 to 96.9% in 2010. This can be seen in Figure 3.3. A likely contribution to this efficiency trend is Horizons fuel efficiency (Kwan et al., 2013). Horizon, and its partner Alaska Airlines, were announced the most fuel-efficient airlines operating in the U.S. in 2010. Horizon flies a lot of turboprops compared to other airlines in the sample, which are the more efficient engines at medium and low altitudes (where most of the fuel burn occurs). In 2012, Horizon completely phased out its Bombardier CRJ-700 regional jets for the more efficient Bombardier Dash 8-Q400 turboprops.

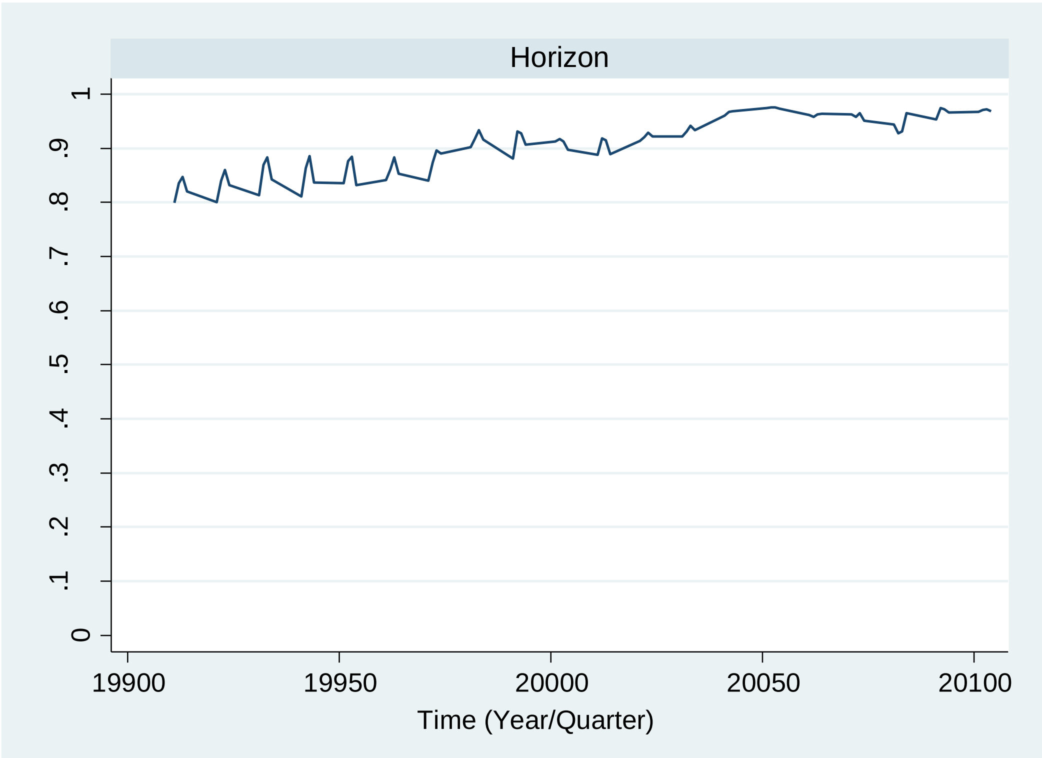

Figure 2.3: Horizon Air cost efficiency trend

2.6.1. TFP analysis:

Table 2.6 presents the technical change obtained by way of coefficients on the time trends variables, which were used to construct a technical change index. This method follows Cantos Sànchez (2000), who defines this rate as the derivative of costs with respect to the proxy variable of technical change (time trend). A negative sign on the coefficient is interpreted as the presence of technical progress and a positive sign as technical regress. It can be seen that in t and $t3$, the coefficients of technical progress presents a positive sign, thus indicating a deterioration in the level of productivity due to technical change. In the case of $t2$, the coefficient is negative. The fluctuations of the signs from positive, to negative to positive mimic the business cycle effect.

Table 2.6: Time trend coefficients obtained from translog estimation

Time trend variable	**Coefficient**	**t-statistic**
t	0.04063	5.56***
t2	-0.00135	-1.63*
t3	0.00048	2.01**

The annual growth rate of total factor productivity (TFP) is presented in Figure 3.4. It is concluded that, averaging over all the airline companies, productivity growth has decreased over the sample period by a total of 50.77%. This represents the movement of the cost function due to technical change.

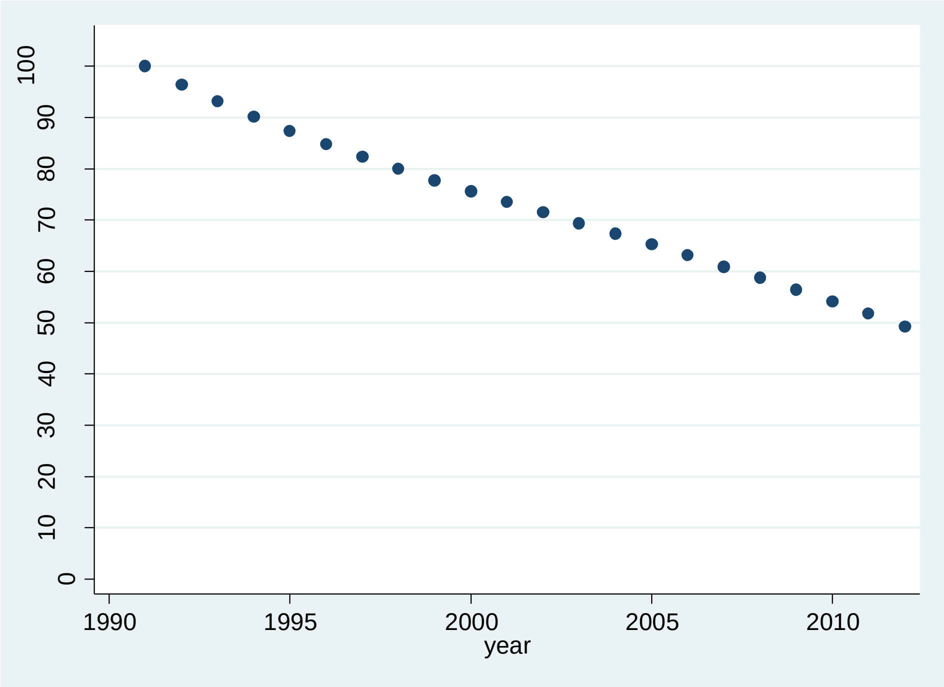

Figure 2.4: Average Technical progress of U.S. Carriers

The movements throughout the cost function due to changes in airlines cost efficiency are offered in Figure 3.5. These have been quite stable over the observed time scale with an overall (minor) increase of 0.2%. Finally, the overall total factor productivity (technical efficiency and cost efficiency together) are presented in Figure 3.6. It is observed that, taking an average of all the companies, total factor productivity has decreased quite steadily over the years with an overall decrease of 50.68%. This decrease was mostly due to technical change and to a much lesser degree due to cost efficiency levels.

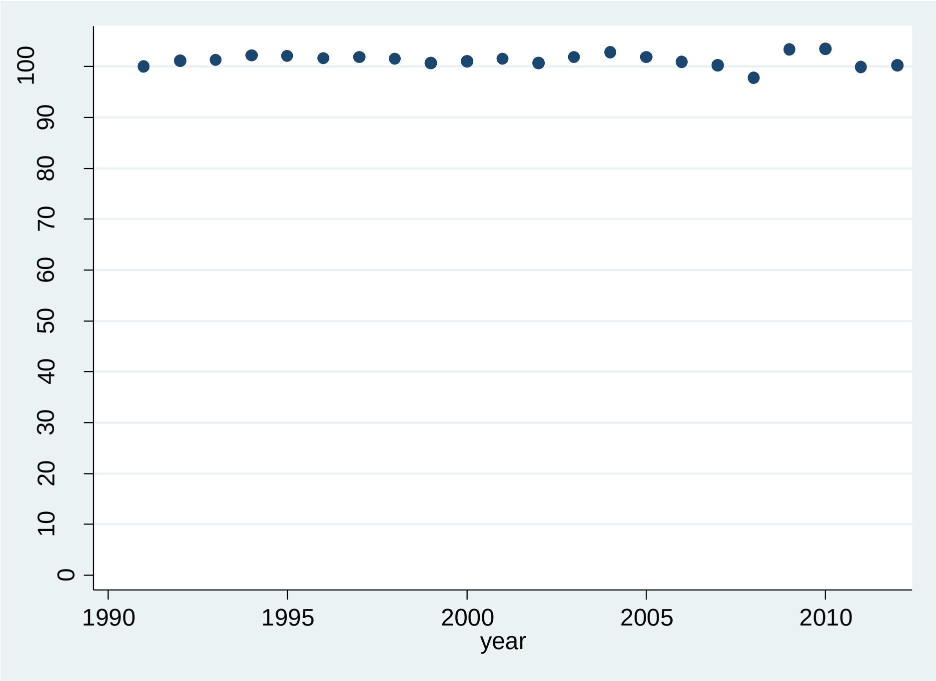

Figure 2.5: Average cost efficiency index of U.S. Carriers

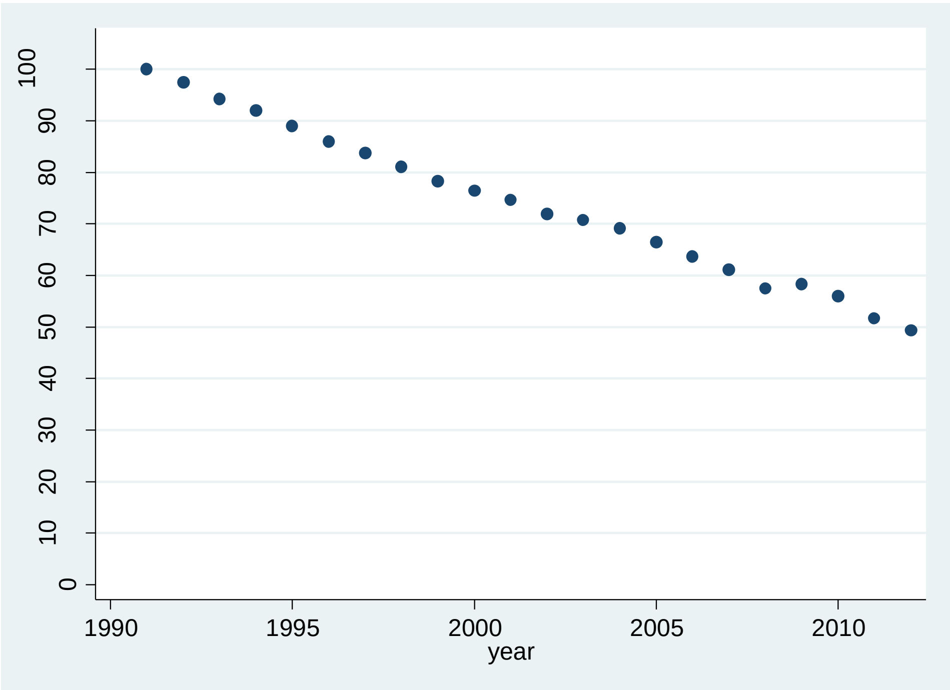

Figure 2.6: Overall Total factor productivity index of all U.S. Carriers

These results can be compared with these obtained by Oum and Yu (1995) and Vasigh and Fleming (2005). However, this presents some difficulties as to date there have been few studies, which present total factor productivity of airlines over a recent and long time scale such as the one presented here.

Oum and Yu (1995) measured and compared productivity of the world's 23 major airlines from 1986-1993. Their data set included 6 of the same airlines as in the data set here. They construct a TFP index which reflects the airlines observed productivity performance. This is referred to as a "gross" TFP index, as it is likely that it will not reflect the "true" productive efficiency. Many factors can impact TFP which are largely beyond the control of the airline, such as economic conditions. This should be kept in mind when considering results. Focusing only on the comparable years (1991-1992) they find that many of the airlines (including Asian and European) experienced a reduction of TFP and they suggest this is most likely due to the reduced demand caused by the Gulf war and economic recession. Continental airlines, was the only U.S. airline out of the six, to demonstrate an overall decrease in TFP over the whole sample period, with the average annual TFP change of -1.2 %.

Vasigh and Fleming (2005) analyse and asses TFP of the U.S. airline industry comparing national airlines to major airlines for the years 1996 through 2001. This study exposes the relatively stronger productivity achieved by the U.S. national airlines as compared to the U.S. major airlines. They observe a decline in productivity of the major airlines over the analysed period, while national airlines demonstrated a more consistent and higher trend in productivity. However, they do not examine the relatively poor performance of the major airline group with American, United and

Delta airlines having the lowest productivity. The average total factor productivity for their work is presented in Table 2.7. Those airlines, which are in italics, are also present in the data set used here. It is interesting that these airlines have some of the lowest productivity scores overall. This could be a contributing factor the lower (decreasing overall TFP) productivity results obtained in this analysis. It could also be possible that as the data set used for this analysis is a combination of major and national airlines, the average TFP scores are being skewed by the lower scores of the major airlines.

Table 2.7: Average total factor productivity for U.S. airlines (1996-2001), (Vasigh and Fleming, 2005)

Airline	**TFP**	**Airline**	**TFP**
Aloha	0.89	American Trans Air	0.71
Horizon	0.87	*American West*	0.56
Spirit	0.86	*Southwest*	0.49
Midwest Express	0.83	*Continental*	0.38
Frontier	0.81	*U. Airways*	0.33
World	0.81	*Northwest*	0.28
Airtran	0.73	*Delta*	0.22
Hawaiian	0.73	*United*	0.13
Alaska	0.60	*American*	0.10

Vasigh and Fleming (2005) have offered a number of potential contributing factors to this decreasing trend TFP observed in the airline industry. The most likely explanation could be due to the hub-and-spoke system, which emerged following the deregulation of the industry. While the hub-and-spoke structure has been recognised as allowing for the efficient provision of air transportation to smaller markets and routes, the relative productivity rankings of their analysis and the one presented here, suggest that perhaps these hub-and spoke systems decrease TFP. For example, Southwest Airlines, a point-to-point carrier, has significantly outperformed the remaining major carriers. Southwest has been profitable by consistently keeping its costs lover than the industry average. The lower productivity of the major airlines may in fact arise from the inefficient use of assets and expenses associated with the operation of hub systems. A number of airlines have faced this issue with efforts of “de-hubbing” such as Continental, Delta, U.S. Airways and American Airlines to name a few. Overall, the results from this analysis of the TFP index are somewhat inconclusive, and future work could provide a more significant validation of the TFP index.

From 1979 until the end of 2009, U.S. airlines lost $59 billion (in 2009 dollars) on domestic operations Borenstein (2011). Fuel costs increases have undeniably been a significant component of losses in some years, most notably in 2008. Interestingly, the average tax as a percentage of the base ticket price has increased steadily throughout deregulation according to Borenstein (2011). He suggests that the industry’s problem appears to be not that the taxes have increased, but that base fares have fallen and stayed low. Finally, another potential main driver of the U.S. airlines losses, are the large cost differentials between major airlines and the low cost carriers, which has continued even as their price differentials have significantly declined.

