ISCTE Business School
Instituto Universitário de Lisboa

THE GLOBAL AIRLINE INDUSTRY: AN ASSESSMENT OF THE IMPACT OF LOW-COST CARRIERS ON THE TECHNICAL EFFICIENCY OF FULL-SERVICE AIRLINES

Bernardo Almeida Pinho

Dissertation submitted as partial requirement for the conferral of

Master in Economics

Supervisor:

Prof. Henrique Monteiro, ISCTE Business School, Departamento de Economia

November 2017

THE GLOBAL AIRLINE INDUSTRY: AN EFFICIENCY ASSESSMENT

Bernardo Almeida Pinho

ISCTE Business School
Instituto Universitário de Lisboa

- Spine –

Abstract

Since the emergence of the first low-fare airline, Southwest Airlines, we have witnessed the spread of the low-cost phenomenon in different regions of the world. The simplicity, the low fares and the focus on core business (flying) have been the critical basis for their success, and the concern of traditional operators who see their market positioning threatened. To remain competitive, full-service operators have been forced to redefine their business model.

With great interest in the innovative nature of low-cost carriers, literature has covered inter-business model comparisons of efficiency, as well as on the analysis of the strategies carried out by full-service to adapting to the increased competition. However, there seems to be no study on the impact of low-cost operators on the technical efficiency of full-service airlines. Thus, this thesis aims to analyse the impact of the low-cost regional market share on the technical efficiency of full-service airlines domiciled in the same region. In order to pursue this analysis, a two-stage Data Envelopment Analysis was implemented. Initially, bootstrapped efficiency scores were estimated for a set of 137 passenger airlines. Subsequently, the estimated efficiency measures were used as a dependent variable in a truncated bootstrap regression to identify the determinants of the technical efficiency. Results suggest that larger low-cost market shares are associated with lower input uses for the same full-service carriers' output levels based on that region. This relationship might be explained by the adoption of better management practices that approach the full-service model to the low-cost model.

Keywords: Two-stage Data Envelopment Analysis; Air transportation; Low-cost and full-service carriers.

JEL Classification Codes: C24 and L93.

Resumo

A criação da primeira companhia aérea de baixo-custo, a *Southwest Airlines*, impulsionou o desenvolvimento mundial de tantas outras no sector da aviação. A simplicidade, os preços baixos e o foco no principal objetivo da atividade (voar) têm sido a chave do seu sucesso e, simultaneamente, uma ameaça às companhias aéreas tradicionais. Inevitavelmente, os operadores de serviço-completo têm vindo a realizar mudanças no seu modelo de negócio para conseguirem manter-se competitivas.

Recentemente, alguns estudos têm-se focado na comparação entre os dois modelos de negócio e na análise das estratégias das transportadoras tradicionais ao aumento concorrencial. No entanto, parece não existir qualquer investigação acerca do impacto dos operadores de baixo-custo na eficiência técnica dos tradicionais. Assim, este estudo foca-se na relação entre a quota de mercado regional das transportadoras de baixo-custo e a eficiência técnica das companhias aéreas tradicionais sediadas nessa região. Para prosseguir esta investigação, foi implementada uma Análise por Envoltória de Dados de duas etapas. Inicialmente, foram estimadas as pontuações de eficiência técnica com métodos de *bootstrap* para 137 transportadoras de passageiros e, posteriormente, as pontuações foram usadas como variável dependente numa regressão *bootstrapped* truncada para identificar as fontes de eficiência. Os resultados sugerem que uma maior concentração de operadores de baixo-custo numa dada região está associada a uma menor utilização de recursos, por parte dos operadores tradicionais dessa região, para o mesmo nível de produção. Esta relação poderá ser explicada por práticas de gestão mais adequadas que aproximam o modelo tradicional do modelo de baixo-custo.

Palavras-chave: Análise por Envoltória de Dados de duas etapas; Transporte Aéreo; Transportadores aéreos tradicionais e de baixo custo.

Códigos de classificação JEL: C24 e L93.

Acknowledgements

Inevitably, these words are informal and not only related to my master thesis. They came about to thank all those who were directly involved in my complete college experience and to remember some lived experiences during that period.

