Comparative Efficiency Analysis of Major International Airlines Using Data Envelopment Analysis: Exploring Effects of Alliance Membership and Other Operational Efficiency Determinants

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Abstract

The establishment of alliance groups during the end of 1990s has marked the beginning of an era that is characterized by increased consolidation among Full-Service Network Carriers (FSNCs). In the context of increased competition, membership in a global airline alliance group has served as the main avenue for FSNCs to maintain or increase market share and attain economic viability. Although previous literature has repeatedly stressed the enhancement of operational efficiency as a major incentive for airline alliance membership, existing research related to the assessment of comparative efficiency between allied and non-allied airlines and among alliance groups is fairly scarce. In the current paper, an integrated methodological framework employing Data Envelopment Analysis (DEA) with super-efficiency and intertemporal approach is implemented to assess the effect of alliance group membership on 30 major international airlines regarding period 2012-2016. Primary findings suggest that alliance group membership is not associated with superior airline efficiency. In addition, airlines with high freight traffic revenue share are found to be more efficient than airlines demonstrating lower freight traffic revenue share. Finally, a statistically significant superior efficiency of Asian and European air carriers over American air carriers is substantiated.

Keywords: *global airline alliance groups, airline efficiency, data envelopment analysis*

1. Introduction

Airlines around the world have developed various cooperation forms, commonly referred to as alliances, in order to overcome various regulatory and financial obstacles. In general, airline alliances comprise any collaborative arrangement between two or more carriers involving joint operations, with the declared intention of improving competitiveness and thereby enhancing overall performance (Morrish and Hamilton, 2002). The consolidation of global airline industry has subsequently led to the formation of alliance groups. These are in essence multilateral, formal networks of airlines which have established sets of alliances with each other or with the group itself (Kleymann and Seristö, 2004).

Especially during the last two decades, the three global alliance groups (i.e. Star, SkyTeam, Oneworld) have become dominant stakeholders of the global airline industry, thus shaping its modern structure. The pace by which the aforementioned global alliance groups have expanded is truly astonishing. More specifically, from five airlines initially forming Star alliance group in 1997, currently there are in total 62 airlines participating in the three global alliance groups. Another striking figure in regard to the global alliance groups is the fact that between 2012 and 2016, they have consistently accounted for over 60 percent of the total global passenger traffic (Flight Airline Business, September 2017).

Apart from becoming standard practice in the global airline industry, airline alliances have constituted a major research topic for several scholars and practitioners. Research efforts related to the specific field of study have gained a really critical mass, thus covering an immense spectrum of facets like air transport networks (Bissesur and Alamdari, 1998; Dennis, 2000; US DOT, 2000; Dennis, 2005; Gillen, 2005; Iatrou and Oretti, 2007), airline economics (Oum et al., 2000; Brueckner, 2001; Kleymann and Seristö, 2004; Vinod, 2005; EC and US DOT, 2010), airline operations (Oum and Park, 1997; Oum and Zhang, 2001; Brueckner and Pels, 2005; Button, 2009) etc. In this context, the impact of airline alliances with respect to various aspects within or outside the airline industry has been a special focus among researchers. Though, the quantification of those impacts has comprised a serious challenge for the researchers, which has been conducted through the implementation of various methodological approaches.

A quite controversial topic related to airline alliances and airline industry in general, is the one pertinent to performance evaluation. The most widely used measure of performance in the airline industry is financial performance, which is usually measured by indicators like net profit margin, return on equity and investment, cash flow etc. Another essential measure of performance is operational performance, which is often referred to as productivity. Subsequently, airline productivity has diverse partial measures with the most prominent being labor productivity (on a per employee basis) and aircraft utilization (e.g., load factor) (Kleymann and Seristö, 2004).

As far as concerning the performance measurement methods implemented by airlines, Francis et al. (2005) designated benchmarking as the most widely adopted. Several researchers dealing with the assessment of airline performance have also implemented benchmarking by implementing a wide array of relevant methodologies. Among the various benchmarking methodologies implemented for airline performance assessment, Data Envelopment Analysis (DEA) has gained an elevated

significance in the course of time. As a matter of fact, the number of research efforts dealing with airline performance using the methodological approach of DEA is steadily increasing, thus highlighting the emerging interest over the particular special topic.

The research efforts conducted in the framework of assessing airline performance implementing DEA, have primarily focused on operational productivity, which is otherwise referred to as efficiency. Although previous relevant research has investigated the effects of a wide array of financial and operational aspects on airline efficiency using DEA, the potential impact of alliance membership on airline efficiency has not been sufficiently addressed in existing literature. In this context, the current paper primarily aims to investigate the impact of alliance membership on the efficiency of major international airlines. Additionally, airline efficiency is further explored with respect to freight traffic revenue share and the continent to which air carriers belong (America, Europe, Asia, Oceania). The research contribution of the current paper is threefold, thus reported as follows:

- Evaluate the effect of airline alliance membership on airline efficiency, albeit implementing a differentiated DEA methodological approach and a more recent timeframe compared to the research of Min and Joo (2016) which involved the same topic.
- Assess the effect of freight traffic revenue share on airline efficiency, thus attempting to verify the findings of the research effort of Hong and Zhang (2010).
- Compare the efficiencies of air carriers belonging to different continents, for the purpose of identifying statistically significant differences in a similar way to Joo and Fowler (2014).

The structure of the rest of the current paper is as follows: Section 2 describes the research background and the relevant literature, specifically focusing on DEA methodologies and the selection of inputs and outputs in the framework of the assessment of airline efficiency by previous research. Section 3 deals with the production model of the airlines under investigation, for the purpose of providing a strong theoretical basis for the subsequently adopted DEA model. Section 4 gives a description of the DEA methodological approach, thus providing proper justification with respect to the input and output data and the DEA model that shall be implemented. In addition, Section 4 contains the criteria for selecting the airlines under investigation, along with the sources that relevant input and output data were extracted from. Subsequently, in Section 5, the efficiency results of the implemented DEA model are provided with respective post-hoc analysis related to alliance membership and other relevant aspects. Moreover, in Section 5 results of the post-hoc analysis are discussed, taking into account the conclusions of previous relevant research. Finally, Section 6 summarizes the concluding remarks of the paper and discusses some recommendations for future research.

2. Research Background and Relevant Literature

The research pertinent to transport comprises the fourth most popular research field associated with the application of DEA, for the time period 1978-2010 (Liu et al., 2013). In the current paper, a review of the previous research solely dealing with application of DEA for airline efficiency shall be performed, thus focusing on the aspects of the implemented methodological approaches. Therefore, a comprehensive understanding of previous research efforts shall be developed, subsequently comprising a link to better comprehend the DEA methodological approach implemented in the framework of the current paper.

2.1. DEA Models for the Assessment of Airline Efficiency

Previous research concerning the evaluation of airline efficiency using DEA shall be cited in a time sequence context, thus designating its evolution over time. The first research effort involving DEA application for the assessment of airline efficiency is the one conducted by Schefczyk (1993). In the particular research effort, the CCR (Charnes, Cooper, Rhodes) input-oriented basic DEA model is implemented in order to evaluate the efficiency of 15 large international airlines for 1990. The subsequent research of Banker and Johnston (1994) implements the BCC (Banker, Charnes, Cooper) input-oriented basic DEA model to evaluate the efficiency of 12 major US air carriers for the period 1981-1985.

The CCR input-oriented DEA model is also deployed by Good et al. (1995) for the efficiency evaluation of the eight largest European and U.S. airlines for the period 1976-1986. Following a differentiated methodological framework, Sengupta (1999) implements an own-developed Dynamic Efficiency DEA model to evaluate the efficiency of 14 international airlines during the period 1998-1994. Fethi et al. (2000) and Scheraga (2004) also implement the CCR DEA model for the purpose of assessing the efficiency for 17 European and 38 international airlines, respectively. The former deals with time period 1991 to 1995, while the latter deals with years 1995 and 2000. Subsequently, the research of Chiou and Chen (2006) implements both CCR and BCC basic DEA models, attempting to evaluate the efficiency of a single Taiwanese air carrier for various domestic routes during the year 2001. Notable feature of the specific research effort is the assessment of both production and service efficiency utilizing the aforementioned methodologies.
Research conducted by Greer (2006) is deemed quite novel, on the grounds that the super-efficiency methodological approach originally developed by Andersen and Petersen (1993) is implemented along with the CCR input-oriented DEA model, to compare efficiency of seven U.S.-based full-service network carriers (FSNCs) and seven U.S.-based low-cost carriers (LCCs) for the year 2005. Equally notable is the research of Greer (2008), which combines the CCR DEA model with the Malmquist index, for the purpose of evaluating efficiency changes over time for 12 major U.S.-based airlines between years 2000 and 2004.

The BCC DEA model is utilized by Barbot et al. (2008), Barros and Peypoch (2009), and Bhadra (2009) for assessing efficiency of 49 international, 27 European, and 13 U.S.-based airlines, respectively. Though, model orientations differ among the aforementioned research efforts, with Barbot et al. (2008) adopting input orientation and the other two adopting output orientation. On the other hand, the research efforts of Chow (2010) and Hong and Zhang (2010) employ the CCR input-oriented DEA model, for the purpose of evaluating the efficiency of Chinese and international air carriers respectively. Moreover, Lee and Worthington (2010) adopt both CCR and BCC DEA models using input orientation, for the efficiency assessment of 53 international airlines for 2006.

The research effort of Zhu (2011) is considered of high importance, due to the fact that it incorporates the novel own-developed Two-Stage Network DEA model, in order to evaluate 21 international airlines for the period 2007-2008. The aforementioned Two-Stage Network DEA model is subsequently implemented by Gramani (2012) for the purpose of evaluating efficiency of two major U.S.-based and two Brazil-based air carriers for the period 1997-2006, while Lu et al. (2012) use the same methodology to assess the efficiency of 30 U.S.-listed air carriers for 2006.

Another novel methodological approach is the Slacks-based Measure DEA adopted by Lozano and Gutiérrez (2011), for evaluating the efficiency of 17 European air carriers during year 2006. Also, Yu (2012) adopts the Enhanced-Russel Method (ERM) Network DEA, in order to evaluate the route performance of a single Taiwanese air carrier for year 2001 (same evaluation sample as Chiou and Chen, 2006). In addition, the DEA B-Convex model implemented by Barros et al. (2013) aims at assessing the efficiency of 11 US-based carriers for the period 1998-2010.

Adopting a more conventional approach, Merkert and Hensher (2011), Wang et al. (2011), Pires and Fernandes (2012), Merkert and Morrell (2012), and Merkert and Williams (2013) implement both CCR and BCC basic DEA models with input orientation, in order to evaluate the efficiency of international and European air carriers. Following a slightly modified framework, Assaf and Jossiasen (2011) implement an output-oriented BCC DEA model with efficiency score bootstrapping, for the purpose of assessing the performance of 15 UK-based air carriers for the period 2002-2007.