2.7. Conclusions

This chapter uses stochastic frontier analysis to measure and compare estimates of cost inefficiencies for twenty-four U.S. carriers. The estimates are based on panel data observations during the time period 1991Q1 to 2012Q3.

An extensive effort was implemented in order to assemble a reliable panel of data. This was then used to compute a translog cost frontier function. In developing the translog cost frontier, a detailed representation is established of the relationship between aircraft costs and the variables that influence it. The efficiency scores were then calculated and examined in order to compare them across carriers. Relationships are found between costs and environmental variables and other dummy variables not previously documented in stochastic frontier literature. The primary results of this study are as follows.

Of the twenty-four airlines in the study it was found that they are, on average over all years, operating at 92.12% efficiency. In the final reporting year, 2012 the average efficiency score for all airlines was 90.91%. Thus to operate efficiently in 2012, airlines could (on average) reduce their input costs by 9.09% without decreasing their outputs. For the purposes of this analysis, airline outputs were defined as revenue ton-miles, the revenue tons (of passengers and cargo) transported per miles flown. The coefficient on the output variable was significant at 0.956, suggesting nearly constant returns to scale. The average cost efficiency of air transportation carriers over time, ranged between 92.88% and 88.29% with a standard deviation of 1.05%. All first order terms were found to be statistically significant and are in line with previous studies (for example see: Caves et al. (1984), Gillen et al. (1990), Oum and Zhang (1991), Bauer (2000)). It was determined that the environmental variables for passenger load factor and for average stage length were statistically significant. This is not always seen in previous work using frontier analysis, and often they are dropped due to insignificant coefficients. Of further interest are the results on the September 11th indicator variables. This analysis separates the effects of September 11th into its temporary effects and its lasting impacts. It is found that the initial temporary outcome was a small but positive (increase) to airline costs of approximately 9.4%, and a negative on-going effect of around 9% (decrease) in costs. Both are statistically significant. A possible explanation for the decline in costs over the long run could be that with the increased number of bankruptcy filings after the attack many carriers have been engaging in dramatic cost-cutting programs (Ito and Lee, 2005). Another possibility is that the airlines were able to cut their security costs due to the implementation of the Aviation and Transportation Security Act. As far as the long term effects of September 11th, there is some controversy as to what the true impacts are. This is due to fact that weak economic conditions were present before September 11th, and persisted well after. Future work will endeavour to assess the impacts of the September 11th attacks and it's after effects on U.S. airline costs in a more robust manner.

It was also observed that on average, taking account of all companies, productivity growth for the study period due to technical change had deteriorated overall by 50.8% over the twenty-two year period. Although results are somewhat inconclusive, one possible explanation for this decline in TFP could be due to the hub-and-spoke configuration which developed following deregulation. It is thought that this could have resulted in the inefficient use by airlines, of assets and expenses related with operating these hub systems. The total factor productivity of U.S. carriers over a more recent and longer time scale is an area which needs further attention and will be returned to in future work. Key future research in this field will include the analysis of total factor productivity through the industry recession.

3. Determinants of airline efficiency in the U.S.: A longitudinal DEA and SFA approach

3.1. Introduction

With competition having increased in many airline markets across the world, and now being at an all-time high, demand for premium travel services (particularly first-class seating) has suffered a significant decline. Given that premium fares are typically four times the price of economy fares, this translates to a substantial loss in revenue. In an industry with such slim margins, this is a significant reduction and only adds to the current downward pressure on profits. In addition, the rapid expansion of low cost carriers (LCCs) has drastically altered the nature of competition within the traditional airline industry (Brueckner et al., 2013). This is particularly the case on shorter-haul routes and has caused regional airlines to react or to fail. Rising labour costs and fluctuating fuel prices impact all airlines. Fuel is now approximately 30-40% of airlines costs, compared to 13% in 2001 (Zou and Hansen, 2012). The significant rise and high volatility in jet fuel costs further complicates the situation where the strategic response can take many forms, but all involve improving cost efficiency. More than at any time in the past, this has made efficiency a top priority for airline management (Merkert and Hensher, 2011).

While cost management has always been an important part of airline administration, in recent years it has become a crucial part of the airline survival strategy. In the decade following the September 11th attacks in 2001, U.S. airlines have shown considerable resilience (all of the legacy carriers have received government support and have undergone Chapter 11 restructuring), with most having been able to recently improve their financial position and return to profitability as a result of significant consolidation and capacity discipline (IATA, 2014). However, it remains too early to tell if more airlines have yet to face financial difficulties or will be forced into further merger and acquisition activities. While initiatives to reduce costs are not unusual in the course of economic recessions, the efforts carried out by the airline industry have been considered extreme. These efforts have included scaling back workforces, changes to service and wage reductions from employee groups. Furthermore, these airlines have had to restructure themselves considerably, financially as well as operationally, regardless of whether they pursued bankruptcy protection or not.

It is therefore important to understand what operational measures airlines should adopt in order to remain competitive in the market and to perform well under turbulent market conditions. One strategy has been to adopt the low cost carrier (LCC) model, by either setting up a subsidiary low cost operation (such as American Airlines who is a subsidiary of the AMR corporation) or by adopting the no-frills model, which most aviation markets have experienced in the past. Another strategy seen in the industry is that of increasing market power by way of forming alliances, as well as growth through mergers and acquisitions (such as United/Continental in 2011). However, it could be the case that airlines can become too large to operate cost efficiently (Merkert and Morrell, 2012). Previous literature (Merkert and Hensher, 2011; Merkert and Williams, 2013) suggests that operational factors have significant impacts on costs and efficiency of airline operations. For example, passenger load factor, aircraft size and stage length have a huge impact on airline costs, with larger and fuller aircraft being able to spread unit costs over longer routes.

The intent of this study is to build on Merkert and Hensher (2011) and to analyse the impact of fleet planning and strategic management decisions on airline efficiency, comparing data envelopment analysis (DEA) and stochastic frontier analysis (SFA) results. While this study follows the approach they used for airlines around the world, it applies it to U.S. airlines only. The sample here however, includes 9 of the 10 U.S. airlines found in Merkert and Hensher (2011). In this way, both methods can be compared in terms of estimates and also robustness. As in Merkert and Hensher (2011), a two-stage DEA approach will be undertaken, with partially bootstrapped random effects Tobit regressions in the second stage. These results will then be compared to SFA results.

This chapter further contributes to the literature on airline efficiency by undertaking a much larger comparison of airline performance in the United States (twenty-two in total) as compared to Merkert and Hensher (2011). As well as significantly increasing the number of U.S. airlines in the sample set, this chapter will extend the number of years in the sample period, applying data from 2006-2012 for the twenty-one U.S. airlines. Such panel data makes the use of SFA approaches appealing. Pitt and Lee (1981) and Schmidt and Sickles (1984) both noted the advantages of using panel data to estimate frontiers, such as consistent cost/technical inefficiency estimates and richer analysis of the behaviour of firms over time provided by panel data. The time period 2006-2012 was chose for two reasons. The first was that this included the time period covered in Merkert and Hensher (2011). The second was that this was the largest time period available for which data on characteristic variables, such as number of manufacturers and aircraft families, was offered.

The remainder of this study is organised as follows: Section 3.2 presents a brief review of previous literature; Section 3.3 to 3.3.3 describes research design, including a two-stage DEA methodology, truncated regression, SFA model specifications, collection of the sample data and the criteria for variables to evaluate performance; Section 3.4 and 3.5 presents empirical data and an analyses of the results. The second-stage Tobit regressions confirm results found in Merkert and Hensher (2011) and are consistent with the SFA estimates. Section 3.6 presents the conclusion and offers some discussion regarding possible directions for future work.

3.2. Literature review

Airline efficiency has been previously examined adopting either the index numbers approaches, such as the Tornquist total factor productivity index (Barbot et al. (2008), Coelli (2003), stochastic frontier models (Coelli et al. (1999), Kumbhakar (1990), Inglada et al. (2006), Sjogren and Soderberg (2011)) or DEA models (Adler and Golany (2001), Merkert and Hensher (2011).

Almost all previous analyses use the International Civil Aviation Organization (ICAO) data sets and compare U.S., Asian and European airlines against each other with the main focus of study being the comparison of efficiency among these airlines. Recent studies using DEA to evaluate the performance of airlines, which adopt the use a second stage bootstrapped truncated regression include Lee and Worthington (2014), who, looking at a sample of international and domestic U.S. airlines for the year 2006, find that private ownership, status as a low-cost carrier, and improvements in load factor contributed to better organizational efficiency. Barros and Peypoch (2009), contribute some valuable insight to the literature by their use of the Simar and Wilson (2007) bootstrapped truncated regression approach, which assessed the impact that environmental variables had on efficiency. From a sample of twenty-seven European airlines over the period 2000-2005, Barros and Peypoch (2009) find that the demographic aspect of the airlines home country (representing economies of scale) and membership in an alliance network, impacts significantly on airline efficiency. Economies of scale are also confirmed in Barbot et al. (2008). Using data for 49 airlines from different parts of the world, the study found that low cost carriers typically perform more technically efficient than full service carriers, and that larger airlines are more efficient than smaller ones.

Methodologically, an obvious pattern is detected from the above literature; namely that they have confined their analysis to the estimation of technical efficiency and do not include all three aspects of efficiency into their analysis. There are two ways that this can limit their findings (Merkert and Hensher 2011). The first is that most of the previous literature uses both physical and cost data as input factors to estimate technical efficiency. A producer is technically efficient if an increase (decrease) in any output (input) requires a reduction (increase) in at least one other output (input) or an increase in at least one input (Koopmans, 1951). It can therefore be argued that technical efficiency is concerned with measurement of output to input ratios and should as a result, consist of physical measures. Secondly, cost efficiency is considered to be more relevant to decision-making in airline management and is central to an airlines competitiveness and success (IATA, 2006). Cost efficiency, has technical and allocative components. The concept of allocative efficiency is concerned with combinations of correct inputs proportions at the least cost in a production process to achieve a desired level of output using current technological constraint (Coelli et al., 2005). Given the value of technical efficiency, the overall cost efficiency (CE) can be written as a product of technical and allocative efficiency values (Coelli et al., 2005):

$$CE = TE \times AE \tag{3.1}$$

It can be maintained that only an analysis of the values of all three types of efficiency will lead to a more meaningful and complete picture of the efficiency of the airlines concerned. The positive impacts of airline size and business model (implying the different cost structures adopted by airline companies in their operations such as low cost or full service) on technical efficiency is well documented in existing literature. What is lacking prior to Merkert and Hensher (2011) however, is an in-depth study on allocative and cost efficiency, which is not fully understood at present.

Merkert and Hensher (2011) add to this literature by looking at the potential impact of fleet mix on the cost efficiency of airlines. They show that airline size and key fleet mix characteristics have significant impact on all three types of airline efficiency and are consequently more relevant to successful cost management of airlines than other effects of route optimisation. Average stage length for example, is found to be limited to airline technical efficiency only. Their analysis includes fifty-eight international passenger airlines over the two fiscal years of 2007/2008 to 2008/2009, ten of which are U.S. airlines. Importantly, they note that none of the previous studies on airline efficiency recognise the potentially significant impacts of fleet mix and stage length on all three areas of efficiency. It is therefore clear that there is a gap in the literature regarding these kinds of questions. Therefore, the motivation for this chapter stems from the evolving trend in studies looking at airline efficiency while further developing the very limited literature on impacts of fleet mix and stage length. Particular focus is on U.S. airlines and a more recent and longer time period.

Stochastic frontier analysis has also been used in the airline literature mostly from a production function perspective with a focus on technical efficiency only. In addition, few have adjusted their functions to account for environmental/characteristic influences such as those presented here. Coelli et al. (1999) obtain results for technical efficiency of thirty-two international airlines from 1977 to 1990 using a stochastic frontier production function, comparing two approaches. The first assumes that characteristic (also referred to as “environmental”) factors influence the shape of the technology while the other assumes that they directly influence the degree of technical inefficiency. Characteristic variables considered include stage length, aircraft size and load factor, which they note are unlikely to capture all characteristic influences. Both sets of results provide similar rankings of airlines but lead to differing degrees of technical inefficiency. They observe that this study is the first empirical analysis to apply these two approaches and that future work is needed in order to shed some light on the generality of the results found in their study.

Several authors have studied cost elasticities on the basis of an econometric study of airline cost functions, typically using the translog functional form. These studies include, but are not limited to Caves et al. (1984), Gillen et al. (1990), Atkinson and Cornwell (1994), Inglada et al. (2006), Ryerson and Hansen (2013) and Zou and Hansen (2012). In Table 3.1 some of these studies are summarised and the inclusion of characteristics variables are highlighted. As it can be seen, these characteristic variables were included as regressors in the cost functions themselves. Typically, stage length and load factor were the variables most often included. Only those input variables which match those in the study here are reported in order to make a comparison for the SFA results in Section 3.5.

Finally, despite the mounting literature investigating technical efficiency in airlines, there is none (with the exception of Merkert and Hensher 2011) examining the potentially significant impacts of fleet mix characteristics and stage length on technical, allocative and cost efficiency. There are also no studies which address those characteristics while accounting for the panel structure of that data, which is best done using SFA models. This study gives emphasis to U.S. airlines only, including a larger number of carriers and a longer more up to date time period than in Merkert and Hensher (2011). However, this study aligns with the two fiscal years of 2007/2008 and 2008/2009 of Merkert and Hensher (2011) and keeps the time period from 2006-2012 in order to avoid complex modelling issues when considering data availability on characteristic variables.

Table 3.1: Studies on Airlines Cost function and their reported coefficients

Authors	Variables (Output-Input)	Sample
Caves et al. (1984)	Output: - TKA (0.804) Inputs: - Labour price (0.356) - Fuel price (0.166) - Material/capital price (0.478) Characteristic: - Average stage length (-0.148) - Load factor (-0.264) - Aircraft size (0.153)	U.S. (15) 1970-1980
Gillen et al. (1990)	Output: - RPK+RTK (0.971) Inputs: - Labour price (0.322) - Fuel price (0.199) - Material/capital price (0.478) Characteristic: - Average stage length (-0.181) - Load factor (0.734)	Canadian (7) 1964-1981
Atkinson and Cornwell (1994)	Output: - ATM (-0.940) Inputs: - Labour price (0.750) - Materials (0.521) Characteristic: - Average stage length (1.477) *All significant at the 10% level	U.S. (13) 1970Q1- 1981Q4
Inglada et al. (2006)	Output: - ATK (0.679) Inputs: - Labour price (0.106) - Material/capital price(0.373/0.291) Characteristic: - Average stage length* - Average load factor* *Characteristics variables dropped due to insignificance	Internationals (20) 1996–2000
Ryerson and Hansen (2013)	Inputs: - Labour price (0.296) - Fuel Price (0.408) - Materials price (0.302)* Characteristic: - Average stage length (0.803) - Average Age (0.037) - Seats (0.400) *Insignificant	U.S. (26) 1996-2006
Zou and Hansen (2012)	Output: - RTM (0.4875) Inputs: - Labour price (0.3858) - Fuel Price (0.2016) - Materials/capital price (0.4126/-0.0547) Characteristic: - Average stage length (-0.2172)	U.S. (9) 1995-2007

3.3. Methodology and model specification

Methods of measuring efficiency can be broadly classified into two methods: non-parametric, and parametric. Non-parametric approaches include indices of partial and total factor productivity, and data envelopment analysis (DEA). DEA is essentially a linear programming based technique. Parametric methods involve the estimation of stochastic cost and production functions, for example stochastic frontier analysis.