First to my parents, who provided me access to excellent education and always gave me the choice to choose my path, as they were supporting me and trusting in my decisions. To my siblings, for lending me the laptop and making jokes about this thesis. To my grandmothers, for always being available to help.

To *Bárbara*, who had always stood by my side on the *Entrecampos* lunch route, on *Telheiras* Tuesdays, on the university parties with or without *sentido de orientação*, in Madrid or Helsinki, for text revisions and spreading confidence when most needed…

To my friend *Afonso*, hoping that these words will lead him to fulfil the promise of a trip to Madrid, as he proved to be a *máno* for life.

To my friend *Duda*, for all lifts, train journeys, celebrated masses and for emptying my wallet to drink coffee at *Toni*. To my friend *Uva* for all help, for sharing the *Tricampeonato* and introducing *Apache*.

To all *Antti Korppins*, *Lucinda*, *Luís* and Mr Ambassador for sharing Finland experience.

To *CVO*, *Canita* and my athletes for friendship and giving me experience and expertise that I could not acquire in school.

To all my professors and ISCTE staff for gave me tools and better chances to follow a successful path.

The last, but for sure not the least, to my thesis supervisor, Professor *Henrique Monteiro*, I would like to thank you for guiding me at this stage that ends a cycle of 5 years. Your splitting hairs style, fully availability to help and encouraging words were crucial to draw up this thesis with a seal of quality.

Contents

List of Figures

List of Tables

List of Abbreviations & Glossary

This section presents a set of definitions and abbreviations, following the alphabetical order, frequently used throughout this thesis.

ATK – "*Available Tonne Kilometres: The number of tonnes of capacity available for the carriage of revenue load (passenger and cargo) multiplied by the distance flown"* (ICAO, 2014)

ASK – "*Available Seat Kilometres: The sum of the products obtained by multiplying the number of seats available for sale on each flight stage by the corresponding stage distance*" (ICAO, 2014:20)

BCC - Banker, Charnes and Cooper (1984)

CCR - Charnes, Cooper and Rhodes (1978)

CRS – Constant Returns to Scale

DMU - Decision Making Unit

DEA – Data Envelopment Analysis

Freight - Includes express and diplomatic bags but not passenger baggage

FTK – Freight Tonne Kilometres

FSC – Full-Service Carrier

IATA – International Air Transport Association

ICAO – International Civil Aviation Organization

LCC – Low-cost Carrier

Mail – "*Dispatches of correspondence and other objects carried on an aircraft, which have been dispatched by and intended for delivery to postal administrations"* (European Union, 1995)

NDEA – Network Data Envelopment Analysis

NIRS – Non-Increasing Returns to Scale

PLF – "*Passenger Load Factor: The revenue passenger-Kilometres as a percentage of the available seat-Kilometres"* (ICAO, 2014:22)

PTE – Pure Technical Efficiency

Revenue Load for 1 Revenue Passenger: When no data is available, 100kg is the standard weight suggested by ICAO (70% for the passenger and 30% for its checked baggage) (ICAO, 2014)

RPK – "*Revenue Passenger Kilometres: Sum of the products obtained by multiplying the number of revenue passengers carried on each flight stage by the corresponding stage distance"* (ICAO, 2014:17)

RTK - Revenue Tonne Kilometres: The revenue load in tonnes multiplied by the distance flown (ICAO, 2014)

SBM – Slacks-Based Measure

Scheduled flights – "*Flights scheduled and performed according to a published timetable, or so regular or frequent as to constitute a recognizably systematic series which are open to use by the public; extra flights occasioned by overflow traffic from scheduled flights; and preparatory revenue flights on planned air services."*

(IATA, 2016:95)

Stage Length – The distance travelled by an aircraft from take-off to landing

TE – Technical Efficiency

VRS – Variable Returns to Scale

WATS – World Air Transport Statistics

Weight Load Factor – "*Tonne kilometres performed expressed as a percentage of tonne-kilometres available"* (ICAO, 2014:29)