The research efforts of Arjomandi and Seufert (2014) and Lee and Worthington (2014) attempt to assess the efficiency of international airlines for the periods 2007-2010 and 2006 respectively, implementing BCC output-oriented DEA model. In a similar pattern, Joo and Fowler (2014) utilize output-oriented CCR and BCC DEA models, to evaluate the efficiency of international airlines for the year 2010. Additionally, Wu and Liao (2014) follow a quite unique approach, which combines CCR and BCC DEA models with Balanced Scorecard in order to assess the efficiency of 38 international air carriers for 2012.
Another advanced methodological approach for evaluating airline efficiency is the Slacks-based Network DEA model, which has been implemented by Lozano and Gutiérrez (2014) and Tavassoli et al. (2014). The former research effort assesses the efficiency of 16 European airlines for 2007, while the latter assesses the efficiency of 11 Iranian airlines for 2010. A subsequent more advanced approach comprises the Three-Stage Network DEA model developed and adopted by Mallikarjun (2015), specifically aiming to evaluate the efficiency of 27 U.S.-based airlines for year 2012.

The Virtual Frontier DEA is also a novel methodology for airline efficiency assessment, with the most notable research efforts being Cui and Li (2015) and Li et al. (2015). In the former case Virtual Frontier Benevolent (VFB) DEA Cross Efficiency methodology is implemented for the efficiency assessment of 11 international airlines during period 2008-2012, while in the latter case Virtual Frontier Network Slacks-based methodology (adopting a three-stage production framework) is used for evaluating the efficiency of 22 international airlines for the same period.

Recent distinctive research effort implementing own-developed DEA methodologies is the Two-Stage Dynamic Network DEA model of Omrani and Soltanzadeh (2016) for assessing the efficiency of 8 Iranian airlines for the period 2010-2012. The same methodological approach is also used by Yu et al. (2017) for evaluating the efficiency of 30 international airlines for year 2010. Other distinctive own-developed models are the Dynamic Epsilon-based Measure model of Cui and Li (2017a) and the Dynamic By-Production Model of Cui and Li (2017b). The former research effort evaluates the efficiency of 19 international airlines for period 2008-2014, while the latter assesses the potential efficiency of 29 international airlines for period 2021-2023 using panel data from period 2008-2015.

Finally, latest research efforts have repeatedly opted for the basic DEA models, namely the CCR and BCC models. In regard to the former basic DEA model, Greer (2016) and Min and Joo (2016) implement CCR input-oriented DEA model for efficiency evaluation of major U.S.-based and international airlines respectively, while Sjögren (2016) implements output-oriented CCR DEA model for assessing the efficiency of 41 international airlines. In regard to the latter basic DEA model, Saranga and Nagpal (2016) use an input-oriented BCC model to evaluate efficiency of Indian air carriers for period 2005-2012, Choi (2017) uses an output-oriented BCC model for assessing the efficiency of 14 U.S. airlines for period 2006-2015, while Seufert et al. (2017) use an non-oriented BCC model to evaluate stage efficiency and productivity of 33 international airlines for period 2007-2013. Moreover, a notable research effort is the one conducted by Merkert and Pearson (2015), where BCC model is employed using both input and output orientations along with efficiency scores' bootstrapping, for the purpose of assessing efficiency determinants concerning 116 international airlines for period 2011-2012.

2.2. DEA Input and Output Selection for Airline Efficiency

Apart from the selection of DEA model that shall be implemented in the framework of evaluating airline efficiency, the appropriate inputs and outputs are equally vital for attaining the aims of the undertaken research effort. The selection of the inputs and outputs should definitely take into account the scope of the research, thus dictating the need for prior meticulous determination in accordance with the needs of each individual topic under investigation.

The previous research pertinent to airline efficiency evaluation using DEA has adopted a remarkable variety of inputs and outputs in order to evaluate airline efficiency. However, there are specific measures of inputs and outputs that have been implemented by a wide array of researchers. For the case of inputs, Available Tonne-Kilometers (ATKs) are a quite popular measure among researchers (Schefczyk, 1993; Fethi et al., 2000; Scheraga, 2004; Lee and Worthington, 2010; Merkert and Hensher, 2011; Merkert and Morrell, 2012). In some rare instances where metric system is not adopted, the specific measure is expressed as Available Tonne-Miles (ATMs) (Lu et al., 2012; Lu et al., 2014). Nevertheless, ATK has also been implemented as output (Arjomandi and Seufert, 2014; Lee and Worthington, 2014; Lozano and Gutiérrez, 2014). It is important to stress that researchers usually implement ATKs in a combined way, thus including both passengers and freight in the particular measure.

Another popular input measure for airline efficiency evaluation is total operating cost, which is mainly reported in million U.S. Dollars (Schefczyk, 1993; Sengupta, 1999; Fethi et al., 2000; Scheraga, 2004; Barros and Peypoch, 2009; Lee and Worthington, 2010; Barros and Couto, 2013; Barros et al., 2013). However, in some research efforts specific costs are implemented as input measures like fuel cost (Chiou and Chen, 2006; Lozano and Gutiérrez, 2011; Lozano and Gutiérrez, 2014; Wu and Liao, 2014), labor cost (Chiou and Chen, 2006; Gramani, 2012; Lozano and Gutiérrez, 2014; Wu and Liao, 2014), or fleet cost (Chiou and Chen, 2006; Lozano and Gutiérrez, 2011; Lu et al., 2012; Lu et al., 2014).

The size of personnel also comprises a widely implemented input measure for airline efficiency evaluation. However, the specific input is expressed by researchers in various forms, with the most prominent being simple headcount (Barros and Peypoch, 2009; Hong and Zhang, 2010; Wang et al., 2011; Barros and Couto, 2013; Barros et al., 2013; Tavassoli et al., 2014; Omrani and

Soltanzadeh, 2016; Cui and Li, 2017a) and number of full-time equivalent (FTE) employees (Greer, 2008; Chow, 2010; Merkert and Hensher, 2011; Lu et al., 2012; Merkert and Morrell, 2012; Merkert and Williams, 2013; Arjomandi and Seufert, 2014; Merkert and Pearson, 2015; Greer, 2016; Saranga and Nagpal, 2016). In addition, personnel size has been alternatively expressed in some rare cases as average number of employees (Lee and Worthington, 2014) or number of full-time employees (Cao et al., 2015).

Except for ATKs, the input measure of Available Seat-Kilometers (ASKs) has been also very popular among researchers dealing with airline efficiency assessment using DEA (Hong and Zhang, 2010; Merkert and Williams, 2013; Barros and Couto, 2013; Merkert and Pearson, 2015). The particular input measure exclusively expresses the passenger traffic capacity of the airlines, while in certain research efforts it has been also utilized as output measure (Barbot et al., 2008; Lozano and Gutiérrez, 2014; Seufert et al., 2017). Additionally, instead of using ATKs and ASKs as input measure for expressing capacity, numerous researchers have adopted the number of operated aircraft, which is commonly referred to as fleet size (Good et al., 1995; Barbot et al., 2008; Barros and Peypoch, 2009; Wang et al., 2011; Zhu, 2011; Cao et al., 2015). Moreover, some researchers have also utilized aircraft seating capacity as an input measure for the purpose of specifically expressing passenger traffic capacity (Greer, 2006; Greer, 2008; Chow, 2010; Lu et al., 2012; Lu et al., 2014; Greer, 2016; Sjögren, 2016).

Along with the previously reported input measures in the framework of research pertinent to airline efficiency evaluation using DEA, the aviation fuel consumption has comprised a quite popular input measure, especially when fuel efficiency or environmental impact is to be additionally assessed (Greer, 2006; Barbot et al., 2008; Greer, 2008; Chow, 2010; Gramani, 2012; Lu et al., 2012; Barros et al., 2013; Cao et al., 2015; Li et al., 2015; Greer, 2016; Sjögren, 2016; Cui and Li, 2017b). Taking into account the aforementioned review in regard to input measures, it is evident that air traffic capacity, operating costs and personnel size are the dominant input measures. In a sense, the specific input measures can be considered quite reasonable given their importance for the airline industry as a means for seamlessly conducting air transport services.

As far as the output measures are concerned, the most widely adopted are those representing air traffic volume, namely Revenue Passenger-Kilometers (RPKs) (e.g., Joo and Fowler, 2014; Lozano and Gutiérrez, 2014; Merkert and Pearson, 2015; Min and Joo, 2016; Omrani and Soltanzadeh, 2016; Sjögren, 2016; Cui and Li, 2017a) which solely pertains to passenger traffic, and Revenue Tonne-Kilometers (RTKs) (e.g., Barros and Couto, 2013; Lozano and Gutiérrez, 2014; Tavassoli, 2014; Cao et al., 2015; Sjögren, 2016; Cui and Li, 2017a), accounting for either freight-only traffic or aggregate passenger and freight traffic. Nevertheless, the output measure for passenger traffic is occasionally reported in non-metric format, namely Revenue Passenger Miles (RPMs) (e.g., Barros et al., 2013; Lu et al., 2014; Mallikarjun, 2015).

Revenue comprises another frequently implemented output measure for airline efficiency evaluation using DEA, almost solely reported in million U.S. Dollars. In a similar manner to costs, revenue is specifically expressed as total revenue (Hong and Zhang, 2010; Barros et al, 2013; Cui and Li, 2017b), operating revenue (Wu and Liao, 2014; Mallikarjun, 2015), non-passenger revenue (Schefczyk, 1993; Sengupta, 1999; Fethi et al., 2000; Lee and Worthington, 2010; Wang et al., 2011; Lu et al., 2012; Lu et al., 2014), or passenger revenue (Zhu, 2011). Moreover, researchers

have occasionally opted for implementing load factor as output measure (Good et al., 1995; Zhu, 2011; Barros et al., 2013; Joo and Fowler, 2014; Choi, 2017). The latter is considered as a metric for determining the ratio of utilized capacity divided by the available capacity. Hence, load factor can represent capacity utilization in regard to passenger-only traffic (RPKs divided by ASKs), freight-only traffic (RTKs divided by ATKs), or mixed passenger/freight traffic (aggregate passenger/freight RTKs divided by aggregate passenger/freight ATKs). The inputs and outputs implemented in the previous research efforts along with the features of airline sample under investigation are summarized in Table 1.

As previously stressed, the selection of inputs and outputs in the framework of evaluating airline efficiency using DEA is of paramount importance. In this context, every research effort dealing with the particular methodology should carefully examine the appropriateness of each selected input or output with respect to the aspects under investigation. The input and output selection process should be initially justified on the basis of the types of airline efficiency that shall be assessed, which is concurrently associated with the suitable DEA model that is going to be adopted.