This chapter follows Merkert and Hensher (2011) and applies a two-stage DEA efficiency approach to determine impact factors on airline efficiency. For the first stage bootstrapped and non-bootstrapped DEA approaches are used to measure the efficiency of the airlines in the sample (for details on bootstrapping see (Simar and Wilson (1998) Simar and Wilson (2007)). This is followed by a second stage random effects Tobit regression models. The intent here is to analyse and evaluate the impact that strategic management and fleet planning have on the three areas of efficiency (technical, allocative and cost). Measures of cost efficiency from a stochastic frontier cost function which has been adjusted to account for characteristic variables are then compared to results in the DEA analysis.

The measurement of efficiency began with Farrell (1957), who defined a simple measure of firm efficiency that took into account multiple inputs. DEA was first proposed by Charnes, Cooper and Rhodes (Charnes et al., 1978), who built on the frontier concept initiated by Farrell (1957). The model they specified was the first to be widely applied, having an input orientation and assuming constant returns to scale

(CRS). DEA is based on a linear programming technique to measures the relative efficiencies of Decision Making Units. It constructs a non-parametric frontier over the observed data, and efficiency measures are constructed relative to this frontier. Therefore, DEA optimises at each observation for constructing an efficient frontier, the maximum output empirically obtainable for any decision-making unit (in this case airlines) in the data, given its level of inputs.

The cost frontier is defined by Forsund et al. (1980) as the minimum cost for a particular level of output, given the technology and the prices of the inputs used. Following the methodology developed by Schmidt and Sickles (1984) using panel data, presented below is a single equation cost function. The stochastic cost frontier function for panel data, for the i^{th} airline (*i*=1,2,…,N) during the t^{th} period (*t*=1,2,..,T) is defined as:

$$C_{it} = \alpha + C(P_{it}, Y_{it},; \beta) + \ v_{it} + u_i \quad (3.2)$$

Here C is the observed cost; α is the constant; P is the input price vector; Y is the output and β represents parameters to be estimated. The term $v_{it} + u_i$ is a composite error term with v_{it} representing statistical noise (or randomness). The error component for statistical noise is assumed to be independently and identically distributed, with zero mean and constant variance. The term u_i in this case is the cost inefficiency of cost for the i^{th} airline company with properties,$u_{it} \approx iidN^{+}(0, \sigma_\mu^2)$. It then follows that $u_{it} \geq 0$ for all$i$, and that it is identically distributed with mean μ and variance σ_μ^2 and is independent of v_{it}.

When dealing with a cost frontier, firms that lie on the frontier are efficient, with firms above the frontier being inefficient. The most cost efficient firms will be directly on the frontier and so it is undesirable to be above the frontier. When obtaining efficiency estimates from frontier models, values closest to 1 represents a more efficient firm and values closer to zero represent firms that are less efficient. Therefore, a value between 0 and 1 denotes the degree to which an airline succeeds in minimizing cost given input and output prices. For the purpose of this chapter, cost efficiency can be written as follows:

$$CE_{it} = \exp(-u_{it}) \tag{3.3}$$

3.3.1. Data Envelopment Analysis

A DEA production frontier can be operationalised non-parametrically either with an input or output orientation, under the alternate assumptions of constant returns to scale (CRS) or variable returns to scale (VRS). An input oriented function fits more naturally in this case, as it assumes that the airlines have a greater influence on the inputs rather than their outputs. Output volumes are heavily influenced by macro-economic factors and are often determined well in advance by long-term slot contracts.

The input-oriented CRS model and efficiency score for firm i in a sample of I firms is estimated through the following equation (Coelli et al., 2005):

$$
\begin{aligned}
&\min_{\theta,\lambda} \theta, \\
&\text{s.t} -q_i + Q\lambda \geq 0 \\
&\theta x_i - X\lambda \geq 0 \\
&\lambda \geq 0
\end{aligned} \tag{3.4}
$$

where λ represents the weights for the inputs and outputs which is a $I \times 1$ vector of constants. X and Q are input and output matrices, and θ measures the observed distance between the observations x_i and q_i and the frontier (where the frontier represents efficient operation). More simply, the distance of θ obtained is the efficiency score for the i^{th} firm. It satisfies $\theta \leq 1$, with a value of 1 indicating a point on the frontier and therefore representing an efficient firm located on the deterministic frontier, according to the Farrell (1957) definition. The linear programming problem must be solved I times, once for each firm (airline company) in the sample and a value of θ is then calculated for each firm.

The main drawback to the CRS model is that this assumption is only appropriate when firms are operating at their optimal scale, which is unlikely in the airline industry with considerable evidence of on-going structural change (Lee and Worthington, 2014). Imperfect competition and financial/regulatory constraints are factors, which contribute to firms not operating at their optimal scale. This was demonstrated in the U.S. airline industry of the early 2000s with many airlines operating under Chapter 11 bankruptcy protection and facing borrowing constraints. In addition to these reasons, the data set includes airlines of a range of sizes.

Therefore, as well as the CRS, an estimation of the efficiency scores for the assumption of VRS is undertaken. In order to ensure that inefficient firms are only benchmarked against firms of a similar size, the VRS evaluation must adopt an additional convexity constraint ($I1'\lambda = 1$). For technical efficiency, by calculating and comparing CRS and VRS scores, any observed differences would indicate scale inefficiency. While CRS and VRS models are calculated, VRS is likely to be the relevant model for analysis as it is difficult for airlines to change their scale of operation in the short run (Coelli and Rao, 2005). Therefore, as the evidence would suggest that the VRS scores are a more likely context than the CRS, allocative and cost efficiency scores focus on the VRS scores and the second-stage regressions are based on VRS scores only. Following Coelli et al. (2005), allocative and cost efficiency is estimated using:

$$\min_{\lambda, x_i^* w_i' x_i^*}$$

$$\text{s.t} - \mathrm{q_i} + \mathrm{Q}\lambda \geq 0$$

$$\xi^* - \mathrm{X}\lambda \geq 0$$

$$I1'\lambda = 1$$

$$\lambda \geq 0 \tag{3.5}$$

where w_i' represents a N×1 vector of input prices and x_i^* denotes the cost-minimising vector of input quantities for the i-th firm. The former requires pre-assigning and the latter is estimated by the linear programming technique. All other notions are as define for technical efficiency. Cost efficiency is therefore calculated as:

$$CE = \frac{w_i' x_i^*}{w_i' x_i} \quad (3.6)$$

And allocative efficiency is defined as the ratio of cost efficiency to technical efficiency:

$$AE = \frac{CE}{TE} \quad (3.7)$$

The second stage of the analysis follows previous work by Merkert and Hensher (2011). This applies a two-stage model, which regresses the first-stage DEA efficiency scores (dependent variable) against explanatory variables in the second stage.

The bootstrapped technical efficiency results are tested in addition to the conventional non-biased corrected efficiency scores in the second stage regression models. The reason for this is that unless the DEA efficiency scores are corrected by a bootstrapping procedure, a two stage approach will lead to inconsistent and biased parameter estimates (for example as a result of the dependence of the DEA efficiency scores on each other) (Simar and Wilson, 2007, Simar and Wilson, 2008). In addition, the SFA cost efficiency results are also tested. In the DEA literature, Tobit regression has been used to investigate whether performance would be affected by observation-specific variables. Following Merkert and Hensher (2011) the random effects Tobit regression model below is used, controlling for both cross-firm and time errors in the censored panel data set:

$$ES_{it} = \beta_1 AIRLINESIZE_{it} + \beta_2 AIRCRAFTSIZE_{it} + \beta_3 STAGELENGTH_{it} + \beta_4 FLEETAGE_{it} + \beta_5 AIRCRAFTFAMILIES_{it} + \beta_6 AIRCRAFMANUFACTURERS_{it} + time + v_{it} + u_i \quad (3.8)$$

where ES_{it} is the VRS efficiency score of the individual airlines *i* in the relevant year *t*. $AIRLINESIZE_{it}$ represents the available ton miles for that airline (used as a proxy for its size), $AIRCRAFTSIZE_{it}$ designates the average number of seats on the aircraft in service under the relevant airline in the relevant year, $STAGELENGTH_{it}$ indicates the average stage length that has been flown by the aircraft of the airline, $FLEETAGE_{it}$ reflects the age of the airline's fleet, and $AIRCRAFTFAMILIES_{it}$ describes the number of different aircraft families[13] (i.e. B747 or A380) of which the relevant airline fleet consisted of at that time. Finally, $AIRCRAFTMANUFACTURERS_{it}$ represent the number of different manufacturers in the airline fleet (e.g. Airbus or Embraer). As in Merkert and Hensher (2011), this analysis groups the aircraft at the aircraft family level (e.g. aircraft that the same pilots can fly) rather than the unique aircraft type level. Required assumptions of the random effects Tobit model are that the v_{it} is uncorrelated across periods, that the random effect u_i is the same in each period, and that all effects are uncorrelated across firms (see StataCorp, 2013).

[13] To illustrate, the A318, A319, A320, and A321 aircraft types are all part of the A320 family (with the A380 being the largest aircraft family) whilst at Boeing the aircraft types from B737-200 to B737-900 are, for example, all members of the B737 family (including ER (extra range) types). These criteria were sourced from the airline manufacturers' websites directly as well as U.S. DoT Form 41.

3.3.2 Stochastic Frontier Analysis

In the econometric estimation of cost frontiers, a functional form must first be specified. The cost efficiency results that are obtained depend critically on the model assumed. Therefore, specification and estimation of model parameters, which may not be of primary interest here, are nevertheless a major first step in the model construction process. A number of functional forms have been applied in empirical studies of airline costs. Among all the empirical implementations, the majority of analyses using SFA have employed the translog or Cobb-Douglas forms of production and cost. The most widely used flexible functional form in a cost minimizing framework is the translog cost function and therefore, this analysis presents results for the translog specification. Equation (3.9) describes the translog total cost stochastic frontier function. The deviation from the frontier occurs because of the random shocks and statistical noise (v_{it}) as well as technical inefficiency (u_{it}).

$$lnTC_{it} = \alpha \quad + \alpha_T t + \beta ln(Y_{it}) \; + \sum_j \gamma_j \ln\left(P_{jit}\right)$$

$$+ \frac{1}{2}\eta_{YY}[\ln(Y_{it})]^2 + \frac{1}{2}\sum_j \sum_k \phi_{jk} \ln\left(P_{jit}\right) \ln(P_{kit})$$

$$+ \sum_k \theta_{Yk} \ln(Y_{it}) \ln(P_{kit}) + v_{it} + u_{it} \tag{3.9}$$

and

$$u_{it} = \delta_1 AIRLINESIZE_{it} + \delta_2 AIRCRAFTSIZE_{it} + \delta_3 STAGELENGTH_{it} + \delta_4 FLEETAGE_{it} + \delta_5 AIRCRAFTFAMILIES_{it} + \delta_6 AIRCRAFTMANUFACTURERS_{it} + \theta_{it} \tag{3.10}$$

where $\ln TC_{it}$ is the total cost for airline a in time period t. On the right hand side, the first line contains all first order terms; second-order terms appear in the remaining lines. A time trend t is included; Y_{it} is the quantity of the output for airline i in time period t; P_{jit} the j^{th} input price for airline i in time period t.

In addition, Christensen et al. (1973) state that a translog cost function must satisfy certain regulatory conditions. These ensure that a cost function is consistent with cost minimisation. A cost function must be linearly homogeneous in the input prices, requiring the following restrictions to be imposed:

$$\sum_j \gamma_j = 1 \qquad \sum_j \phi_{jk} = 0(\forall k) \quad \sum_k \theta_{Yk} = 0 \tag{3.11}$$

where subscripts k refers to, respectively, the k^{th} input in the second and third sub-equations.

Equations (3.11) ensure that a proportional increase in all input prices results in a similar increase in total costs. These equations state that the first order coefficients for the input prices must sum to one, and that the second order coefficients involving input price must add to zero. The total cost and the regressors have all been transformed into natural logarithms. The data has also been demeaned such that the dependent and independent variables, including environmental characteristic variables, are estimated about the mean values in the dataset. This allows for the first order coefficients to be interpreted as cost elasticities evaluated at the sample mean.

In order to take into account the environmental characteristics variables, these factors are introduced as explanatory variables of economic inefficiency. Equation (3.3) is a one-sided term reflecting cost inefficiency. There are a number of assumptions with respect to the distributional assumptions of the inefficiency term and how airline characteristics and environments are modelled with regards to the stochastic frontier. Following the Battese and Coelli (1995) model for panel data, airline characteristics or environment factors enter as a set of covariates in the determination of the inefficiency term. The model assumes that the inefficiency effects are stochastic and directly impact on the mean of the inefficiency distribution. It also allows for the measurement of both technical (cost) changes in the stochastic frontier and time-varying technical (cost) inefficiencies. The distributional assumption on the inefficiency effects is truncated normal with non-zero mean and constant variance.

3.3.3. Strengths and weaknesses of SFA and DEA

Both the SFA and DEA methods are estimating the same underlying efficiency values but they can give different efficiency estimates for the units under analysis. This is due to differences in the underlying assumptions. Although the two approaches are traditionally thought to be competing there is no consensus as to which is the most appropriate technique; each has its own strengths and weaknesses (Coli et al, (2007). The main strength of DEA is that it is able (even for relatively small samples) to incorporate multiple inputs and outputs, and provides a scalar measure of relative efficiency by comparing the efficiency achieved by a decision-making unit (DMU) with the efficiency obtained by similar DMUs. As the implied frontier is derived from an observed data set (empirical observations), it measures the relative efficiency of DMUs that can be obtained with the existing technology, fleet strategy or managerial strategy. The first drawback of DEA, is that it assumes all deviations from the efficient frontier are due to inefficiency (including any statistical noise, measurement errors, omitted variables and other mis-specifications). As it is a nonparametric technique, statistical hypothesis tests are not possible.

The SFA technique in contrast, assumes that deviations from the efficient frontier can either be a result of inefficiency or random error. The main advantage of SFA is that there are a number of well-developed statistical tests to examine the validity of the model specification. Another benefit of SFA is that if an irrelevant variable is included, it will have a very small or possibly even a zero weighting in the calculation of the efficiency scores, allowing its impact to be insignificant.

3.4. Data and variables

The data set is composed of information obtained from U.S. Department of Transport (DoT) Form 41 for twenty- two airlines in the United States for the period 2006-2012. There are a total of 124 observations in the panel. This is due to some airlines having merged and dropped out over the time frame. The data used in the DEA calculations represents a panel of U.S. airlines, which have differing financial and operational characteristics. In line with previous studies and with Merkert and Hensher (2011) the major trade-off in airline management is assumed to be between capital and labour. Following Merkert and Hensher (2011), as both need to be operationalised available ton miles (ATM) is used as a proxy for capital and full-time equivalent (FTE) staff as the measure of labour. These are useful for the evaluation of technical efficiency as they are both physical measures. As the focus here is on all three aspects of efficiency, in order to account for the allocative and cost efficiencies, included are variables for the price of a unit of capital, proxied by capital price (found by dividing the sum of all operating costs[14], not including staff costs, by ATM) and average staff costs as the unit price of labour.