1. Introduction

What is globalisation? Are we living in a global world? The world is becoming smaller as the time goes by. People are becoming more and more connected through businesses, job market, migration, tourism, as with many other causes. Distance no longer exists virtually where the general access to the internet is guaranteed and physically is also vanishing as technology develops to provide greater and cheaper access and mobility. Many factors are responsible for this change, but none of this would happen if transport evolution were not fostering globalisation. Nevertheless, this phenomenon will keep on rolling as more developments are arising in the years to come. The Hyperloop will travel at over 1000 km per hour, offering a fuel-free service with much cheaper fares and faster travels than air transport. Maglev trains, self-driving smart cars and urban transport pods are also imminent to offer new means of transport for an increasing world population.

Air transport has been having a massive role in the change that we are currently living. For example, in 2016, airlines carried 3.696 billion passengers (The World Bank, 2017b) and freight around 196 billion of tonne-kilometres (The World Bank, 2017a), in line with the increasing trend in previous years. In the words of Tony Tyler, Director General and CEO of IATA, "*There are 31.5 million seconds in a year. In 2015, commercial airlines operated some 37.6 million flights. That means that on average, not a second went by when an aircraft was not landing or taking off somewhere in the world.*"(IATA, 2016:3).

Particularly in this industry, a competitive environment is taking place with the emergence of low-cost operators with an innovative business model combining cheaper fares and quality service (Dobruszkes, 2006). These carriers have been bringing significant worldwide structural changes in this industry which are allowing them to be not only a cause but also an interesting consequence of globalisation (OECD, 2010). It was in this new nature of LCCs which is fighting FSCs market positioning that several studies had been carried out. In one hand, Barbot, Costa, and Sochirca (2008); Barros and Peypoch (2009); Lee and Worthington (2014) proved a relation between efficiency gains and the adoption of the low-cost model. On the other hand, Merkert and Morrell (2012); Pearson and Merkert (2014) preferred to focus their studies on the reactions taken by FSCs, such as mergers and acquisitions and subsidiary airlines, to compete with the growth of LCCs. However, none of the studies strived for measuring the widespread impact of low-cost airlines on the efficiency of FSCs. Thus, this paper expects to contribute to the literature by performing an innovative study on the impact of the regional market share of low-cost on full-service airlines' technical efficiency based in the same region in 2015. At the same time, its relevance also lies in the extensive coverage that provides – 137 passenger airlines within the following worldwide regions: Africa, Asia Pacific, Europe, Latin America, Middle East and North America.

To perform this analysis, we implement a two-stage procedure based on Simar and Wilson (1998, 2000, 2007). In the first stage, we estimate non-bias technical efficiency scores for each airline by using Data Envelopment Analysis with a smooth heterogeneous bootstrap procedure. In the second step, non-bias estimates are regressed against some covariates to detect the sources of technical efficiency by using a bootstrapped truncated regression. By the end of this thesis, we expect to rank all airlines according to operational performance, compare regional technical efficiency, business models, as well understanding the sources of the technical efficiency of airlines. Finally, conclude if the market share of low-cost carriers affects full-service airlines' efficiency domiciled in the same region.

The remainder of this investigation is organised into sections. Section **2** provides an overview of the global airline industry by looking to the process of global market liberalisation, to the features of the low-cost business model and the international context in 2015. The literature review is established in Section **3**. Section **4** presents a description of the database, and the methodology for this study is described in Section **5**. The results along with their discussion are available in Section **6,** and Section **7** presents the main findings of this investigation.

2. The Airline Industry

2.1. Market liberalisation

This section aims to offer a historical review of the airline industry deregulation process before reporting on its current state since it is, to a large extent, the result of the development started in the 1970s.

It was in North America that the first market liberalisation wave appeared, driven by the emergence of the first world low-cost airline (Dobruszkes, 2006). The success of Southwest Airlines, a North American domestic operator created in 1973, inspired the conception of the US Airline Deregulation Act in 1978 which abolished the regulation of fares, routes and schedules in the whole US domestic market (Fu, Oum and Zhang, 2010), and this phenomenon quickly spread in the US (see Figure **1**).