Table 1 : Previous Relevant Research Summary of Airline Performance Evaluation using DEA

Author(s), Year	Airlines	Study period	DEA Model Inputs	DEA Model Outputs
Schefczyk (1993)	15 International	1990	ATK, Operating Cost, Non-flight Assets	RPK, Non-passenger revenue
Banker and Johnston (1994)	12 Major U.S. National & Regional	1981-1985	10 inputs	3 (RPM from 3 types of aircraft)
Good et al. (1995)	8 Largest European & 8 Largest U.S.	1976-1986	Labor, Energy and other Materials, & Aircraft Fleet	Load factor, Stage Length, Percent of fleet wide-bodied, Percent of fleet turboprop, Network size
Sengupta (1999)	14 International	1988-1994	ATK, Total Operating Cost, Total Non-flight Assets	RPK, Non-passenger revenue
Fethi et al. (2000)	17 European	1991-1995	ATK, Total Operating Cost, Total Non-flight Assets	RPK, Non-passenger revenue
Scheraga (2004)	38 International	1995 & 2000	ATK, Total Operating Cost, Total Non-flight Assets	RPK, Non-Passenger RTK
Chiou and Chen (2006)	1 Taiwanese (15 routes)	2001	Fuel Cost, Personnel Cost, Aircraft Cost (Production) Number of Flights, Seat Miles (Service)	Number of Flights, Seat Miles (Production) Passenger Miles, Passenger Number (Service)
Greer (2006)	7 U.S. Full-Service & 7 U.S. Low-Cost	2004	Labor, Aircraft Fuel, & Fleet-wide Aircraft Capacity	ASM

Barbot et al. (2008)	49 International	2005	Number of core workers, Number of operated aircraft, Fuel consumed	ASK, RPK, RTK
Greer (2008)	12 US	2000-2004	Number of Employees (FTE), Fuel consumed, Fleet seating capacity	ASM
Barros and Peypoch (2009)	27 European	2000-2005	Number of Employees, Operational cost, Number of Aircraft	RPK, EBIT

Author(s), Year	Airlines	Study period	DEA Model Inputs	DEA Model Outputs

Table 1 (contd)

Author(s), Year	Airlines	Study period	DEA Model Inputs	DEA Model Outputs
Rhodra (2009)	13 US	1985-2006	ASM, Fuel consumed, Ratio of flight stage miles to trip stage miles, Aircraft utilization (hours/day), Number of seats per aircraft, Number of aircraft	
Chow (2010)	Chinese state-owned & privately-owned	2003-2007	Number of Employees (FTE), Fuel consumed, Fleet seating capacity	RTK (passenger & cargo)
Lee and Worthington (2010)	53 International	2006	ATK, Operating Cost, Non-flight Assets	RPK, Non-passenger revenue
Hong and Zhang (2010)	29 International	1998-2002	Number of Employees, ASK	Total Revenue, RPK, RTK
Assaf and Jossiasen (2011)	15 UK-based airlines	2002-2007	Labor expenses, Aircraft Fuel&Oil Expenses, Aircraft Value (total value – depreciation)	ATK (passenger & cargo), Total Operating Revenue
Lozano and Gutiérrez (2011)	17 European	2006	Fuel costs, Fleet costs, Operating Costs	RTK (passenger & cargo)
Merkert and Hensher (2011)	58 International	2007-2009	ATK, Number of Employees (FTE)	RTK, RPK
Wang et al. (2011)	30 U.S.-listed	2006	Number of employees (headcount), Fuel expenses, Number of aircraft	ASM, RPM, Non-passenger revenue
Zhu (2011)	21 International	2007-2008	CASM, Salary per ASM, Wages per ASM, Benefits per ASM, Fuel expense per ASM	Load factor, Fleet Size (1st stage output & 2nd stage input) RPM & Passenger revenue (2nd stage output)
Gramani (2012)	2 Major U.S. & 2 Major Brazilian	1997-2006	CASM, Labor costs, Fuel consumed	1st Stage efficiency score (1st stage output & 2nd stage input) Flight revenue, flight income (2nd stage output)

Table 1 (contd)

Author(s), Year	Airlines	Study period	DEA Model Inputs	DEA Model Outputs
Lu et al. (2012)	30 U.S.-listed	2006	Number of employees (FTE), Fuel consumed, Fleet seating capacity, Cost of flight equipment, Maintenance expenses, Cost of property and equipment	ASM, ATM (1st stage output & 2nd stage input) RPM, Non-passenger revenue (2nd stage output)
Merkert and Morrell (2012)	66 International	2007-2009	ATK, Number of employees (FTE)	RPK, RTK, Revenue
Pires and Fernandes (2012)	42 International	2001-2002	Financial leverage (ratio of total assets to equity)	Firm size (net sales), Asset tangibility (ratio of fixed to total assets), Profitability (ratio of net profit to total assets)
Yu (2012)	1 Taiwanese (15 routes)	2001	Personnel Cost, Fuel Cost, Aircraft Cost (1st Stage) Number of Flights, Seat-Miles (2nd Stage)	Number of Flights, Seat-Miles (1st Stage) Passenger-Miles, Embarkation Passengers (2nd Stage)
Merkert and Williams (2013)	18 European	2007-2009	ASK & Number of Employees (FTE)	RPK, Flight Departures
Barros and Couto (2013)	23 European	2000-2011	Number of Employees (headcount), Operational cost, ASK	RPK, RTK
Barros et al. (2013)	11 U.S.	1998-2010	Total cost, Number of employees (headcount), Fuel consumed	Total Revenue, RPM, Passenger Load Factor
Arjomandi and Seufert (2014)	48 International	2007-2010	Capital (total number of flying hours divided by average daily revenue hours), Number of Employees (FTE)	ATK (both passengers & cargo), Carbon dioxide emissions
Joo and Fowler (2014)	90 International	2010	Expenses	Revenues, Passengers, RPK, Load Factor
Lee and Worthington (2014)	42 International	2006	Average Number of Employees, Total assets (USD), Kilometers flown	ATK
Lozano and Gutiérrez (2014)	16 European	2007	Fuel cost, Non-current assets, Wages and salaries cost, Other operating costs (1st Stage inputs), Selling costs (2nd stage input)	ASK, ATK (1st stage output & 2nd stage input) RPK, RTK (2nd stage output)

Table 1(contd)

Author(s), Year	Airlines	Study period	DEA Model Inputs	DEA Model Outputs
Lu et al. (2014)	30 U.S. listed	2006	Number of employees (FTE), Fuel used, Seating capacity, Cost of flight equipment, Maintenance expenses, Cost of ground property and equipment (1st Stage) ASM, ATM (2nd Stage)	ASM, ATM (1st Stage), RPM, Non-passenger revenue (2nd Stage)
Tavassoli et al. (2014)	11 Iranian	2010	Number of passenger planes, Number of cargo planes, Number of employees (headcount)	Passenger Planes and Cargo Planes (1st stage output & 2nd stage input) RPK, RTK (2nd stage output)
Wu and Liao (2014)	38 International	2012	RPK, Number of passengers, Fuel cost, Capital cost, Material cost, Labor costs, & Other operating expenses per employee	Operating revenue, Return on investment, Return on assets, & Net income
Cao et al. (2015)	Chinese state-owned & privately-owned	2005-2009	Number of employees (full-time), Fuel consumed, Number of operated aircraft	Total number of flights, RTK (both passenger & cargo)
Cui and Li (2015)	11 International	2008-2012	Number of Employees, Capital Stock, Tonnes of Aviation Fuel	RPK, RTK (both passenger & cargo), CO_2 emission decrease index
Li et al. (2015)	22 International	2008-2012	Number of Employees, Capital Stock, Aviation Fuel consumed (Operations), ASK, ATK (both passenger & cargo), Fleet Size (Services), RPK, RTK (both passenger & cargo), sales costs (Sales)	ASK, ATK (both passenger & cargo), Fleet Size (Operations), RPK, RTK (both passenger & cargo) (Services), Total Business Income (Sales)
Mallikarjun (2015)	27 U.S.	2012	Operating expenses (1st stage), ASM (2nd stage), RPM (3rd stage)	ASM (1st stage), RPM (2nd stage), Operating revenue (3rd Stage)
Merkert and Pearson (2015)	116 International (107 with SkyTrax ranking available)	2011-2012	Number of Employees (FTE), ASK	Custom Rank (service quality), Margin (operational profit/loss), RPK
Greer (2016)	14 Major U.S. (2005) & 12 Major U.S. (2013)	2005 & 2013	Number of Employees (year-round average FTE), Fuel consumed, Fleet-wide seating capacity (year-round average)	ASM

Table 1(contd)

Min and Joo (2016)	59 International	2010	Operating expenses, Under-utilization (Load factor subtracted from unity)	Number of passengers, RPK, Service rating (qualitative)
Sjögren (2016)	41 International	1990-2003	Labor, Fuel consumed, Aircraft capacity (1st model & 3rd model) Hours flown, Aircraft departures, Kilometers flown (2nd model)	Hours flown, Aircraft departures, Kilometers flown (1st model), RPK, RTK (2nd model & 3rd model)
Omrani and Soltanzadeh (2016)	8 Iranian	2010-2012	Number of employees (headcount) (1st stage), ASK, Number of scheduled flights (2nd stage)	ASK, Number of scheduled flights (1st stage), RPK, Passenger Tonne-kilometer (2nd Stage)
Saranga and Nagpal (2016)	72 observations from Indian airlines	2005-2012	ASK, Number of Employees (FTE), Expenditure per ASK, Expenditure per FTE	RPK
Choi (2017)	14 U.S.	2006-2015	CASM (Cost per Available Seat-Mile)	Revenue per ASM, Passenger Yield, Load Factor
Cui and Li (2017a)	19 International	2008-2014	Number of employees (headcount), Fuel consumed	RTK, RPK, Total Revenue
Cui and Li (2017b)	29 International	2008-2015	Number of Employees (headcount), Aviation Fuel Consumed, Previous Year Fleet Size (Dynamic Factor Input)	Total Revenue (Desirable Output), Greenhouse Gases (Undesirable Output), Current Year Fleet Size (Dynamic Factor Output)
Seufert et al. (2017)	33 International	2007-2013	Capital(Total number of flight hours divided by average daily revenue hours), Staff(Number of pilots and flight attendants)	ATK (both Passenger & Cargo), CO_2 Emissions
Yu et al. (2017)	30 International	2009-2012	Labor Expenses, Size of Leased Fleet, Fuel Expenses, Other Operational Expenses (1st Stage), ASK, ATK (Freight Only) (2nd Stage)	ASK, ATK (Freight Only) (1st Stage), RPK, RTK (Freight Only) (2nd Stage)

2.3. Investigated Determinants of Airline Efficiency Using DEA

Previous relevant research has been mainly conducted in the framework of comparative efficiency analysis with respect to various determinants, mainly of operational and financial texture. The airline business model as a determinant of airline efficiency has received quite increased attention, with the most distinctive examples being the efforts of Greer (2006), Barbot (2008), and Worthington (2010) which compare efficiency of FSNCs and LCCs. The common conclusion of all the aforementioned efforts is the superior efficiency of air carriers implementing the LCC business model over air carriers implementing the FSNC business model, thus confirming the competitive advantage of the former business model. In a similar framework, the research efforts of Chow (2010) and Cao et al. (2015) investigate the association of airline ownership status with efficiency, comparing the productive efficiency of state-owned and privately-owned Chinese airlines for different time periods. Both studies conclude that privately-owned air carriers have surpassed state-owned air carriers in terms of productive efficiency.