The first part of the analysis involves deriving a scalar measure of relative efficiency for 21 DMUs following Merkert and Hensher (2011). To do this, airlines are defined in all DEA models as producing two separate outputs; revenue passenger miles (RPM) and revenue ton miles (RTM).

Variables included as explaining inefficiency, which seek to capture fleet optimization, are number of different families of aircraft, number of different manufacturers in the fleet and fleet age. As mentioned previously, a more homogeneous fleet seems to allow airlines to keep costs lower for things such as crew, maintenance and safety etc. Therefore it is expected that as the variables for the number of manufacturers and number of aircraft families increase, total costs will also increase. This could be one reason why LCCs such as Southwest have only one type of aircraft (Boeing 737) in service. In contrast, airlines such as American Airlines and United Airlines have a substantial range of different families of aircraft in their fleet (7 and 8 respectively). It is therefore interesting to study whether the fleet mix has an impact on the airlines overall efficiency. Fleet age would be assumed to be correlated with fuel efficiency and is expected to increase costs as the age increases. There are differences among airlines in terms of seat configuration (number of seats in different

[14] Operating costs include rent/leasing charges and depreciation but do not include taxes and interest expenses.

classes, number of seats in each aisle, etc.). Merkert and Hensher (2011) find that number of seats has a positive effect on all three types of efficiency. They suggest that this is expected due to aircraft regulations. To illustrate, employees on staff (1 crew member per 50 seats is required) add to aircraft costs, regardless of whether these seats are filled or not. Stage length was chosen to evaluate the impact of route/network optimisation on airline efficiency whilst aircraft size was chosen to assess whether the earlier discussed productivity measures of individual aircraft would have an impact on overall airline efficiency. Both are typically found to be inversely related to costs in the airline literature. A description of these variables is found in Table 3.2 and descriptive statistics in Table 3.3.

Table 3.2: Variables for first and second stage DEA analysis

Variable Name	Variable Description
First stage DEA models	
Output	
RPM	Revenue passenger miles- One revenue passenger transported one km in revenue service. Revenue passenger miles are computed by summation of the products of the revenue aircraft miles on each inter-airport segment multiplied by the number of revenue passengers carried on that segment
RTM	Revenue ton miles - One revenue km transported one km
Inputs	
Labor (FTE)	Number of full time equivalent staff
ATM	Available ton miles (proxy for capital)-
FTE_Price	Price of a unit of labor (total costs spent on labor divided by FTE)
ATM_Price	Price of a unit of capital (determined by dividing the total capital costs by ATM)
Second-stage explanatory variables	
Airline Size (ASM)	Available seat miles- The aircraft miles flown in each inter-airport segment multiplied by the number of seats available for revenue passenger use on that segment
Stage length (km)	Average stage length- Revenue aircraft miles divided by revenue number of departures
Aircraft size (seats)	Average seats per aircraft across the operated fleet
Fleet age (years)	Age of the fleet
Aircraft families (#)	Number of different families of aircraft (example: A320 vs A380)
Aircraft manufacturers (#)	Number of different manufacturers (example: Airbus or Embraer)

Table 3.3: Descriptive statistics for first and second stage analysis

	N	Mean	Std. Dev.	Min	Max
First-Stage DEA models					
Output 2006-2012					
RPM (x 10^{10})	124	8.14	9.38	0.00297	35.9
RTM (x 10^{10})	124	0.904	1.08	0.00134	4.08
Input 2006-2012					
LABOUR (FTE)	124	236285.5	264196.8	2507.0	986301.0
ATM (x 10^{10})	124	1.47	1.76	0.00443	6.51
FTE_Price (USD/FTE)	124	1.698408	0.396194	0.784603	2.893865
ATM_Price (USD/ATM)	124	0.000561	0.000402	0.000137	0.003229
Second-stage explanatory variables 2006-2012					
AIRLINE_SIZE (ASM) (x 10^{10})	124	10.0	11.4	0.00646	43.3
STAGE_LENGTH (miles)	124	173944.3	239780.3	2566.929	1102827
AIRCRAFT_SIZE (seats)	124	125.9747	55.83600	8.330	289.75
FLEET_AGE (years)	124	8.232177	3.877793	1.640	23.57
AIRCRAFT_FAMILIES (#)	124	3.104839	2.155796	1	10
AIRCRAFT_MANUFACTURERS (#)	124	1.887097	0.921378	1	6

3.5. Results

The results for the first-stage DEA results are presented in Table 3.4. Following Merkert and Hensher (2011) the scores were estimated separately for each year in the data set. The results suggest that the airlines' average technical, allocative and cost efficiency deteriorated between 2007 and 2009, with another decrease in 2011. Similar results for the years 2008-2009 were found in Merkert and Hensher (2011) who covered the two fiscal years 2007/2008 and 2008/2009. They suggest that this decrease in efficiency can be explained by the fact that airlines faced a more difficult business environment in 2008/2009 compared to 2007. The year 2008 saw the beginning of the global financial crisis with high and very volatile fuel prices and a number of airline failures. During this time for example, Continental and Southwest Airlines, who were two of the most reputable U.S. airlines, announced that fuel costs had led to lower than expected quarterly earnings and they responded by lowering their growth plans.

As in Merkert and Hensher (2011), and following Simar and Wilson (1998) a bootstrap approach to generate a set of bias-corrected estimates of our first-stage DEA efficiency scores is performed. The bias-corrected efficiency scores are preferred over the original DEA scores since bias-corrected efficiency scores improve the robustness of the second-stage regression results. Values for the uncorrected average technical efficiency scores (TE^{VRS}) are as expected and are higher than those for the bias-corrected scores (TE_{CORR}^{VRS}).

This confirms that a traditional DEA model, without the bootstrapping approach, will generally overestimate technical efficiency for the sample. All DEA estimates are computed using the software package DEAP 2.1 (Coelli et al., 2005) except the bootstrapped scores, which were calculated using the FEAR 2.0 (Wilson, 2013) package. While DEAP 2.1 can provide calculations for cost, allocative and technical efficiency, it is not able to apply any bootstrapping procedures. The benefit of FEAR 2.0 is that it is able to provide bootstrapped results. These packages were chosen in order to stay consistent with the methodology in Merkert and Hensher (2011).

Table 3.4: First stage DEA results

	Computed with DEAP 2.1			Computed with FEAR	
Year	TE^{VRS}	AE	CE	TE^{VRS}	TE^{VRS}_{CORR}
2006	0.9015	0.9525	0.8589	0.9015	0.8494
2007	0.9049	0.9518	0.8606	0.9049	0.8483
2008	0.8995	0.9525	0.8565	0.8996	0.8367
2009	0.9056	0.9716	0.8810	0.9057	0.8385
2010	0.9425	0.9521	0.8986	0.9425	0.8964
2011	0.9117	0.9642	0.8801	0.9116	0.8512
2012	0.9286	0.9811	0.9128	0.9286	0.8718
Average 2006-2012	0.9120	0.9600	0.8760	0.9119	0.8543
Av. 2006-2012 Results by Airline					
Northwest	1	0.9020	0.902	1	0.9089
Southwest	0.9453	0.9327	0.8843	0.9453	0.8898
Horizon	0.8425	0.9553	0.806	0.8425	0.8042
Hawaiian	0.8627	0.8757	0.7516	0.8628	0.8158
Continental	1	1	1	1	0.9181
Delta	0.9894	0.9690	0.9593	0.9893	0.9176
American	0.9791	0.9986	0.9777	0.9791	0.9018
Alaska	0.8723	0.9952	0.8675	0.8723	0.8344
United	1	0.9659	0.9659	1	0.9177
American West	0.849	0.9940	0.8440	0.8493	0.8110
Air Wisconsin	0.7046	0.9396	0.6566	0.7044	0.6649
SkyWest	0.8350	0.9560	0.7983	0.8351	0.8056
ATA	0.7960	0.9460	0.7520	0.7955	0.7562
Midwest	0.8053	0.9917	0.7983	0.8052	0.7599
US Airways	0.8906	0.9853	0.8781	0.8905	0.8471
Allegiant	1	1	1	1	0.9082
Eagle	0.8257	0.9324	0.77	0.8257	0.7963
Jet Blue	0.9999	0.9729	0.9726	0.9998	0.9424
Comair	0.8082	0.9365	0.7568	0.8084	0.7766
Air Tran	0.9711	0.9969	0.9683	0.9713	0.9184
USA Jet	1	1	1	1	0.8931
Virgin	0.9510	0.8625	0.8135	0.9509	0.8721

In terms of TE_{CORR}^{VRS}, the most efficient airline in our sample is Jet Blue followed by Continental/Delta/United and Air Tran[15]. A number of airlines, including American, Alaska and Air Tran were among the highest ranking in terms of *AE*, with Continental, Allegiant and USA Jet scoring most efficient at *AE* = 1. Comair and Northwest demonstrate efficiency scores which were quite poor relative to the rest of the airlines. In terms of *CE*, Continental, Allegiant and USA Jet also all come out most efficient with a score of 1, with Comair Hawaiian and ATA lowest around the 0.75 mark.

The stochastic frontier analysis results are presented in Table 3.5 and Table 3.6. Table 3.5 presents the estimation results obtained for the translog stochastic frontier regression. The second-stage regression results for the DEA model are summarised together with the SFA model results, which can be found in Table 3.8. The variable for number of aircraft manufacturers had to be dropped due to its strong correlation with the variable for number of families. The variable available seat miles (ASM) was also dropped due to strong correlation. Based on the partial correlation coefficients between the remaining explanatory variables, no other multi-collinearity issues were found. A further discussion of the results is found following these Tables.

[15] Now Southwest Airlines.

Table 3.5: Stochastic frontier analysis results

Variable	Coefficient	Standard error
lnRPM	0.1335	0.2210
lnRTM	0.8586	0.2133***
lnATMprice	0.8709	0.0406***
½(lnRPM)^2	-2.9296	0.7035***
½(lnRTM)^2	-4.3825	0.9554***
½(lnATMprice)^2	0.0392	0.0569
lnRPMlnRTM	3.6632	0.8289***
lnRPMlnATMprice	1.2835	0.3371***
lnRTMlnATMprice	-1.2583	0.3300***
Time	-0.0096	0.0043**
Constant in the equation of cost inefficiency	-0.5392	0.1085***
Usigma		
lnSTAGE_LENGTH	-0.3079	0.0403***
lnAIRCRAFT_SIZE	-0.1499	0.0787*
lnFLEET_AGE	0.5934	0.1039***
lnAIRCRAFT_FAMILIES	0.0838	0.0624
$\boldsymbol{\sigma_u^2}$	0.0039	0.0212***
$\boldsymbol{\sigma_v^2}$	0.0063	0.0061***
$\boldsymbol{\lambda = \frac{\sigma_u^2}{\sigma_u^2 + \sigma_v^2}}$	0.3854	0.0241***

Log (Likelihood) 130.1359
*Variables are significant at the 10% level.
**Variables are significant at the 5% level.
***Variables are significant at the 1% level.

The individual coefficients reflect the sensitivity of airline total costs to various regressors at the sample mean. The first-order coefficient for the input price indicates that at the sample mean, capital inputs account for 87.09% of the airlines total costs. As the capital input price variable takes into account all operating costs, other than staff costs, this is similar (though slightly higher) to results found in previous literature that report capital and materials combined, to be around 50-70% of costs. The higher value on our capital input is likely due to the fact that we do not include fuel costs into the analysis. As the model was divided through by labour input price, this leaves the labour input to account for 12.91% of the total costs, and follows previous literature where it is reported as anywhere between 10-40% of costs.

The estimated coefficients of the characteristics variables cannot be interpreted the same way in terms of magnitude as those of the input prices. As discussed in Battese and Coelli (1995) the focus in on the sign of the coefficient of a characteristic variable, which illustrates the impact on inefficiency. Therefore, in order to interpret the impact on efficiency the signs must be reversed. With this specification, the coefficients on stage length and aircraft size indicate a positive impact on the cost efficiency of airline companies, which is consistent with expectations and confirms results found in our DEA analysis and in Merkert and Hensher (2011). Fleet age is found to have a negative impact on efficiency, or in other words older fleets are less cost efficient than younger ones. These are consistent with the predictions made in Merkert and Hensher (2011) but do not follow their results, which suggest (counter-intuitively) that average fleet age has a significant positive impact on cost efficiency. Finally, though aircraft families was found to be insignificant, it displayed a positive sign consistent with previous findings.

Results presented here have incorporated the characteristic variables as transformed de-meaned logs. Alternative models for the specification of the inefficiency term were estimated for a total of five variations, but all were rejected due to a higher log-likelihood on the preferred model presented here. The tested models are as follows: Model 1 which includes characteristic variables as de-meaned logs in the inefficiency term, model 2 has characteristics as logs in the inefficiency term, model 3 including logged stage length in the frontier and all other characteristics as logs in the inefficiency term, model 4 with all characteristics variables untransformed in the inefficiency term and model 5 which includes the characteristic variables as de-meaned logs in the frontier. In model 4 without any transformation, the variable average stage length was dropped due to the estimation running only without the inclusion of this variable. On the basis of these results, a correlation analysis is presented among the five measures obtained. The results appear in Table 3.6. In this table a high correlation is observed between all five models (with the exception of model 2), suggesting that the exact specification of the characteristic variables is not significant enough to impact results. Perhaps unexpectedly, model 2 produced unreasonable and insignificant coefficients on all variables. The lowest correlations are those associated with the scores obtained from this model, which includes characteristics as logged de-meaned variables in the inefficiency term. The key point to make is that the selection of method does not have a significant impact upon the size of the efficiency scores obtained, apart from the model logging characteristic variables. Therefore, model 1 is presented as it provides the most sensible and statistically significant estimates of the characteristics variables and has the highest log-likelihood.