***Figure 1**: Low-cost Market Share in the US (% of total passengers)*

	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002
AirTran†				0.0	0.6	1.4	1.0	0.9	1.2	1.3	1.5	1.6	1.9
ATA	0.1	0.1	0.1	0.4	0.7	1.0	0.9	0.8	1.1	1.2	1.3	1.6	1.9
Frontier					0.0	0.2	0.3	0.3	0.3	0.5	0.6	0.6	0.8
JetBlue											0.3	0.8	1.3
Southwest	7.0	8.2	9.6	11.3	12.7	13.6	14.1	13.8	13.8	14.3	14.9	16.2	15.8
Other LCCs			0.2	1.9	2.4	2.3	2.8	2.4	2.2	2.2	2.0	2.1	2.0
Total LCCs	7.0	8.3	10.0	13.7	16.3	18.4	19.0	18.2	18.5	19.4	20.6	22.9	23.7

Source: Ito and Lee (2003:4)

In 1995, the low-cost concept started its establishment in Europe with the emergence of Ryanair (Dobruszkes, 2006). A few years later, in November 1999, 44 African countries met in Ivory Coast to adopt the Yamoussoukro Decision where they agreed to implement an open skies air transport policy across the continent (Barros and Wanke, 2015). This intention was later reinforced by the Declaration on the Establishment of a Single African Air Transport Market signed in 2015. In South America, between 1991 and 1999, and in the Caribbean in 2008, deregulation initiatives were taken by the adoption of several agreements to harmonise local policies and to promote open air traffic and market access (ICAO Secretariat, 2016). It was also in 2008 that the Association of Southeast Asian Nations (ASEAN) adopted a Multilateral

Agreement on Air Services which supported air transport industry liberalisation in the region (Tan, 2010).

As we have noted, many regions in the world took steps to deregulate fares, routes and schedules in different time periods, but how are these decisions impacting the industry? The competitiveness generated by market liberalisation gave rise to structural changes in the airline industry in which the international spreading of the low-cost innovative business model, combining the focus on cost minimisation and the core activity of this business (flying) to provide lower fares, was the most relevant feature (see Table **1**).

Table 1*: The Beginning of Low-Cost Developments by Region*

Region	Year	First low-cost airline
USA	1971	Southwest Airlines
EU	1986	Ryanair
Australia	1990	Compass Airlines
New Zealand	1994	Kiwi Travel International Airlines
Canada	1996	WestJet
Japan	1998	Skymark Airlines
Malaysia	2001	Air Asia
Brazil	2001	GOL
South Africa	2001	Kulula
Gulf States	2003	Air Arabia
India	2003	Air Deccan
Thailand	2004	Nok Air
Singapore	2004	Tiger Airways
China	2005	Spring Airlines

Source: Adapted from Gross and Lück (2016:6)

Traditional airlines, threatened by the emergence of low-cost carriers (LCCs), were forced to introduce some changes in their business models to remain in the market (OECD, 2010). One of the global steps that they took was the development of network alliances (see Figure **2**) in which we can highlight Star Alliance, OneWorld, and SkyTeam (ICAO Secretariat, 2016). These alliance members transported more than 1.943 billion passengers and represented 61.2% of the world total Scheduled Passenger–Kilometres in 2015 (IATA, 2016).

***Figure 2**: Main Airline Alliances in 2015*

oneworld	SKYTEAM		STAR ALLIANCE	
Members	**Members**		**Members**	
Air Berlin	Aeroflot	Delta Air Lines	Adria Airways	Ethiopian Airlines
American Airlines	Aerolineas Argentinas	Garuda Indonesia	Aegean Airlines	EVA Air
British Airways	Aeromexico	Kenya Airways	Air Canada	LOT
Cathay Pacific	Air Europa	KLM	Air China	Lufthansa
Finnair	Air France	Korean Air	Air India	Scandinavian Airlines
IBERIA	Alitalia	Middle East Airlines	All Nippon Airways	Shenzhen Airlines
Japan Airlines	China Airlines	Saudia	Air New Zealand	Singapore Airlines
LAN Airlines	China Eastern	TAROM	Asiana Airlines	South African Airways
Malaysia Airlines	China Southern	Vietnam Airlines	Austrian	SWISS
Qantas	Czech Airlines	Xiamen Air	Avianca	TAP Portugal
Qatar Airways			Brussels Airlines	Thai Airways
Royal Jordanian			COPA	Turkish Airlines
S7 Airlines			Croatia Airlines	United Airlines
Sri Lankan			Egyptair	
TAM				