Other determinants of airline efficiency that have been investigated by previous research are those dealing with traffic volume or capacity. Prominent effort is the one conducted by Hong and Zhang (2010), which investigates the interconnection of airline efficiency to freight traffic revenue share, thus concluding their positive association. Subsequently, Merkert and Morrell (2012) investigate the association of passenger traffic capacity and airline efficiency, drawing the conclusion that optimal airline size lies between 32 and 54 billion ASKs, while efficiency of airlines with capacity above 100 billion ASKs and especially above 200 billion ASKs is found to be negatively affected by diseconomies of scale.

Certain researchers have investigated airline efficiency with view to time periods preceding and/or succeeding major events/milestones. The early research of Banker and Johnston (1994) has investigated the airline efficiency following U.S. airline deregulation, while Scheraga (2004) and Pires and Fernandes (2012) studied pre- and post-9/11 terrorist attack effects on operational and financial efficiency of international air carriers. In a similar pattern, Greer (2016) compares the efficiency of major U.S. air carriers before and after mergers, concluding that efficiency has not been enhanced following the executed mergers. Moreover, the research of Cui and Li (2017a) examines efficiency of international airlines for the period 2008-2014, concluding that the highest efficiency change occurred in year 2010, following the 2008 global financial crisis.

The examination of potential association of the geographical origin of the air carriers with their efficiency has also attracted attention among researchers. In particular, Lee and Worthington (2014) evaluate the efficiency of 42 international air carriers for the year 2006, concluding that Asian carriers like Singapore Airlines and Cathay Pacific comprise global benchmarks. Similarly, Joo and Fowler (2014) assess the efficiency of 90 international air carriers located in Asia, Europe, and North America, subsequently suggesting that European airlines' efficiency is inferior to all other regions' air carriers, while they also suggest that efficiency differences between air carriers based in Asia and North America are not statistically significant. In addition, the research of Arjomandi and Seufert (2014) deals with the assessment of 48 international airlines from six different regions, with the primary findings suggesting that air carriers from China and North Asia are the most technically efficient and that European air carriers are the best performers in terms of environmental efficiency.

However, the interconnection of airline alliance membership and efficiency using DEA has not drawn much attention from researchers. To the best of the authors' knowledge, the only research

effort primarily dealing with the comparative efficiency analysis of air carriers with respect to alliance membership using DEA methodology is the one conducted by Min and Joo (2016). Despite the continuously increasing interest among researchers regarding airline alliances, the assessment of airline efficiency using DEA with respect to alliance membership is therefore deemed quite limited. In this context, the current paper shall comprise a subsequent effort to that of Min and Joo (2016), albeit with a quite different approach in terms of the implemented DEA methodology, in terms of the selected inputs and outputs, and the selected timeframe. As previously reported, apart from the investigation of airline efficiency in regard to alliance membership, the interconnection of airline efficiency to air traffic revenue share and geographical region (continent) shall be additionally investigated, following the research framework of Hong and Zhang (2010) and Joo and Fowler (2014) respectively.

3. Airline Production Model

The air carriers around the world are predominantly involved with passenger transport operations, with freight transport usually being an activity of lower significance or business priority. However, in many instances air freight transport comprises a significant portion of the earned revenue, especially in long-haul routes (e.g., Transatlantic, Europe-East Asia, Transpacific), where revenue contribution can reach 20 percent (Abeyratne, 2012). International air carriers (mainly FSNCs) conduct air freight transport operations deploying passenger aircraft, exploiting available volume in the aircraft's lower deck compartment, thus treating air freight transport as a by-product of passenger transport service. Additionally, there is a continuously increasing trend for transporting air freight using dedicated freighter aircraft, with the global air freight traffic volume share carried by dedicated freighter aircraft surpassing 50 percent (Morrell, 2011; Boeing, 2016). Nevertheless, the remaining share of global air freight traffic volume (over 40 percent) as part of passenger transport operations is by no means negligible (Budd and Ison, 2017).

In regard to the operational model adopted for conducting air freight transport operations, air carriers can be classified as follows (Morrell, 2011; Abeyratne, 2012; Budd and Ison, 2017; Dresner and Zou, 2017):

- Combination Carriers: The main operational focus of these carriers involves passenger air transport, with air freight carried in the lower deck compartment (alternatively referred to as "belly freight"). Especially for the case where wide-body aircraft are deployed (e.g., Boeing 777, Airbus A330), freight transport capability of up to 30 tonnes is feasible. Also, there are instances where air freight transport operations are conducted by dedicated freighter aircraft, which usually comprise a pretty small portion of the airline fleet. Sometimes, the dedicated freighter aircraft belong to a wholly owned subsidiary solely involved with air freight transport (e.g., Singapore Airlines, Lufthansa, Cathay Pacific). Consequently, these carriers can significantly augment their revenues by ensuring that available freight capacity is sufficiently utilized.

- Freight-Only Carriers: They exclusively conduct air freight transport operations by deploying dedicated freighter aircraft, hence no involvement in passenger transport operations takes place (e.g., Cargolux, Nippon Cargo Airlines, Aerologic). Due to the fact that freight-only carriers primarily focus on air freight transport without developing sufficient marketing capabilities, they usually rely on air freight forwarders in order to book and arrange freight shipments.

- Integrators: These are practically enterprises providing door-to-door services, mainly involving time-sensitive and relatively small weight/volume shipments (parcels). They own and operate large fleets of dedicated freighter aircraft, along with road transport assets for last-mile pick-up or drop-off. In some instances where additional capacity is required, they contract freight-only carriers or even combination carriers. In addition, they are involved in providing other related services like freight forwarding, customs clearance etc. Consequently, integrators possess significant advantages over freight-only carriers mainly in terms of flexibility, sources of revenue streams, and direct interface with the customers.

The current paper shall solely deal with major international air carriers primarily involved in passenger transport operations, additionally conducting freight transport operations in various ways (belly freight or dedicated freighter aircraft), hence classified as combination carriers. Even in the case of LCCs, where freight transport operations are deemed minimal, data available on their websites and transport statistics websites (US DOT Bureau of Transportation Statistics, Statistics Canada) corroborate the fact that despite their fairly low freight traffic volumes, they maintain freight transport departments. Hence, it can be assumed that even LCCs (e.g., Southwest, Norwegian, WestJet) are in essence combination carriers, although they largely lag behind FSNCs in terms of freight traffic volume and subsequently freight traffic revenue. Consequently, the DEA model that shall be implemented in the framework of the current study, shall take into account the operational model of combination carriers.

In the case of airline industry and combination carriers in specific, the production framework is generally described as two-stage process (Banker and Johnston, 1993; Lu et al., 2012; Lozano and Gutiérrez, 2014; Lu et al., 2014; Omrani and Soltanzadeh, 2016; Cui and Li, 2017a). In the first stage, the production of capacity takes place where the available inputs like aircraft, personnel, and financial resources (mainly in the form of operating costs) are converted into Available Seat-Kilometers (ASKs) for the passenger transport segment and Available Tonne-Kilometers (ATKs) for the freight transport segment. The outputs of the first production stage are also referred to as "output capacity" (Banker and Johnston, 1993). Subsequently in the second stage, the capacity is marketed and sold to the end customers primarily in the form of passenger and freight transport services, where the final outputs are produced. The final outputs pertinent to operational aspects are exclusively represented by Revenue Passenger-Kilometers (RPKs) and Revenue Tonne-Kilometers (RTKs) (for passenger and freight transport respectively), while the final output pertinent to financial and marketing aspects is represented by revenue (Banker and Johnston, 1993; Lu et al., 2012; Lozano and Gutiérrez, 2014; Lu et al., 2014; Cui and Li, 2017a). The above described two-stage production model for combination carriers is graphically represented in Figure 1.

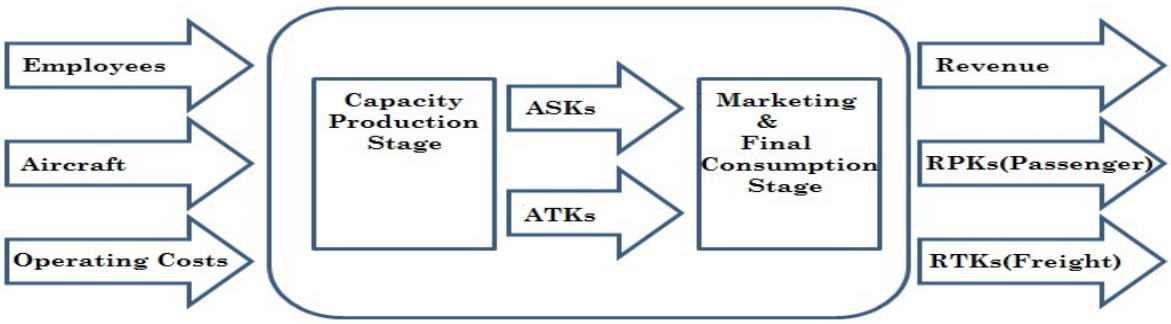

Figure 1 : Two-Stage Production Framework of a Combination Air Carrier

It is of paramount importance to highlight that the measures of ATKs and RTKs should exclusively refer to freight transport, thus being differentiated from the numerous instances found in airline annual reports and previous literature, where the specific measures refer to aggregate passenger and freight traffic (i.e. passengers are translated into weight). Due to the fact that passenger transport services and freight transport services are segmented in the airline level and they subsequently result in individual revenue streams, in the current paper we shall assume that ATKs and RTKs solely represent freight traffic. Moreover, the frequently adopted input measure of fuel quantity consumed is deemed as improper for the purpose of the current study. In particular, fuel quantity consumed as input measure is more suitable for assessing environmental efficiency. For the purposes of our paper, the particular input measure is essentially incorporated in the input measure of operating costs.

By properly conceptualizing the production framework of combination air carriers, the subsequent selection of appropriate input and output measures and DEA model is ensured. As previously stressed, the developed production framework is in line with several researchers (e.g., Lu et al., 2012; Lozano and Gutiérrez, 2014; Cui and Li, 2017a), thus highlighting its soundness from both theoretical and operational perspective. Apart from the combination air carriers, the developed production framework could be potentially modified for the purpose of assessing efficiency of freight-only air carriers, by simply omitting the ASK and RPK measures. In general, the developed production framework is considered to sufficiently represent the operational concept of the big majority of international air carriers, thus enabling increased degree of uniformity in the ensuing efficiency evaluation.