Table 3.6: Correlation among alternative SFA efficiency measures

	Model 1	Model 2	Model 3	Model 4	Model 5
Model 1	1.0000				
Model 2	0.4108	1.0000			
Model 3	0.9125	0.3659	1.0000		
Model 4	0.9132	0.3664	0.9999	1.0000	
Model 5	0.6578	0.3487	0.6154	0.6191	1.0000

The significant estimate on the parameter, lambda, indicates the relative contribution of the variance in the inefficiency term compared to the variance in random noise, and indicates that inefficiency is in fact present in the model. Generalised likelihood-ratio tests[16] of the null hypothesis, that the inefficiency effects are absent or that they have simpler distributions, are presented in Table 3.7. These tests follow the methodology in Battese and Coelli (1995). The first null hypothesis, which specifies that the inefficiency effects are not present in the model, is strongly rejected. The second null hypothesis, which specifies that the inefficiency effects are not stochastic, is also strongly rejected. The third null hypothesis specifies that the inefficiency effects are not a linear function of the average stage length, aircraft size, the aircraft's average age and aircraft families. This null hypothesis is rejected at the 5% level of significance. This indicates that the joint effect of these four characteristic variables on the inefficiency of cost is significant, although the individual effects of one or more of these variables may not be statistically significant. The inefficiency

[16] The likelihood ratio test statistic, LR = -2ln(L(m1)/L(m2))=2(ll(m2)-ll(m1)), where L(m*) denotes the likelihood of the respective model, and ll(m*) the natural log of the models' likelihood. This statistic is distributed chi-squared with degrees of freedom equal to the difference in the number of degrees of freedom between the two models (i.e. the number of variables added to the model).

effects in the stochastic frontier are clearly stochastic and are not unrelated to the stage length, size, age and number of families of the airlines. It can therefore be shown that the presented inefficiency stochastic frontier cost function is the preferred model in terms of the results (i.e. it is an improvement over the stochastic frontier which does not involve a model for the inefficiency effects and other tested models).

Table 3.7: Tests of hypothesis for parameters of the inefficiency frontier model[17]

Null Hypothesis	Test statistic*	$\chi^2_{0.95-value}$	Decision
$H_0: \gamma = \delta_0 = \cdots = \delta_4 = 0$	131.435	12.592	Reject H_0
$H_0: \gamma = 0$	81.576	5.991	Reject H_0
$H_0: \delta_1 = \delta_2 = \delta_3 = \delta_4 = 0$	32.260	9.488	Reject H_0

Table 3.8 summarises the annual SF cost efficiency scores obtained from 2006 to 2012 for each individual airline. The cost efficiency scores indicate stable growth for some but not others. To be able to face a more competitive environment, most airlines were forced to restructure their aircraft fleet and their network flight destinations during the financial crisis that began in 2008. Delta, Continental, Hawaiian and Horizon demonstrate the best improvement in cost efficiency over the

[17] The log-likelihood values are as follows: OLS = 64.42, OLS with inefficiency terms = 89.35, a pooled model with no inefficiency effects = 114.01. These were all tested against the BC95 full model presented here with LL= 130.14. The calculations for the test statistics are as follows: The first null hypothesis, which specifies that the inefficiency effects are not present in the model (df=6); -2*((64.418397)-(130.1359)) = 131.435. The second null hypothesis which specifies that the inefficiency effects are not stochastic (df=2); -2*((89.348054)-(130.1359)) = 81.576. The third null hypothesis specifies that the inefficiency effects are not a linear function of the average stage length, aircraft size, the aircraft's average age and aircraft families (df=4); -2*((114.00614)-(130.1359)) = 32.260.

period. Conversely, JetBlue, Comair and Eagle present some reductions in CE over the period.

A comparison of the average efficiency scores obtained from SFA with those found in DEA demonstrates a relatively low correlation with a value of 0.46. This could be due to the fact that some airlines (America West and ATA) report for only one year each.

Table 3.8: Cost efficiency results from stochastic frontier analysis[18]

	2006		2007		2008		2009		2010		2011		2012	
Airline	**SFA**	**DEA**	**SFA**	**DEA**	**SFA**	**DEA**	**SFA**	**DEA**	**SFA**	**DEA**	**SFA**	**DEA**	**SFA**	**DEA**
Northwest	0.994	0.896	0.993	0.912	0.990	1.000	0.656	0.959						
Southwest	0.994	0.865	0.996	0.873	0.991	0.995	0.618	0.962			0.869	0.949	0.991	0.983
Horizon	0.994	0.866	0.996	0.990	0.991	0.995	0.484	0.977	0.992	0.999	0.745	0.941		
Hawaiian	0.995	0.981	0.996	1.000	0.991	1.000	0.443	0.753	0.992	0.993	0.700	0.854	0.988	1.000
Continental	0.974	0.857	0.996	1.000	0.991	0.998	0.422	0.981	0.992	0.995	0.994	0.969		
Delta	0.951	0.863	0.996	1.000	0.992	1.000	0.414	1.000	0.992	0.996	0.993	0.930	0.991	1.000
American	0.943	0.878	0.996	1.000	0.993	0.999	0.938	0.958	0.992	0.996	0.994	0.934	0.980	1.000
Alaska	0.936	0.998	0.996	1.000	0.994	0.997	0.927	0.963	0.995	1.000	0.993	0.987		
United	0.934	1.000	0.996	1.000	0.994	0.999	0.883	0.960	0.994	1.000	0.993	0.992	0.970	1.000
America West	0.972	1.000												
Air Wisconsin	0.790	0.941	0.993	0.911	0.993	0.978	0.865	0.962	0.994	1.000	0.991	1.000	0.622	1.000
SkyWest	0.820	0.950	0.993	0.926	0.995	0.983	0.836	0.968	0.991	1.000	0.989	0.998	0.680	1.000
ATA	0.801	0.952												
Midwest	0.800	0.951	0.993	0.946	0.993	0.968								
US Airways	0.832	1.000	0.993	1.000	0.994	0.945	0.883	0.962	0.991	1.000	0.843	0.944	0.622	1.000
Allegiant	0.855	0.938	0.995	1.000	0.993	0.975	0.864	0.919	0.992	1.000	0.822	0.939	0.457	1.000
Eagle	0.995	0.849	0.995	1.000	0.994	0.941	0.995	0.946	0.992	1.000	0.813	0.950	0.996	0.827
Jet Blue	0.994	0.796	0.995	1.000	0.992	0.949	0.987	0.992	0.929	0.944	0.765	0.940	0.994	0.795
Comair	0.994	0.781	0.991	1.000	0.995	1.000	0.982	0.991	0.956	0.945	0.767	0.934		
Air Tran	0.992	0.929	0.991	1.000	0.983	0.994	0.937	0.992	0.956	0.951	0.730	0.912	0.996	0.831
USA Jet			0.989	1.000	0.784	0.945	0.992	0.926			0.994	0.997		
Virgin							0.991	0.992	0.909	0.943	0.992	0.998	0.995	0.997
Average	**0.928**	**0.915**	**0.994**	**0.975**	**0.992**	**0.984**	**0.773**	**0.956**	**0.983**	**0.988**	**0.875**	**0.948**	**0.857**	**0.953**

18 Note that all scores are “gross” scores

As Table 3.9 shows, the second-stage regression models based on the DEA efficiency scores produced varied statistically significant results. The coefficients, based on the SFA cost efficiency scores, have been discussed in detail in the previous Section. From the DEA results, Time having a significant positive impact on cost efficiency is found and is expected, mainly as a result of the rising fuel cost over the analysed period. This is not found in the SFA results which report a negative and significant value of -0.0096. Stage length has a positive and significant impact on both cost and allocative efficiency. This result is also found in the SFA cost efficiency results as well as in Merkert and Hensher (2011), although their findings were not significant. These results confirm the prediction that longer sectors result in lower unit costs due to increases in fuel efficiency. The size of the airline displays a relatively small positive impact on technical efficiency, but is not significant. Merkert and Hensher (2011) find a positive and significant result on size and note that this positive sign seems counterintuitive at first. However, if this result is considered from an entire fleet perspective, it is apparent that new fuel-efficient aircraft are expensive in terms of depreciation. As most US airline fleets consist of earlier generation planes (the first Boeing 737 entered service in 1968), they are probably fully depreciated and therefore represent no further capital cost). Turning now to the results on the age variable, it is only found significant in the SFA case and is positive, which indicates it has a negative effect on cost efficiency. This is expected as typically younger aircraft tend to be more fuel-efficient and older fleet are less cost efficient in comparison. For example, the youngest aircraft in the sample (Virgin Airlines with an average age of eighteen months) are seen to be comparatively efficient. As noted in Merkert and Hensher (2011), in 2008 North American Airlines retired a large number of their older aircraft from service (primarily the least fuel efficient ones). Those airlines with relatively older fleets subsequently became more allocatively and cost efficient. Aircraft families has a significant negative impact on cost efficiency, though is not found to be significant in our DEA results. This negative coefficient would suggest that more homogeneous fleets, or airlines with fewer families, tend to be more cost efficient.

Table 3.9: Second-stage truncated regression based on DEA scores and SFA scores

	TE_{CORR}^{VRS}	TE^{VRS}	CE	AE	SFAce
Constant	0.77077***	0.81559***	0.95637***	0.78767***	-0.53918***
TIME	0.001339	-0.00001	0.00539**	0.00560	-0.00959**
STAGE LENGTH	5.08e-08	7.26e-08	6.82e-08*	1.29e-07*	-0.30789***
AIRCRAFT_SIZE	0.00053***	0.00055**	-0.00014	0.00035	-0.14990*
FLEET_AGE	0.00115	0.00281	-0.00194	0.00026	0.59338***
AIRCRAFT_FAMILIES	-0.00263	-0.00332	0.00159	-0.00136	0.08377
Sigma (u)	0.04793***	0.06245***	0.03696***	0.80520***	-5.53118***
Sigma (v)	0.06685***	0.07260***	0.03840***	0.07096***	-5.06481***

Both SFA and DEA have produced similar coefficient results on environmental variables from the data as seen in Table 3.9. Both techniques provide the same magnitude effects for stage length, fleet age and aircraft families. This concordance is reassuring. However, this study finds that the results for cost efficiency from applying SFA and DEA lack some consistency in the cost efficiency scores (as seen by the low correlation between the output), despite the use of exactly the same variables and data. Despite this, both models demonstrate a similar pattern in the direction of the trend for the efficiency scores as seen in Table 3.8. There are two main reasons for discrepancies in the efficiency estimates derived from the two broad analytical approaches. The first are differences in how the techniques establish and shape the efficiency frontier, while the second is due to differences in how the techniques determine how far individual observations lie from the frontier (Coelli et al., 2005). Considering the strengths and weaknesses of the two techniques, the following observations are specific to the objective of measurement of cost efficiency. Both SFA and DEA can estimate cost efficiency scores, and while the scores themselves may not be highly correlated; the movement (increase or decrease) from year to year of these scores are comparable. As far as coefficient results, SFA and DEA magnitudes are quite similar, although SFA produces more significant values.

3.6. Conclusion

This study applies multiple efficiency measurement methods to analysing the impact of aircraft characteristics on airline efficiency from a technical, allocative and cost perspective. In the first stage, a DEA analysis is used in order to derive efficiency scores for the three aspects of efficiency. Bootstrapped technical efficiency scores are then calculated in order to form a comparison with non-bootstrapped scores. A second stage Tobit regression model is then presented. As in Merkert and Hensher (2011), our findings establish that bootstrapping of the first-stage efficiency scores does not greatly improve the second-stage random effects Tobit regression results. This re-iterates that regression results based on non-bias corrective technical efficiency are as dependable as the regression results of the bias-corrected scores.

Previous studies of airline efficiency largely focused only on the technical efficiency side in a DEA context from either a single or a small number of years. By studying a larger number of years and further including a stochastic frontier approach, this study simultaneously estimates the cost efficiencies and the factors that determine it.

Measures for cost efficiency are obtained from a stochastic frontier cost function which has been adjusted to account for the characteristic influences presented in the DEA and Tobit analysis. In comparing the results from the SFA analysis with the DEA Tobit regressions, we observe that the SFA produces similar estimates but is found to be more robust in terms of significance. Results are also comparable and consistent with those found in Merkert and Hensher (2011). A comparison of the efficiency scores obtained from SFA with those found in DEA demonstrates a very low correlation. This could be due to the fact that some airlines (America West and ATA) report for only one year each.

The findings for the impact of the age of the airlines' fleets are somewhat inconsistent. The Tobit results confirm those found in Merkert and Hensher (2011) and suggest that a younger fleet does not necessarily result in higher efficiency. SFA results on the other hand, find a highly significant negative relationship between efficiency and age with older aircraft being less efficient than younger ones. Aircraft size shows that the impact of aircraft size on cost and technical efficiency is positive. Stage length was found to have a positive impact on cost and allocative efficiency and is consistent with much of the previous literature. This should be interpreted as the effect on the cost efficiency of flying fewer passengers over a longer stage length (route distance) each to achieve the same level of output. Conversely, and rather surprisingly, the number of aircraft families has no significant impact on any of the three efficiency measures.

It is important to note that the observations in this study are not a perfect empirical analysis. One point worth noting is that the four environmental variables used here may not fully capture all characteristic influences. For example, the inclusion of a network size variable, such as number of points served is often included in previous studies. This analysis, however, is the first attempt to investigate DEA, Tobit analysis in the airline efficiency literature alongside SFA. Therefore future work is needed in order to further validate the detected determinants in this study.

4. Chapter 3: An efficiency analysis of the integrated air cargo industry in the United States: A Stochastic Frontier Approach for FedEx Express and UPS Airlines

4.1. Introduction

The past decade has seen a great increase in the demand for door-to-door shipment of products and packages, rather than just airport-to-airport service as in the early years of airfreight transportation. In addition to the door-to-door shipments, there has been an increase in the demand for fast, overnight service. As a result, air cargo companies have developed (separately from passenger airlines) and expanded quickly while simultaneously strengthening their presence in the airline industry. In so doing, they have become significant to the airline industry (as it relates to airport operators and plane manufacturers). Within the integrated[19] express air cargo sector, the industry has become highly concentrated. The air cargo express market in the U.S. is estimated to generate $70 billion US$ each year. It transports goods worth in excess of $6.4 trillion US$ annually[20] and the market is expected to continue its fast growth in the near and medium term (IATA, 2014). According to the Organisations for Economic Cooperation and Development (OECD), the value of air cargo accounts for more than 33% of the world trade merchandise, while the weight of this airfreight is only 2% of all the total cargo moved worldwide. In a world where time pressures are increasing value, the share of air cargo is steadily increasing commensurately. It is therefore

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[19] "Airlines typically market their freight transportation - the airport-to-airport link- to freight forwarders. Integrators, in contrast, market their logistics solutions directly to shippers, offering an integrated transport chain with door-to-door service. Integrators thus act both as forwarders and carriers. They often have their own trucking and aircraft fleet and provide all the handling services themselves." Source: © 2010 Eno Transportation Foundation. www.enotrans.com | 209 Reprinted from Intermodal Transportation: Moving Freight in a Global Economy. Accessed: 05/09/2014.

[20] http://www.iata.org/whatwedo/cargo/Pages/index.aspx

important to examine elements associated with the costs of air cargo services in order to determine the implications for U.S. operators and policy makers in terms of international trade, as well as (by extension) for global companies.

The four largest airfreight integrators in the world today are FedEx, UPS, TNT Express NV, and DHL Express (DHL). Integrators carry the majority of the market share of U.S. air freight, with DHL, FedEx and UPS holding around 62% of air revenue-tons of freight (Bureau of Transportation Statistics 2010). FedEx is undeniably the largest cargo carrier in the world, with 2014 revenues at the corporation totalling $45.6 billion US$[21].

Despite the high level of concentration, the integrated air freight industry is highly competitive in a number of aspects, such as delivery speed, service dependability and service convenience. This chapter will focus on the FedEx and UPS airlines, which together hold the majority of the market share in North America and represent a dominant position in the air cargo industry. FedEx and UPS have obtained a large share of the smaller cargo shipments by responding to the consumer's need for guaranteed service with late pick up or early delivery, and with direct shipments all over the world to support the model of "just-in-time" manufacturing logistics and supply chain management.