Source: Adapted from Gross and Lück (2016:6)

Looking for economies of density, maximise the use/capacity of the aeroplanes within a network of a given size (Dobruszkes, 2006), alliance members adopted the hub-and-spoke system presented in Figure **3**. By implementing this system, all passengers excluding those whose origin or last stop is the hub, change for a second flight, transfer at the hub to their final destination (Cook and Goodwin, 2008). With this system, airlines benefit from cost savings through fewer aircrafts, flights with greater occupation, significant expansion of their network and the ease to create new routes that only require one new additional flight (Zanin and Lillo, 2013).

***Figure 3**: Hubs by Alliance in 2015*

Alliance belongs each hub by the colour of the circle

Source: ICAO Secretariat (2016:20)

As a result of this competitive environment, a set of mergers and acquisitions, described in Table **2**, was established in an attempt to stay competitive. Through these operations, airlines were hoping to leverage synergies on cost savings, outspread their networks, and increasing the yield through the reduction in the number of suppliers operating the same routes (Merkert and Morrell, 2012; ICAO Secretariat, 2016).

Table 2: *Most Recent Mergers and Acquisitions in Passenger Airlines*

Merging airlines	Merged entity	Year
North America		
Southwest Airlines/Morris Airlines	Southwest Airlines	1993
AirTran Airways/Valujet	AirTran Airways	1997
American Airlines/Reno Air	American Airlines	1999
Delta Air Lines/Atlantic Southeast A.	Delta Air Lines	1999
Delta Air Lines/Comair	Delta Air Lines	1999
American Airlines/TWA	American Airlines	2001
Republic Airways/Shuttle America	Republic Airways	2005
US Airways/America West Airlines	US Airways	2005
SkyWest/Atlantic Southeast Airlines	SkyWest/ASA	2005
Delta Air Lines/Northwest Airlines	Delta Air Lines	2009
Republic Airways/Midwest Airlines	Republic Airways	2009
Republic Airways/Frontier Airlines	Republic Airways	2009
United Airlines/Continental Airlines	United Airlines	2010
Southwest Airlines/AirTran Airways	Southwest Airlines	2011
US Airways/American Airlines	American Airlines Group	2013-2015
Alaska Airlines/Virgin America	Alaska Airlines	2016
Europe		
British Airways/Delta Air	Deutsche BA	1997
easyJet/GoFly	easyJet	2003
Ryanair/Buzz	Ryanair	2003
Air France/KLM	Separate brands	2004
Lufthansa/Swiss Airlines	Separate brands	2005
Lufthansa/SN Brussels	Separate brands	2006
Air Berlin/LTU	Air Berlin	2007
Lufthansa/bmi	Separate brands	2009
Lufthansa/Austrian Airlines	Separate brands	2009
Vueling/Clickair	Vueling	2009
British Airways/Iberia	International Airlines Group (IAG)	2011
Skyways/City Airlines	Skyways	2011
Vueling	International Airlines Group (IAG)	2012
Aer Lingus	International Airlines Group (IAG)	2015
Asia/Pacific		
Air India/Indian Airlines	National Aviation Co. of India	2007
Kingfisher/Air Deccan	Kingfisher	2008
China Eastern/Shanghai Airlines	Separate brands	2009
South America		
Copa/AeroRepublica	Separate brands	2005
Avianca/TACA (in 2010 + AeroGal)	Avianca-TACA	2009
Lan Airlines (+Aires in 2010)/TAM	LATAM Airlines	2010
GOL/WebJet	GOL	2011
Delta/Aeromexico	Delta 3.5% stake in Aeromexico	2011

Source: Adapted from Merkert and Morrell (2012); ICAO Secretariat (2016)

Finally, one of the selected approaches taken by FSCs was also the creation of subsidiary airlines, airlines within airlines to diversify their supply. By using other brands (see Table **3**), but offering a similar service to its low-cost competitors, FSCs were directly competing and, at the same time, avoiding the potential entrance of new firms in short-haul flights (Pearson and Merkert, 2014).