4. Proposed DEA Model

4.1. Data Envelopment Analysis (DEA) Theoretical Background

The DEA methodology was first introduced by the seminal research effort of Charnes et al. (1978), based on the early work of Farrell (1957). It is a non-parametric method measuring the efficiency of entities referred to as Decision-Making Units (DMUs). The DMU term is used to describe any entity responsible for converting inputs into outputs and whose performance is to be evaluated (Cooper et al., 2007). Any set of DMUs can be subjected to DEA methodology, with the fundamental prerequisite of transforming the same type of inputs into the same type of outputs. The common inputs and outputs are treated in a uniform manner, thus comprising a common DEA model for the whole set of DMUs under consideration (Samoilenko, 2014). DMUs can represent business operations (e.g., airlines) or individual processes, which are evaluated upon a set of multiple performance measures in the form of inputs and outputs (Zhu, 2014).

Conceptually, DEA is a methodology which is directed to identifying frontiers instead of central tendencies. While statistical regression techniques aim to fit a regression plane through the center of the data, DEA assigns a piecewise linear surface which rests on top of the observations and comprises the frontier (Cooper et al., 2011; Zhu, 2014). By using Linear Programming techniques, DEA performs comparison of the DMUs under consideration, thus assigning unity (or 100 percent) efficiency ranking to the DMUs belonging to the efficient frontier and below unity efficiency ranking to the DMUs not belonging to the efficient frontier (Samoilenko, 2014).

The first DEA model introduced by Charnes et al. (1978) is otherwise referred to as CCR model (deriving from the initials of Charnes, Cooper, and Rhodes), which along with the subsequently developed model of Banker et al. (1984) or BCC model (from the initials of Banker, Cooper, and Charnes) comprise the basic DEA models (Samoilenko, 2014). The CCR model estimates the gross efficiency of a DMU, which is constituted by technical and scale efficiency, while the BCC model estimates only technical efficiency. Technical efficiency is associated with the efficiency of converting production inputs into production outputs, while scale efficiency is associated with the attained economies of scale. Economies of scale are not feasible to be achieved in all scales of production. Hence, only a unique scale size exists where scale efficiency is 100 percent (Ramanathan, 2003). According to the aforementioned fundamental features, the CCR model is alternatively referred to as CRS (Constant Returns to Scale) model, while the BCC model is alternatively referred to as VRS (Variable Returns to Scale) model (Cooper at al., 2011).

Orientation is an essential element of the basic DEA models and advanced DEA models that were later developed, which takes into account the process of input-to-output transformation. The most commonly implemented orientations are the following (Samoilenko, 2014):

- Input-oriented models: These are concerned with the minimization of input consumption/utilization, for achieving a given amount of outputs when inputs are deemed controllable. A specific DMU is considered as efficient in an input-oriented model, when it is feasible to decrease any of its inputs without affecting any of the other inputs and without decreasing the amount of produced outputs.
- Output-oriented models: The specific models deal with the maximization of the level of the outputs given the level of existing inputs, thus considering outputs as controllable.
- Base-oriented models: The orientation of these models is dual, consequently dealing with the optimal combination of both inputs and outputs. Hence, control has been attained over both inputs and outputs.

A distinctive development of the basic DEA models is the super-efficiency DEA model, introduced by Andersen and Petersen (1993). The fundamental difference between the super-efficiency and the basic DEA models is the fact that the DMU under evaluation is excluded from the reference set, thus based on a reference technology constructed from all other DMUs (Zhu, 2014). In this case, the efficiency scores lose their unity upper bound, with the efficient DMUs taking efficiency scores greater than or equal to unity, while the inefficient DMUs retain their original efficiency scores (Avkiran, 2006; Greer, 2006). In essence, the greater than unity efficiency score for an efficient DMU reflects the radial distance of the DMU under evaluation from the production frontier estimated with the particular DMU excluded from the reference set, hence the maximum proportional increase in inputs preserving unity score (Andersen and Petersen, 1993).

The super-efficiency DEA models can discriminate the performance of the efficient DMUs, although efficient DMUs are not individually benchmarked against the same baseline. The differentiated baseline stems from the fact that the production frontier being formed by the rest of DMUs changes for each efficient DMU under evaluation (Zhu, 2014). However, super-efficiency scores can be used for ranking the whole set of DMUs including the efficient ones, thus eliminating efficiency score ties occurring for efficient DMUs (Avkiran, 2006; Cooper et al., 2007). In addition, super-efficiency DEA models have the potential to detect any DMUs that comprise benchmarking outliers. Given that DEA methodology is an efficient frontier technique, outliers can

substantially affect the scores of the other DMUs under consideration. Hence, in instances where super-efficiency scores are greater than or equal to two, the respective DMUs are deemed as potential outliers. For the case of extremely low efficiency scores (0.2 or less), the evaluated DMU also comprises a potential outlier. In both instances, exclusion of potential outliers from the DMU set under evaluation is dictated by relevant research (Avkiran, 2006; Paradi et al., 2011).

In several research efforts regarding airline efficiency assessment, the variation of efficiency over time has been assessed by employing various methodologies. Though, in several occasions where panel data are used along with DEA methodology, it is quite common to compare DMUs during a single year with the role of time being overlooked. Charnes et al. (1985), in order to evaluate the efficiency of selected maintenance units of the U.S. Air Force, introduced the *Window Analysis* methodology. More specifically, when observations for DMU sets are available over multiple time periods (time series data), it is often advised to perform a panel data analysis in order to discover potential efficiency trends over time. In this context, DEA is performed on a temporal basis, thus DMUs in each different time period are treated as if they were "different" DMUs. Consequently, efficiency evaluation among time periods is feasible for an operational entity, which is preferable over an individual benchmarking for a single time period (e.g., year) (Charnes et al., 1994).

Taking into account the research efforts of Tulkens and Van Den Eeeckaut (1995) and Cullinane and Wang (2010) the following approaches have been developed with respect to evaluating DEA efficiency over time:

- Contemporaneous : In the specific approach, the subset of panel data represents a specific point in time (e.g. one year observations subset from a 3-year observations set).

- Sequential : In this case, a reference production set is constructed for each point in time sequentially using observations from time point (g) (g = 1) to time point (h) (h = 1,2,..,t). The disadvantage of the particular approach is the variation in the number of observations used in order to evaluate efficiency from point (g) to point (h).

- Intertemporal : The particular approach involves construction of a single production set which is comprised of observations made throughout the whole observation set.

- Window Analysis : In essence it constitutes an approach where successive windows are constructed, thus yielding a sequence of reference production sets alternatively referred to as "locally intertemporal". Hence, each DMU is not compared with the whole data set, but only with certain subsets of the panel data, thus relying on a moving average principle (Asmild et al., 2004).

In the current paper we have opted for the intertemporal approach, taking into account the substantial enhancement of discriminative power of the DEA model, due to the fact that the constructed DEA frontier asymptotically approaches the true frontier (Timmer and Los, 2005). The issue of discriminative power of DEA, i.e. the portion of efficient DMUs compared to total number of DMUs under evaluation has drawn a quite increased attention from researchers. In particular, "rules of thumb" propose that the number of DMUs should be greater than two or three times the sum of inputs and outputs, in order to overcome issues associated with low discriminative power (Golany and Roll, 1989; Avkiran, 2006; Sarkis, 2007; Paradi et al., 2011; Cook et al., 2014; Zhu, 2014). Though, a quite effective way to assess whether the implemented DEA model has attained satisfactory discriminative power is the one proposed by Avkiran (2006), which suggests

that sufficient discriminative power has been attained if the portion of efficient DMUs is not more than one third of the total number of DMUs under evaluation.
By pooling DMUs belonging to multiple time periods as the concept of intertemporal approach dictates, an increase of DMU set size is achieved. Consequently, the discriminative power of the implemented DEA model can be significantly increased, thus ensuring that the proportion of efficient DMUs is not surpassing the one third threshold suggested by Avkiran (2006). Intertemporal approach combined with super-efficiency can significantly enhance the robustness of post-hoc statistical analysis due to the fact that the production frontier is formed by a more representative DMU set and efficient DMUs can be concurrently ranked. Moreover, taking into account the research of Asmild et al. (2004), the 5-year time span is quite small in order to avoid unfair comparisons due to significant technological changes, but sufficiently large to obtain an adequate sample size.

4.2. Inputs, Outputs, and DEA Model Selection

The selection of the inputs and outputs for the purpose of evaluating the efficiency of major international air carriers, shall primarily take into account the developed combined air carrier production framework depicted in Figure 1. However, during the search for data pertinent to Available Tonne-Kilometers (ATKs), it was discovered that respective figures were not either available or they referred to both freight and passengers (i.e. passengers translated into weight). As previously stressed, passenger transport and freight transport are segmented operations for air carriers, which subsequently result in different revenue streams. Consequently, the assumption of incorporating passenger and freight traffic into the ATK measure is deemed unacceptable for the purpose of the current research.

In light of the aforementioned observation regarding ATK data, the two-stage production framework for the combination air carriers was rendered infeasible to be implemented. Consequently, the combination air carrier production framework was reconsidered for the purpose of the current research, thus restructured as single-stage production framework. In the context of the required restructure, the first stage inputs and final stage outputs were retained, while the ASK and ATK measures (first stage outputs and second stage inputs of the previous two-stage production framework) were excluded. As a result, the revised production framework assumes that capacity production and marketing/final consumption take place in a single stage, with the initial inputs and the final outputs remaining the same as the previous production framework (Figure 2).

After restructuring and finalizing the production framework, we shall proceed with the determination of the inputs and outputs that are going to be implemented for conducting the subsequent comparative efficiency analysis. Taking into account the revised production framework, these are specified in what follows:

Inputs

- Number of Employees: Personnel comprise the resource associated with planning, performing, and overseeing the whole spectrum of operations. In general, if an airline can produce the same operational and/or financial output by using fewer employees, it is considered more efficient with respect to this input type. Airline reports refer to the particular input as simple headcount (total number of employees) or as number of Full-Time Equivalent (FTE) employees,

Figure 2 : Restructured Single-Stage Production Framework of a Combination Air Carrier

which represents the total working hours as number of employees working full-time. In some other instances, airline reports refer to the size of personnel as year-round average number of employees or average number of FTE employees.

- Total Operating Costs: They represent the cost of all acquired and utilized resources that are deployed for conducting the whole spectrum of operations (fuel, labor, aircraft acquisition/leasing, maintenance, airport fees etc). It should be pointed out that regardless of the degree of vertical integration of each individual airline all the in-house or outsourced activities incorporate a respective associated cost (Holloway, 2008).