The purpose of this study is threefold. The first is to investigate the cost structure of the leading integrated carriers, FedEx and UPS airlines. Cost structures are important for firms considering growth strategies (alliances, adding new types of services etc.). Cost information plays a crucial role in decisions on pricing, investment

[21]Bloomsburg weekly: http://investing.businessweek.com/research/stocks/earnings/earnings.asp?ticker=FDX

levels, frequencies, size of vehicles and network structure. Airport slots are extremely competitive and can be very costly depending on the location and times of the day. International trade made possible by the air cargo industry has huge implications for economic growth in the U.S. Information about their cost structure is therefore extremely valuable for shareholders and government. The second is to compute the efficiency of FedEx and UPS and to explore the relative importance of factors that influence the cost and efficiency of these air cargo delivery services by way of stochastic frontier analysis (SFA). Finally, an evaluation of the economies of scale and density of these two air cargo carriers in the U.S. market is performed. In the airline literature, much attention has been focused on passenger airlines around the time of the Airline Deregulation Act (November 9, 1977). While the air cargo industry was deregulated a year prior to this, it did not result in nearly as much research interest in the ensuing years. To date, no study has taken a stochastic frontier approach to the analysis of air cargo efficiency. It thus becomes clear that there is a lack of information on cost efficiency for the air cargo industry. This chapter seeks to fill this gap in a number of ways. To date, there has been no formal investigation in the cargo airline literature in terms of efficiency scores derived specifically from a stochastic cost frontier analysis[22]. Therefore, contributions can be made not only to the SFA literature, but also to the literature on cargo airline efficiency using this methodology. The efficiency scores derived from the SFA can then be evaluated in order to compare efficiency between UPS and FedEx, as well as highlighting how they have individually progressed over the time period analysed. Conclusions are then drawn on

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[22] While there has been published work (Lakew, 2014) which makes inferences about cargo airlines efficiency it does not do so using SFA.

which airline is most cost efficient in the industry. Finally, the inclusion of variables such as number of points served, average stage length and average load factor is analysed. This model of airline costs follows methodology in Caves et al. (1984), in that it includes two dimensions of airline size; the size of the carriers service network and the magnitude of cargo transportation servcies provided. It is in this sense that a distinction can be made between returns to density (the variation in unit costs caused by increasing cargo services within a fixed network) and returns to scale (the variation in unit costs with respoect to proportional changes in both network size and the provision of cargo services). As noted by Lakew (2014), despite the limited amount of air cargo research and the sparse knowledge of the industry due to lack of data, more interest in the economics of the industry has been emerging in the past decade. This interest stems mainly from the growth and expansion of air cargo companies during this time. Therefore, these findings should offer the first stochastic frontier efficiency results and a clear link between cargo airline performance and industry characteristics during this time period.

This chapter is organised as follows; a brief review of the literature dedicated to the cost structure and efficiency of cargo airlines is presented in Section 5.2. In Section 5.3, the model specification and methodology is presented. The data used to estimate the cost structure of cargo airlines are described in Section 5.5. Parameter estimates and conclusions are presented in Section 5.7, and robustness of the conclusions with respect to model form and type are explored in Section 5.8. Efficiency scores are also presented and discussed. In Section 5.9 the conclusions are given and the contributions and limitations of the present research are offered.

4.2. Literature review

The literature on cost structure, efficiency and economies of density/returns to scale of the air cargo industry is rather sparse. Most of the literature on cargo airlines has been developed following studies that relate to the passenger airline literature. For example, it is typical that the cargo airline literature follows the same rational as passenger airlines when it comes to constructing cost functions. The cargo airlines share many of the same inputs and outputs concepts as passenger airlines such as stage length, load factors, capital, labour, and material input prices. Research dedicated to cost structure analysis of the air cargo industry is limited due to the lack of structured data on cargo carriers, and more specifically, integrators. Large interest was gained in the passenger airline literature around the time of de-regulation. This has prompted a large number of subsequent studies. Findings in the passenger literature consistently suggest that costs per passenger-mile decrease with traffic density on individual airline routes and that carriers exhibit constant returns to scale (Caves et al. (1984), Gillen et al. (1990), Jara-Díaz et al. (2013)). Recognising the need for similar empirical analysis of the air cargo industry, Kiesling and Hansen (1993) characterised the cost structure of FedEx, the largest integrated air cargo carrier at that time.

Kiesling and Hansen (1993) estimated a total Cobb-Douglas cost model for FedEx based on quarterly time series data from 1986 to 1992. While they indicated that they would have preferred to estimate a translog cost model, they were not able to do so due to a limited number of observations. They found that over the time period analysed, FedEx had a cost structure characterized by increasing returns to traffic density and decreasing returns to scale. They introduce a third concept, economies of size. They argue that the degree of returns to size determines if FedEx can maintain its efficiency (keeping costs per unit of output constant) as it grows. Their findings also suggested that cargo airlines had cost structures with properties qualitatively similar, but noticeably stronger, than those of passenger airlines. They further concluded that FedEx fell just short of monopolising the air cargo industry. This current study should shed some light on how out-dated this characterisation is.

Bowen (2012) noted a gap in the literature in the sense that there was relatively little which had been published on the operational geography of FedEx and UPS. His study evaluates the development of the two carriers' network structures. FedEx and UPS are found to operate networks with a high concentration of activity at their principal hubs (Memphis and Louisville, respectively), despite the increase and spread of hub and spoke systems which have emerged over the years. Focusing on some of the factors which have guided this Hub choice, Bowen (2012) reveals how the network structures adopted by FedEx and UPS take into account the right trade-off between sorting costs and transportation. This study also shows the importance of time and how it is a key factor in not only moving goods from point *a* to point *b* but also in affording the integrators customers a chance to receive their items the shortest time.

The most recent work that addresses air cargo cost structures and returns to density and scale are by Lakew (2014) and Onghena et al. (2014).

Lakew (2014) examines the cost structure of FedEx and UPS using data from 2003-2011 and adopts the Cobb-Douglas functional form. Increasing returns to traffic density and constant returns to scale are found. They also include a measure for economies of size, similar to Kiesling and Hansen (1993) in order to make inferences about efficiency. They explain that if for example, strong economies of density occur along with diseconomies of scale efficiency can be sustained if the network expands less than in proportion to output, so that density rises. Controlling for network size-differences between the two carriers, FedEx is found to be more cost efficient than UPS. However, UPS emerges as the most cost efficient when allowing for network size differences. Therefore, individual cost structures of the carriers were examined and it is revealed that (1) FedEx operates under weak economies of density and diseconomies of scale and (2) UPS also operates under diseconomies of scale but demonstrates strong economies of density. Economies of size, is used to capture the combined effects of returns to density and returns to scale on the cost structure of cargo airlines. Both exhibit economies of size, denoting that carriers in the industry can become more cost efficient by suitably adjusting their network size as their output increases.

Onghena et al. (2014) analyse the cost structure of air freight business by way of a translog cost function, rather than the simpler Cobb-Douglas found in Lakew (2014). Using quarterly data for FedEx and UPS from 1990 to 2010, a total and variable cost model is estimated in addition to adopting a static as well as dynamic approach. They introduce a variable for number of points served into their models, in order to make a distinction between economies of density and scale. Their results show that both FedEx and UPS have strong economies of density and of scale, suggesting their growth and business strategies are closely related to their cost structures. Finally, their results indicate that concentration in the air cargo industry is likely to continue as it is expected that both airlines will continue to develop strategies which will allow them to fully exploit the available EOD and EOS.

This study will apply SFA in order to examine the cost structures and efficiency of these integrators. The major contribution of this paper is therefore to calculate efficiency scores derived from the SFA results in order to shed some light on how the two airlines are performing (in terms of cost efficiency). The analysis will also add new evidence to the discussion of FedEx and UPS airlines cost structure, their returns to density and returns to scale.

4.3. Model specification and methodology

The translog is a flexible functional form in the sense of providing a second-order approximation to an unknown cost function. A translog cost functional form is chosen for the purpose of this chapter and is the most common form in the analysis of cost structures in the airline industry and is therefore most applicable to the air cargo industry as well.

The translog stochastic total cost function used for FedEx and UPS in this analysis, is defined as follows:

$$lnTC_{it} = \alpha \quad + \alpha_T t + \ \alpha_T t^2 + \alpha_T t^3 + \beta ln(Y_{it}) \ + \sum_j \gamma_j \ln\left(P_{jit}\right) + \sum_j \delta_j \ln\left(Z_{jit}\right)$$

$$+ \frac{1}{2}\eta_{YY}[\ln(Y_{it})]^2 + \frac{1}{2}\sum_j \sum_k \phi_{jk} \ln\left(P_{jit}\right) \ln(P_{kit}) + \sum_k \theta_{Yk} \ln(Y_{it}) \ln(P_{kit}) + v_{it} + u_{it} \quad (4.1)$$

where $lnTC_{it}$ is the total cost for cargo airline i in time period t. On the right hand side, the first line contains all first order terms; second-order terms appear in the remaining lines. A time trend t, is included; Y_{it} is the quantity of the output for cargo airline i in time period t; P_{jit} the j^{th} input price for cargo airline i in time period t; Z_{jit} the value of the j^{th} environmental characteristic for cargo airline i in time period t. In addition to the characteristic variables, dummies for seasonality were included. The estimated coefficients are $\alpha's$, α_T , β, $\gamma's$, $\delta's$, η, $\phi's$, $\theta's$. The data sources and characteristics of the variables in these models are described in Section 5.5.

The symmetry of coefficients in the above function requires $\phi_{jk} = \phi_{kj}$ for all j and k. In addition, Christensen et al. (1973) state that a translog cost function must satisfy certain regulatory conditions. These ensure that a cost function is consistent with cost minimisation. A cost function must be linearly homogeneous in the input prices, requiring the following restrictions are imposed:

$$\sum_j \gamma_j = 1, \quad \sum_j \phi_{jk} = 0(\forall k), \quad \sum_k \theta_{Yk} = 0 \tag{4.2}$$

where subscripts k refers to, respectively, the k^{th} input in the second and third sub-equations.

The term $v_i + u_i$ is a composite error term with v_i representing statistical noise (or randomness) and u_i expressing cost inefficiency. The error component for statistical noise is assumed to be independently and identically distributed, with zero mean and constant variance. The inefficiency component has similar properties except that it has a non-zero mean (because $u_i \geq 0$). Here, β represents a technological parameter vector to be estimated.

Any deviation from the frontier (4.1) occurs as a result of random shocks and statistical noise (v_{it}) in addition to cost inefficiency (u_i).

In this research, a number of models were analysed. The final model selection in this chapter presents the Battese and Coelli (1992) (hereafter BC92) stochastic cost frontier model. A basic stochastic frontier model can be written with the error term broken into two components; v_{it} and u_i as described above. The subscript on u_i has no time dimension but has a subscript i, so that it is firm (cargo airline) specific but not time specific, in other words it is time-invariant. In BC92, the above is generalised by allowing the error component which represents inefficiency to be time varying, while making some assumptions about its structure. They propose for the u_i to be replaced with the following term:

$$u_i = \exp[-\eta(t-T)]\, u_i; \quad t \,\epsilon\, \Phi\ (i)(i = 1,2, \dots, N) \tag{4.3}$$

where η is a scale parameter to be estimated and $\Phi\ (i)$ represents the set of T_i time periods among the T periods involved for which observations for the i^{th} firm are obtained. The parameterisation above implies that although each cargo airline has its own level of technical (cost) efficiency in the last period, $\exp(-u_i)$, the direction of change of technical (cost) efficiency is common to all airlines. This model is such that the non-negative effects, u_{it} , decrease, remain constant or increase as t increases if $\eta > 0, \eta = 0\ or\ \eta < 0$. In this sense, the time path is monotonous and common to all firms in terms of direction but catch-up (or divergence) is permitted.

It will be assumed that the cost inefficiency term (u_i) is distributed half-normal. For the purpose of this chapter, cost efficiency can be written as follows:

$$CE_{it} = \exp(-u_{it}) \tag{4.4}$$

4.3.1. Economies of scale and economies of density

The introduction of number of points served (NPS) was proposed by Caves et al. (1984) in order to identify economies of scale (EOS) due to network characteristics. The use of number of points served is appropriate when making a distinction between returns to traffic density (the variation in unit costs as output increases on a fixed network) and returns to scale or firm/network size (the variation in unit costs with respect to proportional changes in both network size and output; Gillen et al., 1990). Caves et al. (1984) define economies of density (EOD) as "the proportional increase in output made possible by a proportional increase in all inputs, with points served, average stage length, average load factor and input prices held constant" (p.474). Therefore, EOD are present in the case of a decrease in unit costs made possible by an increase in output over a fixed network (such as by way of larger aircraft, heavier load factors or more aircraft and increased frequency). EOS are defined as "the proportional increase in output *and points served* made possible by a proportional increase in all inputs, with average stage length, average load factor, and input prices held fixed" (p.474). EOS are present if unit costs decrease when a cargo airline adds flights or connections to airports that it had not previously served, and this additon has no effect on load factor, stage length or output per point served (density). This chapter therefore follows the classical methodology of returns to density (RTD/EOD) and returns to scale (RTS/EOS) as found in Caves et al. (1984) as is defined as follows:

$$RTD = \frac{1}{\epsilon_y}, \quad (4.5)$$

where ϵ_y is the total cost with respect to output. Returns to density are said to be increasing, constant, or decreasing, when RTD are greater than unity, equal to unity, or less than unity, respectively.

$$RTS = \frac{1}{\epsilon_y + \epsilon_P}, \quad (4.6)$$

where ϵ_P is the elasticity of total cost with respect to points served. Returns to scale are said to be increasing, constant, or decreasing, when RTS are greater than unity, equal to unity, or less than unity, respectively.

Drawing from this and previous literature results, it would be expected that FedEx and UPS would exhibit strong economies of density since, for a given network, additional output should have little impact on the airlines costs. This is likely to be especially true in the case of cargo airlines for two reasons. The first is that additional cargo is typically accommodated on existing flights rather than through adding additional flights, and secondly, since unit ground distribution costs decrease with traffic density. It will be particularly interesting to see whether decreasing returns to scale, such as those found in Kiesling and Hansen (1993) are in fact outdated.

4.4. Data Sources

This chapter uses SFA to measure and compare estimates of cost inefficiencies. The data is a panel dataset covering the time period 1993Q3 to 2013Q4. Data for FedEx and UPS were obtained from the U.S. Department of Transportation Bureau of Transportation Statistics (BTS). This database collects complete financial and operating statistics on both air cargo carriers. All cost statistics have been transformed into real constant prices (2005=100). The dependent and independent variables are presented in Table 4.1, and procedures for calculating these variables are discussed in section 4.4.1.