Table 3: *Creation of Main Subsidiary Airlines*

Full-service Carrier	Subsidiary	Year
Air Canada	Rouge	2013
Air France-KLM	Transavia.com	2005
	Hop!	2013
Air India	Air India Express	2004
Bmi British Midland	Bmibaby	2002
British Airways	Openskies	2008
Comair	Kulula.com	2001
Garuda Indonesia	Citilink	2001
Iberia	Vueling Airlines*	2004
Korean Air	Jin Air	2008
Mexicana	Click Mexicana	2005
Philippine Airlines	PAL Express	2008
Qantas Airways	Jetstar	2003
	Valuair*	2003
	Jetstar Asia*	2004
	Jetstar Pacific*	2008
Royal Air Maroc	Atlas Blue	2004
Singapore Airlines	Tiger Airways*	2003
South African Airways	Mango	2006
Thai Airways	Nok Air*	2004
Vietnam Airlines	Jetstar Pacific	2009

* denotes minority shareholding

Source: Adapted from ICAO Secretariat (2016:28)

2.2. The low-cost business model

Recently, LCCs have been pushing up such strong changes in the airline industry that it seems relevant to explore its way of working. The following overview focus on the primary low-cost model, on which the vast LCCs majority is still based on, as well on the recent changes to it.

The emergence of LCCs can be mainly explained by three factors: the cyclicality of the airline industry with a demand high dependent on the macroeconomic environment, costly tickets and worldwide market liberalisation processes (Dobruszkes, 2006). Low-cost airlines enjoy from a route system style different than the one traditionally used by FSCs which is, so far, the basis for their successful operation and recognition as an anti-cyclical product provider (Cook and Goodwin, 2008; IATA, 2006). By adopting a point-to-point scheme, which consists of direct flights independent of network connections, these airlines can have more flexibility in its flights' schedule and, at the same time, make travel cheaper and faster due to quicker flights with higher occupation rates (Fageda, Suau-Sanchez and Mason, 2015). It is, of course, crucial to them to concentrate on short and medium haul routes generally operated within their continent of origin. For instance, Ryanair and EasyJet concentrate their principal operations in Europe, Southwest Airlines, and JetBlue flights are mostly in North and Central America (IATA, 2016). In contrast, as previously mentioned in Section **2.1**, FSCs have been betting on hubs to increase their networks, reduce costs and provide more distant destinations as it is described in Figure **3**.

Structuring flights mainly around secondary airports and maximising aircraft and staff productivities are also critical determinants to provide low-fares (ICAO, 2003). The use of secondary airports is particularly useful to save costs and reduce turnaround times given these landing fields tend to be cheaper and less crowded alternatives (Dobruszkes, 2006; Barbot, 2006). Also, as part of its business model, LCCs have been operating a single/few type fleet and pressing their staff to fly more and reduce rest time, even paying less than FSCs (Francis et al., 2006; Dobruszkes, 2006). Thus, economies of density in LCCs are achieved by maximising flying time for each aeroplane and, simultaneously, providing a budget on-board service (Francis et al., 2006; Dobruszkes, 2006). Some novelties were also introduced in airline distribution due to the low-cost model, such as reservations via the Internet and telephone, the online check-in, the advertising on board and additional premium services such as car rentals and hotel reservation. These changes gave LCCs profit advantage for a period (Dobruszkes, 2006). Nowadays this is no longer a lead factor since FSCs also adopted it.

Similarly, as a result of the development of LCCs, we have been observing some changes, mainly in US and European operators, that are reinventing the original low-cost concept. The critical LCCs, such as Ryanair and Southwest Airlines, are now expanding their routes to largest airports, and some facilities that used to be secondary are now becoming the major ones as the Londoners Luton and Stansted (Dobruszkes, Givoni and Vowles, 2017). It will also be worthwhile to see the future developments of the most recent decisions taken by some European LCCs, as Ryanair and Norwegian, to enlarge their routes to long-haul flights between the Atlantic[1].