- Number of Operated Aircraft: Alternatively referred to as flight equipment, aircraft fleet comprises the main means by which airline operations are conducted and in particular the means by which the core service element of air transport is fulfilled. By allocating the proper number and type of aircraft to the various routes, the airlines can respond to the prevailing market conditions, thus concurrently maintaining market share and satisfying customer needs. Either through acquisition or leasing, airlines' decisions concerning the fleet composition are of strategic significance, due to the fact that they are highly intertwined with the business model implemented and the geographic coverage of the markets served (Clark, 2007).

Outputs

- Total Operating Revenue: It comprises the total financial compensation extracted by offering the core service of passenger and freight transport, along with ancillary services like maintenance, catering, ground handling etc (Holloway, 2008). It primarily represents the result of the marketing practices implemented, which aim to establish a certain market position among competitors (Lu et al., 2012).

- Revenue Passenger-Kilometers (RPKs): The specific worldwide implemented passenger traffic metric represents the sum of the products obtained by multiplying the number of revenue passengers carried on each flight stage by the stage distance. Hence, it is equal to the number of kilometers travelled by all revenue passengers (ICAO, 2004). Alternatively, Revenue Passenger-Miles are used for instances where metric system is not adopted.

- Revenue Tonne-Kilometers (RTKs): The particular metric represents the revenue load in metric tonnes multiplied by the distance carried in kilometers (ICAO, 2004). As repeatedly

stressed, the particular metric in the context of the current paper shall exclusively represent a tonne of freight/cargo carried over one kilometer, which is also referred to as Freight Tonne-Kilometer in the relevant literature (Morrell, 2011).

Following the selection of the inputs and outputs, the determination of the DEA model that shall be implemented for the purpose of performing efficiency evaluation is necessary. The CCR input-oriented super-efficiency DEA model has been designated as the most proper for implementation, which is justified as follows:

- The adopted inputs and outputs are incorporating both operational aspects (personnel, aircraft, RPKs, RTKs) and financial aspects (total operating costs, total operating revenue). Hence, overall or gross efficiency (composed of technical and scale efficiency) is aimed to be assessed and not pure technical efficiency, thus rendering implementation of Constant Returns to Scale (CRS) incorporated in the CCR model as the most proper approach. It should be pointed out that under CCR model, a DMU with unity efficiency score is both technically and scale efficient, while for the BCC model a unity efficiency score implies only technical efficiency (Thanassoulis, 2001; Ramanathan, 2003; Samoilenko, 2014). In addition, the inefficiencies regarding airlines are incorporating both technical and scale aspects, with the CRS assumption being consistent with a high portion of existing relevant studies (Sjögren, 2016). Moreover, the property of a DMU being overall efficient is much more significant than being only technically efficient (Thanassoulis, 2001).

- Airlines have greater control over the inputs than other aspects defining performance, while the outputs are primarily influenced by macro-economic factors and long-term contractual aspects (Merkert and Hensher, 2011). Consequently, it is evident that opting for an input-oriented model is deemed as most appropriate for the purpose of assessing airline efficiency, which is by definition focused on achieving a certain level of outputs with minimum level of inputs (Ramanathan, 2003; Lee and Worthington, 2010; Samoilenko, 2014; Zhu, 2014; Joro and Korhonen, 2015).

- In regard to super-efficiency, previous relevant research of Greer (2006) has highlighted its inherent ability to rank efficient DMUs, while retaining the efficiency scores of inefficient DMUs. In this context, the super-efficiency scores can significantly facilitate statistical analysis of the obtained efficiency scores, thus eliminating the efficiency score ties of efficient DMUs (Andersen and Petersen, 1993). Additionally, it is important to stress that super-efficiency scores can significantly aid to identify potential outliers. As previously reported, any DMUs with super-efficiency scores greater than or equal to two should be excluded from the DMU set under consideration as outliers (Avkiran, 2006).

The above described selection process of the inputs, outputs, and DEA model definitely comprises a vital part of the current paper. By properly defining the particular research aspects, the potential for obtaining robust results pertinent to airline efficiency is substantially enhanced, thus increasing the usefulness of the extracted insights.

4.3. Sample Selection and Associated Data Collection

The current sample of international airlines was primarily selected on the grounds of investigating the association of airline efficiency with respect to alliance membership. Hence, it should include a sufficient number of major airlines participating in the three global alliance groups (i.e., Star, SkyTeam, and Oneworld), along with a sufficient number of non-allied airlines. Apart from the

alliance group participation, specific attention was given in order for the sample to include major international airlines originating from diverse geographical regions. In particular, the sample includes airlines from the so-called Transatlantic region (Europe and America) and the Asia-Pacific region (Asia and Oceania). Moreover, similarity in terms of group member number was pursued in order to attain equality regarding the representation of each group, both in terms of alliance membership status and geographical region.

Further elaborating on the selection criteria implemented in order to obtain the airline sample on which the DEA model shall be applied, these are as follows:

- Alliance membership or non-membership of the airline, for the whole time period under investigation (i.e. from year 2012 to year 2016).
- International routes served, at least in the geographical region that each airline belongs to. For example, airlines belonging to the Transatlantic region should at least serve routes between America and Europe, while airlines belonging to the Asia-Pacific region should at least serve international routes between Asia and Oceania.
- Data availability for all types of inputs and outputs implemented in the DEA model. Lack of any data for either inputs or outputs is not acceptable and the airline is excluded from the DMU set.
- Longevity in terms of duration of alliance membership was also considered, thus including airlines which have been consistently involved in the framework of alliances. Hence, higher priority was given to search for data regarding the founding members of global alliance groups.

By implementing the aforementioned selection criteria, it was rendered feasible to obtain relevant input and output data for a total number of 30 major international airlines for the period 2012-2016. In particular, the acquired data pertains to 15 airlines from the Transatlantic region (6 air carriers from America and 9 air carriers from Europe) and 15 airlines from the Asia-Pacific region (12 air carriers from Asia and 3 air carriers from Oceania). In regard to the global alliance groups, eight airlines belong to the Star alliance group, seven airlines belong to the SkyTeam alliance group, eight airlines belong to the Oneworld alliance group, while seven airlines do not belong to any alliance group (Table 2). Hence, it is evident that the sample composition is quite balanced in terms of the number of representatives for each group.

The timeframe under consideration is the time period from year 2012 to year 2016, for which relevant data have been officially published from all the airlines under investigation. In addition, it is important to stress that the particular time period is deemed as fairly stabilized in terms of alliance group membership, with the most prominent event being the merger of American Airlines with US Airways, which took place during year 2014 (Flight Airline Business, September 2017). Due to absence of disrupting events during the timeframe under investigation, the operating environment for every air carrier can be considered as stable, with the achieved efficiency scores being mainly the result of managerial decisions rather than exogenous factors' effects.

The data pertinent to the selected inputs and outputs were primarily collected from the airline annual reports that are posted in the respective corporate websites, which contain a wide array of operational and financial data. Apart from the airline annual reports, subscription to the digital edition of *Flight Airline Business* enabled access to international airlines' annual operational and financial data. The data obtained from *Flight Airline Business* provided a comparison basis for the

data obtained from the airline annual reports, while in some instances data not included in airline

Allied Air Carriers			Non-Allied Air Carriers
Star	**SkyTeam**	**Oneworld**	
Transatlantic			Transatlantic
United Airlines	Delta Airlines	American Airlines	Norwegian Air Shuttle
Air Canada	Air France - KLM	British Airways	Aer Lingus
Lufthansa	Aeroflot	LATAM	Virgin Atlantic
		Iberia	WestJet
		Finnair	
Asia-Pacific			Asia-Pacific
Singapore Airlines	Korean Air	Cathay Pacific	Virgin Australia
Air New Zealand	China Southern Air	Qantas	Emirates
Thai Airways	China Airlines	Japan Airlines	Jet Airways
All Nippon Airways	China Eastern Airlines		
Air China			

annual reports were solely provided by *Flight Airline Business*. In any case, data from *Flight Airline Business* are considered as valid from the research community, as stated in previous relevant research.

Table 2 : Sample International Airlines

For the cases of specific data that were infeasible to be obtained from airline annual reports or *Flight Airline Business*, these were extracted from the website of US DOT Bureau of Transportation Statistics and the statistics website named Statistics Canada. The aforementioned

	Number of Employees	**Total Operating Costs** (million USD)	**Number of Operated Aircraft**	**Total Operating Revenue** (million USD)	**RPKs** (million seat-kilometers)	**RTKs** (million tonne-kilometers)
Type	Input	Input	Input	Output	Output	Output
Max	123,287	41,681	1,549	42,650	359,651	12,900
Min	2,890	1,696	39	1,791	14,523	11
Mean	39,790	13,277	353	14,090	118,183	3,772
Standard Deviation	33,525	10,784	377	11,414	96,438	3,290

websites belong to U.S. and Canadian governments respectively, with several researchers having repeatedly used the particular web sources for obtaining data in the framework of their conducted studies. The descriptive statistics of the obtained input and output data are contained in Table 3.

Table 3 : Descriptive Statistics of Sample Air Carriers for Period 2012-2016

In order to attain uniformity in terms of the units that the individual inputs and outputs are expressed, some required conversions were performed. More specifically, in regard to total operating costs and total operating revenue, the airline annual reports' figures not expressed in U.S. Dollars were respectively converted from the reported currency to U.S. Dollars. The conversion was performed using the respective mean annual exchange rate, as given by the Canadian Forex website. In addition, for instances where non-metric traffic measures were used (e.g., ASM, RPM), these were converted to the respective metric traffic measures (e.g., ASK, RPK).

As far as the number of employees is concerned, it has been previously reported that there are diverse approaches implemented. The data for the specific input measure were exclusively obtained

from airline annual reports. As a matter of fact, airlines comprising the sample under investigation are expressing personnel size in various ways in their annual reports, with the most frequent being number of Full-Time Equivalent (FTE) employees or average number of employees. Despite the aforementioned lack of uniformity, the numerical values contained in the airline annual reports were used in the current research, regardless of the cited units.

5. DEA Results and Post-Hoc Analysis

After performing the steps of input/output selection, DEA model selection, and input/output data for the sample international airlines, intertemporal approach has been incorporated in order to improve evaluation of airline efficiency. In the framework of intertemporal approach, all DMUs (i.e. air carriers from all years) were pooled and benchmarked, thus creating a 5-year window (2012-2016) for efficiency evaluation over the particular timeframe. In order to calculate the efficiency scores, EMS Version 1.3 and Open Source DEA Version 0.2 software tools were particularly utilized, which have been also adopted by previous research (Greer, 2006 and Greer, 2016 respectively). The aforementioned software tools were utilized concurrently in order to verify

Airline	Alliance	Year

the validity of the obtained efficiency scores. Regarding the calculation of super-efficiency scores for the efficient DMUs, the EMS software was exclusively utilized since the Open Source DEA software does not calculate super-efficiency scores. The obtained efficiency and super-efficiency scores are contained in Table 4.