Table 4.1: Descriptive statistics of variables in cost model

Variable (ln)	**Variable Description**	**Mean**	**Standard deviation**	**Minimum**	**Maximum**
TC	Total cost (USD$; x 10^{11}).	1.66	1103007.00	268229.30	4285211.00
Material price	A proxy of the producer price index (PPI)	178.88	68.51	110.41	325.88
Labour price	Price of labour calculated by dividing total labour expenses by the number of FTE employees.	160852.20	203807.10	1909.24	634927.60
Fuel price	Price of fuel which is the ratio of the amount spent on fuel to the reported amount consumed in gallons.	6.36	4.97	1.15	17.57
Capital price	Total cost of depreciation, amortization and rentals divided by available ton miles (ATM).	60568.43	39668.80	10703.83	153763.60
ALF	Average load factor is calculated as the ratio of payload ton-miles used to available ton-miles.	0.60	0.04	0.46	0.66
ASL	Average stage length taken as total distance flown divided by the total number of departures performed.	21022.96	24442.64	2451.01	89714.12
NPS	Number of points served is taken as number of airports served	60.76	17.56	31.00	96.00

4.4.1. Variables

Total costs are calculated as the sum of the operating expenses (aircraft fuel, salaries and related benefits and depreciation, amortization and rentals). Revenue ton miles (RTM) represents the single output measure for the cargo airlines in this data set. This is done by aggregating the freight and mail tons flown on a carriers network to the quarterly level.

The input price of labour is calculated as the carriers total cost of labour, divided by the total number of full time equivalent employees (FTEs). Input fuel price is the total fuel cost divided by the total consumption (in gallons). Materials price is accounted for by way of a proxy of the producer price index (PPI) following Zou and Hansen (2010). This index varies by quarter but not by cargo airline and is collected from the U.S. Bureau of Labour Statistics. The final input for capital price, is taken as the total cost of depreciation, amortization and rentals divided by available ton miles (ATM) following similar methodology in Onghena et al. (2014)[23]. Since the cost of flying one ton of cargo decreases as aircraft size increased (since fixed costs are spread across greater tonnage), larger freighters are quickly replacing smaller cargo aircraft.

In addition to the input price variables outlined above, there are three characteristics variables. The first, NPS, is used as a proxy for size and also included in order to distinguish between EOD and EOS in air cargo operations as outlined in

[23] The option to work with a capital price as defined in Lakew (2014) as 15% of the following property and equipment categories from balance sheets: flight equipment, ground property and equipment (less depreciation), land, construction, and capital lease property (less amortization) was also considered. However, the results were worse than when capital price as define in this analysis was used.

Section 4.3.1.. This variable is calculated as the number of airports served. Finally, variables for average load factor (ALF) and average stage length (ASL) are accounted for. ASL is calculated as the total distance flown divided by the total number of departures performed. ALF is calculated as the ratio of payload ton-miles used to available ton-miles.

4.5. Results of the estimation

Table 4.2 reports the estimation results and cost characteristics for the total translog cost function of both FedEx and UPS. The total cost variable and the regressors have all been transformed into logarithms. The data has been demeaned such that the dependent and independent variables, except dummies and the time trend, are estimated about the mean values in the dataset (divided by their geometric mean). This allows for the first order coefficients to be interpreted as cost elasticities evaluated at the sample mean. Finally, a cubic time trend was tested but was dropped in favour of a single time trend, due to insignificant results on *t*.

Table 4.2: Stochastic total translog cost function results

	Model: BC92		
	Coefficient	**Std.err.**	**Prob.**
Output (RTM)	0.221	0.037	0.000
Capital Price	0.757	0.062	0.000
Labour Price	-0.056	0.035	0.109
Fuel Price	0.167	0.028	0.000
0.5*K^2	0.297	0.070	0.000
0.5*L^2	-0.043	0.170	0.011
0.5*F^2	0.206	0.040	0.000
0.5*RTM^2	0.022	0.004	0.000
lnK1LnL	-0.024	0.020	0.222
lnK1LnF	-0.148	0.031	0.000
lnK1D1nRTM	0.017	0.005	0.000
lnLLnF	-0.005	0.014	0.747
lnLDlnRTM	-0.003	0.003	0.173
lnLFtlnRTM	-0.019	0.004	0.000
Time (t)	0.012	0.004	0.000
Q1	-0.017	0.008	0.035
Q2	-0.018	0.007	0.009
Q3	-0.010	0.006	0.088
lnNPS	0.104	0.023	0.000
lnASL	0.071	0.030	0.017
lnALF	-0.112	0.053	0.037
constant	-1.776	0.339	0.000
$\boldsymbol{\sigma_u^2}$	0.062	0.913	
$\boldsymbol{\sigma_v^2}$ (x 10^1)	0.005	0.000	
$\boldsymbol{\lambda} = \frac{\boldsymbol{\sigma_u^2}}{\boldsymbol{\sigma_u^2} + \boldsymbol{\sigma_v^2}}$	0.992		
EOS at sample mean	3.077		
EOD at sample mean	4.525		

Log likelihood: 358.098

4.6. Discussion

Table 4.2 contains estimation results for the translog cost frontier estimation. As expected, there is a strong positive relationship between total cost and output when all other factors are fixed. The positive cost elasticity of output indicates that total costs increase as output increases. The size of the coefficient indicates that when output (RTM) increases by 1%, total cost will increase by 0.22%. The EOS calculated at the sample mean for the model, indicate that FedEx and UPS airlines exhibit strong scale economies (3.077). The inverse of the cost elasticities on output and number of points served, 0.221 and 0.104 respectively, with standard error of 0.037 and 0.023, is returns to density at the sample mean (4.525). This confirms similar results which are also found in Onghena et al. (2014) for EOS and EOD, who suggest that the EOS explains the expansion and cooperation strategies followed in the past of both these integrators. Importantly, these findings show that some of Kiesling and Hansen (1993) results no longer apply to the air cargo industry. Kiesling and Hansen (1993) found decreasing returns to scale for FedEx (ranging from 0.54 to 0.62). This would imply that the cost structure of FedEx has clearly changed in the decade after their study. The values of estimated EOS and EOD for the air cargo operations in this analysis are larger than the estimates found in passenger airline literature. Caves et al. (1984) for example, report EOD of 1.24 and constant EOS for passenger airlines in the U.S. These larger scale and density estimates for air cargo integrators compared to those found in the passenger industry could be explained in part by the higher share of fixed costs associated with running freight only air cargo services. The cargo airlines are required to invest much more in infrastructure compared to passenger services, such as sorting equipment in their own hubs (Onghena et al., 2014). For simplicity, Table 4.3 compares previous literature results to those found here.

Table 4.3: Studies on cargo airline cost structures. Economies of density and scale

Study	**Cargo Airline(s)**	**EOD**	**EOS**
Results of this analysis	**FedEx and UPS**	**Significant economies of density** **FedEx and UPS: 4.525**	**Significant economies of scale** **FedEx and UPS: 3.077**
Onghena et al. (2014)	FedEx and UPS	Significant economies of density FedEx: 1.749 UPS: 2.059	Significant economies of scale FedEx: 1.445 UPS: 2.043
Lakew (2014)	FedEx and UPS	Significant economies of density FedEx: 1.60 UPS: 3.02	Decreasing economies of scale[24] FedEx: 0.87 UPS: 0.81
Kiesling and Hansen (1993)	FedEx [25]	Significant economies of density Model 1 FedEx and UPS: 2.36 Model 2 FedEx and UPS: 4.07	Decreasing economies of scale Model 1 FedEx and UPS: 0.62 Model 2 FedEx and UPS: 0.54

The coefficients of all first terms are statistically significant at the 1% level and have the expected signs, apart from the labour input price, which was small and

[24] However, constant returns to scale cannot be rejected at the 5% level for FedEx (0.20 standard error).

[25] Kiesling and Hansen (1993) estimated two Cobb-Douglas models. Model 1 which was a total cost model including quarterly dummy variables and Model 2 which was a simplified version of total cost Model 1.

insignificant. The coefficients for input prices show that, at the sample mean, capital, fuel and materials account for respectively 75.7%, 16.7% and 13.21%, of total cost. These results are similar to those found in Lakew (2014) when considering the output variable and Onghena et al. (2014) for input price variables.

All characteristic variables were significant at the 5% level, and show the expected signs apart from average stage length, which is positive. Results suggest that the average load factor of the aircraft in an air cargos fleet has a significant and negative effect on the total costs (-0.112). It is typical in the passenger airline literature to also see a negative relationship between load factor (number of passengers) and total costs. A higher load factor is also desirable as it increases revenue and profitability.

As anticipated, the coefficient on number of points served, around 0.104, suggests that an increase in network size, holding constant the level of output and all other variables, will lead to an increase in total costs. Finally, ASL is found to be positive and significant, meaning that as the average stage length increases, costs increase. This variable is typically found to be negative in cargo/passenger airline studies and can be interpreted as the cost saving effect of flying less cargo (fewer passengers) over a longer segment to obtain the same level of output.

A likelihood-ratio test was performed on the inclusion or exclusion of the characteristic variables NPS, ALS, ALF for the BC92 model. Results indicate a Chi squared value of 28.11 with Probability > chi2 = 0.0000. This result confirms that the inclusion of characteristic variables together, results in a statistically significant improvement in model fit. In addition to the BC92 model outlined in Section 4.3, a number of other models were evaluated. Both a true fixed effects model and a pooled model were first estimated, which resulted in very similar to each other (almost identical) results in terms of values on the coefficients and efficiency scores. The pooled model was observed to perform no better than a simple OLS model, and so this was rejected. The cost efficiency scores for the true fixed effects model were compared to those of the pooled model revealing an extremely high correlation coefficient (0.99) and therefore also rejected. Next, a Battese and Coelli (1995) model was estimated and performed well in terms of significance and reasonable values on coefficients. The Battese and Coelli (1995) model included characteristic variables for number of points served, average stage length and average load factor into the mean of the inefficiency term. However, this model had a lower log likelihood compared to the BC92 and reported an insignificant value on the number of points served variable, and so this model was not reported. It should be noted however, that the Battese and Coelli (1985) model had a very similar pattern to the cost efficiency score as the BC92 model. A Pitt and Lee (1981) model was also estimated. A likelihood ratio test could not reject the OLS restriction, with a Chi squared value of -0.036 a critical value at 95% of 2.706, and therefore the Pitt and Lee was dropped. This is expected as time invariance is not a realistic assumption for such a data set. A likelihood-ratio test was also performed comparing the BC92 model with the Pitt and Lee (1981) model. The Pitt and Lee (1981) model was dropped in favour of BC92 with a likelihood-ratio of 40 and critical value of 2.706 (one degree of freedom). Finally, a Cuesta (2000) model was tested and while it produced similar coefficient estimates as the BC92 model, the cost efficiency scores produced an error message due to model misspecification. It is for this reason that the BC92 model was chosen over the Cuesta (2000) model.

Using the estimated frontier, it is possible to generate indices for cost efficiency (CE), calculated in accordance with equation 4.4. These scores are presented in Table 4.4, which displays the average efficiency scores for FedEx and UPS in each reporting year. Efficiency scores come out comparable between both airlines up until the year 2002. After this time, UPS appears to remain very stable in terms of cost efficiency, while FedEx decreases in efficiency. Averaging over all years, the mean efficiency is 99.85% and 97.17% for UPS and FedEx respectively. This value indicates that averaging over all years, to operate efficiently FedEx could reduce their input costs by 2.83%, and UPS by 0.15% without decreasing their outputs. Interestingly, both carriers start out in 1993 with nearly complete efficiency but UPS reports 99.35% efficiency in the final reporting year while FedEx reports 88.43%. This demonstrates the power of the exponential term in the BC92 formula. Essentially in the final reporting year UPS is efficient, whereas FedEx falls away from the frontier with a total decrease of 11.46% in efficiency. Overall, UPS is found to have higher cost efficiency than FedEx and their larger degree of stability in efficiency scores over the reporting periods, highlights their effective cost control. Findings in Lakew (2014) suggest that if network size differences between carriers are controlled for, such as here, FedEx is found to be more cost efficient than UPS. However, they determine that allowing for network differences between the two carriers; UPS emerges as the more cost efficient carrier. The positive time trend (0.012) is statistically significant at the 1% and can be interpreted as a proxy for technological progress, which means that total costs increase despite the technological progress made over the considered time period.

Table 4.4: Average efficiency scores for FedEx and UPS (all years)

Year	UPS	FedEx
1993	0.9999	0.9989
1994	0.9999	0.9987
1995	0.9999	0.9983
1996	0.9999	0.9979
1997	0.9999	0.9973
1998	0.9998	-
1999	0.9998	0.9956
2000	0.9997	0.9945
2001	0.9996	0.9930
2002	0.9995	0.9911
2003	0.9994	0.9887
2004	0.9992	0.9857
2005	0.9990	0.9819
2006	0.9988	0.9771
2007	0.9984	0.9710
2008	0.9980	0.9634
2009	0.9975	0.9537
2010	0.9968	0.9416
2011	0.9959	0.9265
2012	0.9948	0.9077
2013	0.9935	0.8843
Total Average	**0.9985**	**0.9717**

Note: - represents no reporting information for this year

4.7. Conclusions

The air express delivery service is gaining an increasingly large portion of airfreight distribution. This research has explored the relative importance of factors that influence the adoption of the express delivery service. The SFA, which is based on financial data shows that coefficients of all first terms are statistically significant at the 1% level and have the expected signs apart from the labour input price, which is small and insignificant. A possible explanation for the insignificance on labour input price could be that the model is struggling to disentangle the time trend from the inefficiency change. The coefficients for input prices show that, at the sample mean, capital, fuel and materials account for respectively 75.7%, 16.7% and 13.21% of total cost. Concerning the input costs, it is apparent that capital costs have the biggest impact on the airlines total costs, followed by fuel. This can be explained in part by the high costs associated with capital equipment (air planes, engine maintenance etc.) as well as the steady rise in kerosene prices during the last 10 years. Similar results are found in the literature on passenger airlines. All characteristic variables were significant at the 5% level, and show the expected signs apart from average stage length, which is positive. Results suggest that the average load factor of the aircraft in an air cargos fleet has a significant and negative effect on the total costs (-0.112). A higher load factor is desirable as it increases revenue and profitability. Number of points served (0.104), suggests that an increase in network size, holding constant the level of output and all other variables, will lead to an increase in total costs.

To better understand the cost efficiency differences between carriers, efficiency scores were derived from the stochastic cost frontier. These revealed that UPS is more cost efficient on average than FedEx with a score close to 100% versus 88% respectively. Both carriers begin with nearly complete efficiency in the first reporting year 1993. However, it is revealed that UPS ends up with 99.35% efficiency, while FedEx has 88.43% efficiency in the final reporting year 2012. Overall, UPS is found to be efficient, whereas FedEx falls away from the frontier with a total decrease of 11.46% in efficiency.

By introducing the number of points served variable into the model, a distinction was made between EOD and EOS. Results confirm that both FedEx and UPS exhibit strong EOS and EOD and are in line with previous literature results (Onghena et al. (2014). Importantly, these findings show that some of Kiesling and Hansen (1993) results no longer apply to the air cargo industry. Kiesling and Hansen (1993) found decreasing returns to scale for FedEx (ranging from 0.54 to 0.62). This would imply that the cost structure of FedEx has clearly changed in the decade after their study. The values of estimated EOS and EOD for the air cargo operations in this analysis are larger than the estimates found in passenger airline literature. Caves et al. (1984) for example, report EOD of 1.24 and constant EOS for passenger airlines in the U.S. These larger scale and density estimates for air cargo integrators compared to those found in the passenger industry could be explained in part by the higher share of fixed costs associated with running freight only air cargo services.

As this study is the first of its kind in the stochastic cost frontier literature on the efficiency of cargo airlines, the chapter has also raised several avenues for future research. First, uncovering the potential sources behind the inefficiency remains an interesting area of future research in terms of a more in-depth approach. Second, it will be worthwhile to study the inefficiency differences between UPS and FedEx with other cargo airlines around the world, such as those in the Korean market. Finally, it would be interesting to incorporate a larger number of cargo airlines into a stochastic frontier efficiency analysis if such a data set became available.

5. Overall conclusions

5.1. Motivations and aims of the thesis

As highlighted throughout the thesis, there remains very little information on airline efficiency in the U.S. passenger industry over an extended time period for a large number of firms, certainly from a stochastic cost frontier perspective. As well as significantly increasing the number of U.S. airlines in the passenger sample set, this thesis has extended the number of years in the sample period as well as having extended the number of airlines observed. Most of the literature related to the measurement of airline efficiency has based its analysis either on parametric or non-parametric frontier methods from a production function perspective. This lack of efficiency information is even more true for the air cargo market, which to date has seem no studies which incorporate stochastic frontier analysis into their research.

Methodologically, an obvious pattern is detected from Chapter 3. Most studies have confined their analysis to the estimation of technical efficiency and do not include all three aspects of efficiency into their analysis. There are two ways that this can limit any findings (Merkert and Hensher, 2011). The first is that most of the previous literature uses both physical and cost data as input factors to estimate technical efficiency. A producer is technically efficient if an increase (decrease) in any output (input) requires a reduction (increase) in at least one other output (input) or an increase in at least one input (Koopmans, 1951). It can therefore be argued that technical efficiency is concerned with measurement of output to input ratios and should as a result, consist of physical measures. Secondly, cost efficiency is considered to be more relevant to decision-making in airline management and is central to an airlines competitiveness and success (IATA, 2006). Cost efficiency, has technical and allocative components. The concept of allocative efficiency is concerned with combinations of correct inputs proportions at the least cost in a production process to achieve a desired level of output using current technological constraint (Coelli et al., 2005).

It can therefore be maintained that only an analysis of the values of all three types of efficiency will lead to a more meaningful and complete picture of the efficiency of the airlines concerned. The positive impacts of airline size and business model (implying the different cost structures adopted by airline companies in their operations such as low cost or full service) on technical efficiency is well documented in existing literature. What is lacking however an in-depth study on allocative and cost efficiency. This thesis has now sought to bridge that gap, by looking all three aspects of efficiency on airline costs. Chapter 3 therefore takes an innovative approach to analysing the impact of aircraft characteristics on airline efficiency from a technical, allocative and cost perspective. In the first stage, a DEA analysis is used in order to derive efficiency scores for the three. Bootstrapped technical efficiency scores are then calculated in order to form a comparison with non-bootstrapped scores. As in Merkert and Hensher (2011), findings establish that bootstrapping of the first-stage efficiency scores does not greatly improve the second-stage random effects Tobit regression results. This re-iterates that regression results based on non-bias corrective technical efficiency are as dependable as the regression results of the bias-corrected scores.

A second stage Tobit regression model is then presented. Previous studies largely focused only on the technical efficiency side in a DEA context from either a single or a small number of years. By studying a larger number of years and further including a stochastic frontier approach and applying the approach proposed by Battese and Coelli (1995), this study simultaneously estimates the cost efficiencies and factors of inefficiency from the sample.

In relation to the air cargo industry, the literature on cost structure, efficiency and economies of density/returns to scale of the air cargo industry remain sparse. Most of the literature on cargo airlines has been developed following studies that relate to the passenger airline literature. Research dedicated to cost structure analysis of the air cargo industry is limited due to the lack of structured data on cargo carriers, and more specifically, about integrators. To date, no previous study has taken a stochastic frontier approach to the analysis of air cargo efficiency. Therefore, the findings in this thesis offer the first stochastic frontier efficiency results and a clear link between cargo airline performance and industry characteristics during the analysed time period.

5.2. Summary of findings

5.2.1. Efficiency in the U.S. Airline Industry from 1991-2012: A Stochastic Frontier Approach

Chapter 2 uses stochastic frontier analysis to measure and compare estimates of cost inefficiencies for twenty-four U.S. carriers. The estimates are based on panel data observations during the time period 1991Q1 to 2012Q3. It provides robust estimates for a translog cost frontier function using this data. In developing the translog cost frontier, a detailed representation is established of the relationship between aircraft costs and the variables that influence it. The efficiency scores were then calculated and examined in order to compare them across carriers. Relationships are found between environmental variables and other dummy variables not previously documented in stochastic frontier literature. The primary results of this study are as follows:

Of the twenty-four airlines in the study it was found that they are on average, operating at 92.12% efficiency. Thus to operate efficiently, airlines could (on average) reduce their input costs by 7.88% without decreasing their outputs. For the purposes of this analysis, airline outputs were defined as revenue ton miles, the revenue tons (of passengers and cargo) transported per miles flown. The coefficient on the output variable was significant at 0.97, suggesting nearly constant returns to scale. The cost efficiency of air transportation carriers ranged between 92.88% and 88.29% with a standard deviation of 1.05%. The significant and expected values on all of the first order terms are in line with previous work in the literature. It was determined that the environmental variables for passenger load factor and for average stage length were significant and thus fit the model well. This is not always seen in previous work using frontier analysis, and often they are dropped due to insignificant coefficients. Of further interest are the results on the September 11th indicator variables. This analysis separates the effects of September 11th into its temporary effects and its lasting impacts. It is found that the initial temporary outcome was a small but positive (increase) to airline costs of approximately 9.4%, and a negative on-going effect of around 9% (decrease) in costs. As far as the long term effects of September 11th, there is some controversy as to what the true impacts are. This is due to fact that weak economic conditions were present before September 11th, and persisted well after. Future work will endeavour to assess the impacts of the September 11th attacks and it's after effects on U.S. airline costs in a more robust manner.

It was also observed that on average, taking account of all companies, productivity growth for the study period due to technical change had deteriorated overall by 50.8% over the twenty-two year period.

5.2.2. Determinants of airline efficiency in the U.S.: A longitudinal DEA and SFA approach

Chapter 3 obtains measures for cost efficiency which from a stochastic frontier cost function which has been adjusted to account for the characteristic influences presented in the DEA and Tobit analysis. In comparing the results from the SFA analysis with the DEA Tobit regressions, we observe that the SFA produces similar estimates but is found to be more robust in terms of significance. Results are also comparable and consistent with those found in Merkert and Hensher (2011).

The findings for the impact of the age of the airlines' fleets are somewhat inconsistent. The Tobit results confirm those found in Merkert and Hensher (2011) and suggest that a younger fleet does not necessarily result in higher efficiency. SFA results on the other hand, find a highly significant negative relationship between efficiency and age with older aircraft being less efficient than younger ones. Aircraft size shows that the impact of aircraft size on cost and technical efficiency is positive.

Stage length was found to have a positive impact on cost and allocative efficiency and is consistent with much of the previous literature. This should be interpreted as the effect on the cost efficiency of flying fewer passengers over a longer stage length (route distance) each to achieve the same level of output. Conversely, and rather surprisingly, the number of aircraft families has no significant impact on any of the three efficiency measures.

5.3. An efficiency analysis of the integrated air cargo industry in the United States: A Stochastic Frontier Approach for FedEx Express and UPS Airlines.

Chapter 4 has explored the relative importance of factors that influence the adoption of the express delivery service. The SFA, which is based on financial data shows that coefficients of all first terms are statistically significant at the 1% level and have the expected signs, apart from the labour input price. The coefficients for input prices show that, at the sample mean, capital, fuel and materials account for respectively 75.7%, 16.7% and 13.21% of total cost. Concerning the input costs, it is apparent that capital costs have the biggest impact on the airlines total costs, followed by fuel. This can be explained in part by the high costs associated with capital equipment (air planes, engine maintenance facilities, etc.) as well as the steady rise in kerosene prices during the last 10 years. Similar results are found in passenger airlines. To better understand the cost efficiency differences between carriers, scores were derived from the stochastic cost frontier. These revealed that UPS is more cost efficient on average than FedEx with a score of and 99.85% and 97.17% respectively. Both carriers have displayed an overall decrease in cost efficiency over the years.

By introducing the number of points served variable into the model, a distinction was made between EOD and EOS. Results confirm that both FedEx and UPS exhibit strong EOS and EOD and are in line with previous literature results (Onghena et al. (2014).

5.4. Opportunities for future research

The thesis has revealed new information on airline efficiency in the U.S. passenger industry over an extended time period for a large number of firms. It has further contributed to the stochastic cost frontier literature as it applies to the airline industry. By analysing the impact of fleet planning and strategic management decisions on airline efficiency a comparison was drawn between DEA and SFA results. In this way, both methods were compared in terms of estimates and also robustness. It has also made a first attempt at looking at the air cargo industry and its cost efficiency by applying SFA. This therefore generates opportunities for investigation of the various areas of cost efficiency in the passenger and cargo airline literature.

In Chapter 2, although results are somewhat inconclusive for TFP, one possible explanation for this decline (in TFP) could be due to the hub-and-spoke configuration which developed following deregulation. It is thought that this could have resulted in the inefficient use by airlines, of assets and expenses related with operating these hub systems. The total factor productivity of U.S. carriers over a more recent and longer time scale is an area which needs further attention and will be returned to in future work. Key future research in this field will include the analysis of total factor productivity through the industry recession.

The analysis in Chapter 3 is the first attempt to investigate DEA, Tobit analysis in the airline efficiency literature alongside SFA. Therefore future work is needed in order to further validate the detected determinants in this study.

Finally, Chapter 4 has also raised several avenues for future research in the air cargo literature. First, uncovering the potential sources behind the inefficiency remains an interesting area of future research in terms of a more in-depth approach. Second, it will be worthwhile to study the inefficiency differences between UPS and FedEx with other cargo airlines around the world, such as those in the Korean market. Finally, it would be interesting to incorporate a larger number of cargo airlines into a stochastic frontier efficiency analysis if such a data set became available.

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7. Appendix

Table A 1: Parameter estimates of the Cobb-Douglas cost frontier function.

Variable	Coefficient	t-statistic
lnRTM	0.951	83.75***
lnKM	0.195	16.87***
lnL	0.162	8.55***
lnF	0.367	27.03***
lnPLF	-1.178	-20.23***
lnASL	-0.427	-13.39***
Q1	-0.012	-1.26
Q2	0.018	2.10
Q3	0.018	1.98**
T	-0.004	-0.39
T2	0.001	1.62
T3	-0.000	-0.76
DCh11	-0.026	-1.98**
Dsep11	0.109	4.92***
DPsep11	-0.079	-4.44***
constant	3.341	12.69***
Total number of observations	1516	
σ_u	-2.571	-9.20***
σ_v	1.592	4.69***

Log-likelihood: 1075.9392
*Variables are significant at the 10% level.
**Variables are significant at the 5% level.
***Variables are significant at the 1% level.

7.1. U.S. Department of Transport Form 41 Airline Data

It is required by law in the United States for each U.S. certified airline carrier, whether publicly traded or privately owned, to submit operating and financial information pertaining to their operations[26]. This must be reported on a monthly, quarterly, semi-annually or annual basis. Individual airlines data are submitted to the U.S. Department of Transportation (DOT) on a Form 41. The form is a total collection of 16 “schedules” each with a specific layout that carriers must adhere to. The Form includes balance sheets, income statements, other financials as well as operating and traffic statistics. This information is available in raw data form to the public after the DoT has made the non-confidential aspects published a few months after the reports were submitted.

The number of schedules an airline submits depends on their grouping, which then depends on total operating revenue per 12-month calendar year. The DOT includes Group I; carriers with yearly revenues below $100 million; Group II; carriers with revenues ranging from $100 million and $1 billion and Group III; carriers with revenues greater than $1 billion. Further, each form is reported for each entity the airline operates. By DoT definition, an entity is the component of the airline, which serves either a Domestic, Atlantic, Pacific or Latin American market segment. Therefore, for an airline which serves half of the market segments would report 2 entities to the data base but would still count as 1 at the airline level. Data at the

[26] U.S. Code Title 49 (Transportation) governs the requirement to report, Title 14 (Aeronautics and Space) of the Code of Federal Regulations spells out the reporting details, and the DoT’s Bureau of Transportation Statistics (BTS) Office of Airline Information provides further guidance in the form of Accounting and Reporting Directives.

individual aircraft model level within an entity can be accessed via Schedules T-2 Traffic and Schedules P-5.1 and P-5.2. The former two have typically been referred to as “direct operating costs” data but DOT has labelled them “Total aircraft operating expenses” (TAOE). Data which would be referred to as “indirect operating costs” would be obtained from Schedule P-7, but these are not available at the individual aircraft type level. Rather, these are aggregated to the entity (air carrier) level. The DoT would hold these indirect costs under “All other operating expenses” (AOOE). For my purposes I will be using Schedules T-2 and P-5.2.

Number of schedules each airline submits depends on the airlines grouping, which then depends on its total operating revenue for a 12-month period. In 1999, the DoT placed airlines with yearly revenues greater than $1 billion in Group III; those with revenues in the range of $100 million and $1 billion in Group II; and those with revenues below $100 million in Group I.

Further, Form 41s are submitted for each entity the airlines has. This is defined by the DoT as the airlines component that serves either a Domestic, Atlantic, Latin America or Pacific market segment[27]. Note: the DoT refers to aircraft (i.e. aircraft models) as flight equipment.

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[27] For example; American Airlines serves all four market segments and so contributes 4 entities to the data base but is counted as only 1 at the airline level. Southwest Airlines operates only domestic and is therefore counted as 1 entity and 1 airline.

Table A 2: U.S. Airline Carriers

Carrier Name
Air Wisconsin Airlines Corp: ZW
AirTran Airways Corporation: FL
Alaska Airlines Inc.: AS
Allegiant Air: G4
America West Airlines Inc.: HP (Merged with U.S. Airways 9/05.Stopped reporting 10/07.)
American Airlines Inc.: AA
American Eagle Airlines Inc.: MQ
ATA Airlines d/b/a ATA: TZ
Comair Inc.: OH
Continental Air Lines Inc.: CO
Delta Air Lines Inc.: DL
Hawaiian Airlines Inc.: HA
Horizon Air: QX
JetBlue Airways: B6
Midwest Airline, Inc.: YX (1)
Northwest Airlines Inc.: NW
SkyWest Airlines Inc.: OO
Southwest Airlines Co.: WN
Tower Air Inc.: FF
Trans World Airways LLC: TW
U.S. Airways Inc.: U.S. (Merged with America West 9/05. Reporting for both starting 10/07.)
United Air Lines Inc.: UA
USA Jet Airlines Inc.: U7
Virgin America: VX