		2012	2013	2014	2015	2016
American Airlines	Oneworld	0.8537	0.8839	0.8276	0.8880	0.8718
Delta Airlines	SkyTeam	0.8714	0.8785	0.8695	0.9462	0.9258
United Airlines	Star	0.8045	0.8284	0.8563	0.8900	0.8755
Air Canada	Star	0.8495	0.8506	0.8661	0.8818	0.8942
Lufthansa	Star	0.8126	0.8184	0.8232	0.8021	0.8182
Air France-KLM	SkyTeam	0.8131	0.8402	0.8311	0.8333	0.8551
British Airways	Oneworld	0.8604	0.8871	0.9239	0.9110	0.9293
LATAM	Oneworld	0.7696	0.8055	0.8156	0.8745	0.9001
Iberia	Oneworld	0.7762	0.8058	0.8359	0.8575	0.8860
Aeroflot	SkyTeam	0.8110	0.8429	0.8355	0.9619	1.0420
Finnair	Oneworld	0.8769	0.8819	0.9110	0.9370	0.9344
Singapore Airlines	Star	0.9284	0.9224	0.9226	0.9419	0.9564
Korean Air	SkyTeam	1.3262	0.9162	0.9878	0.9597	0.9800
Cathay Pacific	Oneworld	0.9271	0.9212	0.9515	1.0219	1.0245
Air New Zealand	Star	0.8522	0.8853	0.8991	0.9436	1.0870
China Southern Air	SkyTeam	0.7881	0.7764	0.8008	0.8939	0.9249
Qantas	Oneworld	0.8830	0.8926	0.8515	0.9442	0.9940
Japan Airlines	Oneworld	0.9919	0.9209	0.9088	0.8819	0.8463
Thai Airways	Star	0.8964	0.8185	0.7892	0.8145	0.8958
China Airlines	SkyTeam	1.0175	0.9646	1.0434	1.0216	1.0679
All Nippon Airways	Star	0.9529	0.9003	0.8945	0.8716	0.8889
China Eastern Airlines	SkyTeam	0.7086	0.7820	0.7943	0.8356	0.9667
Air China	Star	0.8180	0.8083	0.8376	0.9359	0.9590
Norwegian Air Shuttle	-	1.0489	0.9916	1.0641	1.0560	1.1334
Aer Lingus	-	0.8639	0.8699	0.8923	0.9076	0.9690
Virgin Atlantic	-	0.9705	0.9951	1.0185	0.9660	0.9271
WestJet	-	0.8600	0.8723	0.8759	0.8795	0.8636
Virgin Australia	-	0.8352	0.7974	0.7461	0.7779	0.7576
Emirates	-	0.9709	0.9946	1.0232	1.0584	1.0497
Jet Airways	-	0.7518	0.6896	0.7512	0.8740	0.8764

Table 4 : DEA Efficiency and Super-Efficiency Scores

Conducting a thorough preliminary investigation of the recorded efficiency and super-efficiency scores, it can be inferred that they are fully satisfactory in regard to discriminative power and potential outliers. More specifically the facts supporting the particular statements are as follows:

- The number of efficient DMUs (super-efficiency score greater than or equal to unity) is 17 out of total number of 150 DMUs (11.33 percent of population). Hence, the discriminative power of the implemented DEA model is very satisfactory, given that the proportion of the efficient DMUs is far below the one third of the total number of DMUs (Avkiran, 2006).

- The maximum observed super-efficiency score is 1.3262, which has been achieved by the DMU representing Korean Air for the year 2012. On the other hand, the minimum observed efficiency score for inefficient DMUs is 0.6896, which has been achieved by the DMU representing Jet Airways for the year 2013. Taking into account the numerical values of the maximum and minimum scores, the likelihood for potential outliers is clearly ruled out (Avkiran, 2006; Paradi et al., 2011).

The theoretical distribution of DEA efficiency scores (henceforth both efficiency and super-efficiency scores shall be referred to as "efficiency scores") is usually unknown, thus dictating implementation of non-parametric statistical tests which inherently deal with cases where observations are statistically independent (Brocket and Golany, 1996; Cooper et al., 2007). The statistical tests for the purpose of the current paper were performed using the IBM SPSS software, and more specifically version 22.

Initially, the post-hoc analysis shall investigate whether there are statistically significant mean efficiency differences between air carriers with alliance membership and air carriers without alliance membership. The mean efficiency scores of those two groups are as follows:

- Mean efficiency of air carriers with alliance membership = 89.11% (n_1 = 115)
- Mean efficiency of air carriers without alliance membership = 91.37% (n_2 = 35)

In order to assess whether the recorded difference of mean efficiency scores of those two groups is statistically significant, the Mann-Whitney rank-sum test shall be performed. The particular non-parametric statistical test tests the hypothesis whether two groups belong to the same population or they differ significantly. Additionally, the validity of Mann-Whitney rank-sum test is enhanced for the case where both groups are comprised of at least 10 observations (Brocket and Golany, 1996; Cooper et al., 2007). Moreover, all the ensuing hypotheses shall be examined at 0.05 significance level.

The hypothesis that shall be investigated for the assessment of the above calculated efficiency differentiation between allied and non-allied air carriers is the following:

H_1: Allied air carriers and non-allied air carriers have identical mean efficiency.

Performing the Mann-Whitney rank-sum test, a Z-value equal to -1.315 and p-value equal to 0.188 are obtained (see Table 5 for further details). Hence, the hypothesis H_1 is not rejected at 0.05 significance level, thus assuming that the mean efficiency of allied air carriers is identical to the mean efficiency of non-allied air carriers.

Table 5 : Mann-Whitney test for hypothesis H_1

Subsequently, it shall be investigated whether there are statistically significant differences in regard

Group	N	Mean Rank	Sum of Ranks
1	115	72.93	8,386.50
2	35	83.96	2,938.50
Total	150		
Mann-Whitney U	1,716.50		
Wilcoxon W	8,386.50		
Z	-1.315		
p-value	**0.188**		

to mean efficiency among the four air carrier groups, namely air carriers belonging to the Star, SkyTeam, Oneworld global alliance groups and the non-allied air carriers. The computed mean efficiency of the particular air carrier groups is as follows:

- Mean efficiency of air carriers not belonging to any alliance group = 91.37% ($n_0 = 35$)
- Mean efficiency of air carriers belonging to Star alliance group = 87.73% ($n_1 = 40$)
- Mean efficiency of air carriers belonging to SkyTeam alliance group = 90.61% ($n_2 = 35$)
- Mean efficiency of air carriers belonging to Oneworld alliance group = 89.16% ($n_3 = 40$)

The hypothesis that shall be investigated for the purpose of evaluating whether the above mean efficiency differences are statistically significant, is the following:

H_2: The four individual air carrier groups (Star, SkyTeam, Oneworld, and non-allied) have identical mean efficiencies.

For the purpose of statistically testing the above hypothesis, the Kruskal-Wallis non-parametric test shall be performed. The specific test assesses whether (k) (where k>2) independent samples are from the same population or from populations with continuous distribution (Marques de Sá, 2007; Aljandali, 2016). After performing the Kruskal-Wallis test a p-value equal to 0.399 is obtained (see Table 6 for further details), hence the H_2 is not rejected at 0.05 significance level and it is therefore assumed that the four air carrier groups have identical mean efficiencies (Table 6).

Table 6 : Kruskal-Wallis test for hypothesis H_2

Group	N	Mean Rank
0	35	83.96
1	40	66.80
2	35	75.89
3	40	76.46
Total	150	
Chi-Square	2.953	
Degrees of Freedom	3	
p-value	**0.399**	

The post-hoc analysis results specifically presented in Table 5 and Table 6, clearly suggest that alliance membership is not either positively or negatively associated with airline efficiency, thus being in agreement with the findings of Min and Joo (2016). Hence, it remains an issue under

question whether airlines participating in alliance groups are enhancing their technical and scale efficiency, which comprise the efficiency types investigated by the current paper and by Min and Joo (2016).

Further proceeding with the comparative efficiency analysis, the interconnection of efficiency to the extent of air carriers' freight business shall be investigated. The specific investigation shall be conducted in a similar manner to Hong and Zhang (2010), thus investigating efficiency in regard to the contribution of air freight traffic revenue to the total traffic revenue. In the framework of this investigation, the contribution of freight traffic revenue compared to total traffic revenue (i.e. revenue collected from passenger and freight transport) was computed for all sample carriers for all years of period 2012-2016. The most notable result of the performed calculations is the fact that there are certain air carriers consistently recording (for all years during the period 2012-2016) air freight traffic revenue share greater than 10 percent of total traffic revenue. The air carriers consistently recording over 10 percent of total traffic revenue as freight traffic revenue during the period 2012-2016 are Singapore Airlines, Korean Air, Cathay Pacific, China Airlines, Emirates, and LATAM. Moreover, it is notable to mention that in the case of Korean Air, Cathay Pacific, and China Airlines the share of air freight traffic revenue steadily represents over 20 percent of total traffic revenue (further details shown in Table 7).

Table 7 : Air Freight Traffic Revenue Share for Selected Air Carriers
(Source: Airline annual reports, *Flight Airline Business* October 2013, October 2014, October 2015
*The figures for years 2012, 2013, 2014 represent freight traffic revenue proportion over total operating revenue)

Airline	Alliance Group	Air Freight Traffic Revenue as Total Traffic Revenue Percentage				
		2012	2013	2014	2015	2016
LATAM	Oneworld	14.97%	14.41%	14.17%	13.65%	12.35%
Singapore Airlines	Star	16.56%	15.30%	15.16%	14.06%	13.24%
Korean Air	SkyTeam	28.72%	30.87%	32.93%	28.41%	30.64%
Cathay Pacific	Oneworld	23.55%	22.56%	22.62%	21.56%	20.28%
China Airlines*	SkyTeam	31.00%	30.00%	31.00%	31.22%	29.06%
Emirates	-	15.25%	14.69%	14.94%	14.07%	13.41%

The mean efficiency scores for the groups under comparison are:

- Mean efficiency of air carriers with annual air freight traffic revenue consistently representing over 10 percent of total annual traffic revenue = 96.88% ($n_1 = 30$)
- Mean efficiency of air carriers not consistently recording annual freight traffic revenue over 10 percent of total annual traffic revenue = 87.82% ($n_2 = 120$)

The hypothesis that shall be tested taking into account the above is the following:

H_3: The mean efficiency of the group of air carriers with annual air freight traffic revenue consistently comprising over 10 percent of total annual traffic revenue, is identical to the mean efficiency of the group comprising of all other air carriers.

The above hypothesis shall be tested performing the Mann-Whitney rank-sum test. The results obtained from the Mann-Whitney test are a Z-value equal to -4.936 and a p-value far less than 0.001 (see Table 8 for more details). Hence, the hypothesis H_3 is rejected at 0.05 significance level,

therefore assuming that the group of air carriers consistently recording annual air freight traffic revenue greater than 10 percent of total annual freight traffic revenue, outperforms the group comprising of all other carriers in terms of mean efficiency. The particular finding is in line with the previous conclusions of Hong and Zhang (2010) concerning 29 airlines during period 1998-2002, while the sample of the aforementioned research effort includes many airlines that are also under investigation in the current paper (e.g., Cathay Pacific, Korean Air, Singapore Airlines, China Airlines, Emirates).

Table 8 : Mann-Whitney test for hypothesis H_3

Another aspect that shall be investigated in regard to its interconnection to airline efficiency is the continent that air carriers belong to, namely America, Europe, Asia, and Oceania. The mean

Group	N	Mean Rank	Sum of Ranks
1	30	110.52	3,315.50
2	120	66.75	8,009.50
Total	150		
Mann-Whitney U	749.50		
Wilcoxon W	8,009.50		
Z	-4.936		
p-value	**0.000**		

efficiency scores of airlines belonging to the particular continents were calculated as follows:

- Mean efficiency of air carriers belonging to American continent = 86.43% (n_1 = 30)
- Mean efficiency of air carriers belonging to European continent = 90.29% (n_2 = 45)
- Mean efficiency of air carriers belonging to Asian continent = 91.24% (n_3 = 60)
- Mean efficiency of air carriers belonging to Oceanian continent = 87.64% (n_4 = 15)

The hypothesis that shall be tested for evaluating whether the differences regarding mean efficiency of the aforementioned groups are statistically significant shall be similar to the hypothesis H_2, thus phrased as follows:

H_4: The four air carrier groups belonging to specific continents (America, Europe, Asia, Oceania) have identical mean efficiency.

For the purpose of statistically testing the above hypothesis, the Kruskal-Wallis non-parametric test shall be performed. The specific test yields a p-value equal to 0.043 (see Table 9 for further details), hence the hypothesis H_4 is rejected at 0.05 significance level and it is therefore assumed that there are statistically significant differences among continent-based air carrier groups.

Table 9 : Kruskal-Wallis test for hypothesis H_4

In a similar manner to Joo and Fowler (2014), we shall subsequently perform pairwise comparisons

Group	N	Mean Rank
1	30	58.50
2	45	77.64
3	60	84.78
4	15	65.93
Total	150	
Chi-Square	8.170	
Degrees of Freedom	3	
p-value	**0.043**	

of the aforementioned continent-based air carrier groups in order to identify which group differences are statistically significant, albeit with a differentiated approach pertinent to the statistical test implemented. After consulting the research of Shingala and Rajyaguru (2015) regarding post-hoc tests, Games-Howell statistical test has been designated as the most suitable for pairwise comparison, given that samples' size and variance is unequal (after verification using Minitab software version 17). As stated in the research of Shingala and Rajyaguru (2015), Games-Howell post-hoc test provides the best performance in regard to pairwise comparisons.

The evaluation of airline efficiency with respect to the continent that sample airlines belong to, has designated that there are statistically significant efficiency differences of the Asian and European continent air carrier groups, when compared to the American continent air carrier group. In particular, Asian and European continent air carrier groups outperform American continent air carrier group at 0.05 significance level, while the mean efficiency differences of air carrier groups belonging to Asia, Europe, and Oceania are not statistically significant (see Table 10 for more details). The particular finding is differentiated from the conclusion drawn by the research of Joo and Fowler (2014), which claims that European airlines' efficiency is inferior to that of Asian and North American airlines, while the efficiencies of Asian and North American airlines are claimed to be identical.

Table 10 : Games-Howell Test for Pairwise Comparison of Continent-based Air Carrier Groups

*Statistically significant at 0.05 significance level

(I) Continent	(J) Continent	Mean Difference (I-J)	p-value	95% Confidence Interval	
				Lower Bound	Upper Bound
1	2	-0.038532	0.040*	-0.075841	-0.001224
	3	-0.048088	0.011*	-0.087648	-0.008528
	4	-0.012117	0.960	-0.082427	0.058193
2	1	0.038532	0.040*	0.001224	0.075841
	3	-0.009556	0.955	-0.057851	0.038738
	4	0.026416	0.760	-0.047989	0.100821
3	1	0.048088	0.011*	0.008528	0.087648
	2	0.009556	0.955	-0.038738	0.057851
	4	0.035972	0.562	-0.039415	0.111359
4	1	0.012117	0.960	-0.058193	0.082427
	2	-0.026416	0.760	-0.100821	0.047989
	3	-0.035972	0.562	-0.111359	0.039415

After consulting the data set pertinent to DEA model inputs, fleet size is the most prominent feature of American continent air carriers with Air Canada and LATAM consistently operating over 320 aircraft, while all U.S.-based air carriers of the sample consistently operate over 1,200 aircraft. More specifically, American continent air carriers have recorded an average fleet size of 813 aircraft for the period 2012-2016, while the average fleet size of air carriers belonging to Asia, Europe, and Oceania for the same period is 262, 225, and 183 aircraft respectively. Taking into account the research of Merkert and Morrell (2012), it can be inferred that American continent air carriers and especially U.S.-based air carriers present diseconomies of scale as a result of their increased fleet size, hence negatively affecting their scale efficiency and consequently their gross efficiency.

6. Concluding Remarks

The present paper has attempted to evaluate the effects of significant aspects on airline efficiency, with the primary effort focused on alliance membership. However, evaluation of airline efficiency with respect to freight traffic revenue share and continent which air carriers belong to is also considered of high interest. The findings are largely in line with the relatively few previous research efforts pertinent to airline efficiency assessment in regard to the aforementioned aspects, thus comprising a potential motivation for similar future attempts.

In accordance with the combined air carrier two-stage production framework which is represented in Figure 1, the most appropriate methodological approach would be the adoption of the Two-Stage Network DEA model developed by Zhu (2011) and subsequently implemented by Lu et al. (2012), Lozano and Gutiérrez (2014), Tavassoli et al. (2014), and Lu et al. (2014). However, the CCR input-oriented super-efficiency DEA model that has been implemented in the current paper due to lack of ATK data, is estimated to comprise the most suitable alternative methodological approach for evaluating combination air carrier efficiency. The particular statement is supported by the following facts:

- The increased significance of gross efficiency (i.e. combined technical and scale efficiency) evaluation over technical efficiency evaluation (Thanassoulis, 2001).
- The increased degree of control of airlines over inputs (Merkert and Hensher, 2011).
- The ability of super-efficiency methodology to rank efficient DMUs, thus increasing the results validity of non-parametric statistical tests. Moreover, super-efficiency enables the detection of potential outliers (Greer, 2006; Avkiran 2006).

The additionally implemented methodological concept of intertemporal approach over the whole timeframe under consideration (i.e. 2012-2016) is deemed to considerably enhance the robustness of the input-oriented CCR super-efficiency DEA model, mainly on the grounds that it further enhances discriminative power. Consequently, the validity of the non-parametric test results is further augmented, taking into account that they are based on ranks and not on numerical value means.

Another feature of the herewith presented methodological approach, are the data collected for the relevant inputs and outputs of the implemented DEA model. The particular data are considered to incorporate a high degree of reliability, which is mainly attributed to the credibility of the sources. The airline annual reports are definitely the most reliable source, while supplemental sources like

Flight Airline Business and U.S. and Canadian government transport statistics websites are also of high credibility, mainly on the grounds that they have been repeatedly used by researchers dealing with airline efficiency evaluation (e.g., Greer, 2008; Min and Joo, 2016). In addition, the time proximity and the fairly stable membership status of the global alliance groups during the period 2012-2016 are certainly contributing to the validity of the attained results.

However, the lack of uniformity in annual airline reports concerning the number of employees comprises a non-negligible limitation. As previously stated, figures reported by airlines are expressed in diverse ways, thus imposing a considerable restriction on similar research efforts where the number of employees is incorporated. Also, the lack of uniformity with respect to ATK and RTK data reported by airlines is definitely another source of ambiguity for researchers. Taking into account the above issues pertinent to data reporting, it is of paramount importance for airlines to align their reporting framework, in order to concurrently enable benchmarking with reduced bias.

In regard to the lack of positive association of alliance membership with airline efficiency, it is rendered imperative for future research efforts to further investigate the particular operational aspect. More specifically, future research could investigate more extensively the aforementioned association with respect to the timeframe spectrum (e.g., 10 years) and most importantly with view to various types or aspects expressing airline cooperation forms (e.g., type, number, intensity, longevity). For example, potential differences in airline efficiency as a result of adopting different types and various airline collaboration forms/schemes with different intensity (e.g., codeshare agreements, joint ventures) represents an interesting area of future research. Additionally, the investigation of airline efficiency changes with respect to joining an alliance or switching an alliance following a merger/acquisition, merits further attention in the framework of future research. In any case, the limited number of research efforts primarily dealing with alliance membership and airline efficiency using DEA comprises a major motivation for further research in this direction. However, the implemented methodological approaches should attain a sufficient uniformity level, in order for the respective findings to refer to a common basis.

The finding concerning positive association of increased freight traffic revenue share with airline efficiency is also considered an important outcome of the current paper. As previously stressed by Hong and Zhang (2010), combination air carriers should pay increased attention to the freight segment of their operations. Apart from the enhancement in terms of airline efficiency, the exploitation of passenger transport operations for the purpose of attaining increased freight traffic is consequently leading to the enhancement of profitability as the freight revenue stream is increased. Along with the fact that over 40 percent of global freight traffic is performed using passenger aircraft (Morrell, 2011; Boeing, 2016), it becomes obvious that air carriers should increase their efforts to market the available freight capacity, especially the portion related to passenger aircraft. As a result, fleet rationalization can be achieved and economies of scale and scope can be attained. Moreover, the research effort of Coto-Millán et al. (2016) has similarly designated the positive effect of increased cargo business portion on airport efficiency, thus further highlighting the importance of freight segment in aviation industry from both airline and airport perspective. In this context, airline and airport managers and executives should reconsider their mid- and long-term strategy by getting involved in freight operations in a more focused manner, in order to gain an improved competitive position.

Finally, the observed statistically significant mean efficiency differences regarding Asian and European continent air carriers when compared to American continent air carriers, comprise evidence pertinent to the effectiveness of the implemented airline management practices across various aviation markets. As previously stated in Section 5 following the results contained in Table 10, fleet size is an airline management aspect that needs increased attention from the airline executives, taking into account the diseconomies of scale that can result beyond a certain threshold of airline size. From a managerial perspective, it is widely acknowledged that fleet rationalization constitutes a major determinant for operational flexibility and economic viability. In this framework, it is rendered important for future research to further investigate the interconnection of airline size and efficiency, thus providing insight to airline executives with respect to decisions regarding fleet structure. In addition, air carriers should perform route planning in a more holistic way, thus taking into account operational requirements and financial constraints.

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