In conclusion, Table **4** summarises full-service and low-cost business models' characteristics to be clear to understand them.

Table 4: *Differences between Low-Cost and Full-Service carriers*

Product features	Low-cost carrier	Full-service carrier
Brand	One brand: low fare	Brand extensions: fare+service
Fares	Simplified: fare structure	Complex fare: structure+yield management
Distribution	Online and direct booking	Online, direct, travel agent
Check-in	Ticketless	Ticketless, IATA ticket contract
Airports	Secondary (mostly)	Primary
Connections	Point-to-point	Interlining, code share, global alliances
Class segmentation	One class (high density)	Two class (dilution of seating capacity)
Inflight	Pay for amenities	Complementary extras
Aircraft utilisation	Very high	Medium to high: union contracts
Turnaround time	25 min turnarounds	Low turnaround: congestion/labour
Product	One product: low fare	Multiple integrated products
Ancillary revenue	Advertising, on-board sales	Focus on the primary product
Aircraft	Single type: commonality	Multiple types: scheduling complexities
Seating	Small pitch, no assignment	Generous pitch, offers seat assignment
Customer service	Generally under performs	Full service, offers reliability
Operational activities	Focus on core (flying)	Extensions: e.g., maintenance, cargo

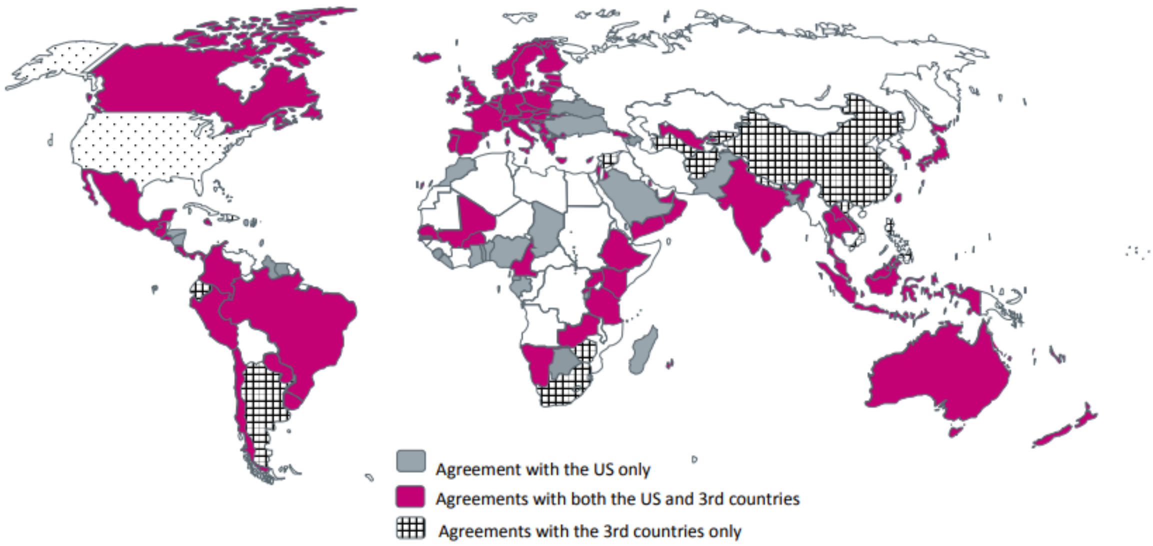
Source: Adapted from O'Connell and Williams (2005:260)

[1] Available in http://metro.co.uk/2017/03/16/ryanair-to-offer-flights-to-new-york-6512888/.

2.3. International context: 2015

Besides all world regions have been taking adequate measures to deregulate their air transport industries, the airline business faces different development stages across the globe (see Figure **4**). Market liberalisation is, in some regions, a long-standing reality but for others is just an utopia[2].

Figure 4*: Bilateral Open-skies in 2016*



Source: ICAO Secretariat (2016:3)

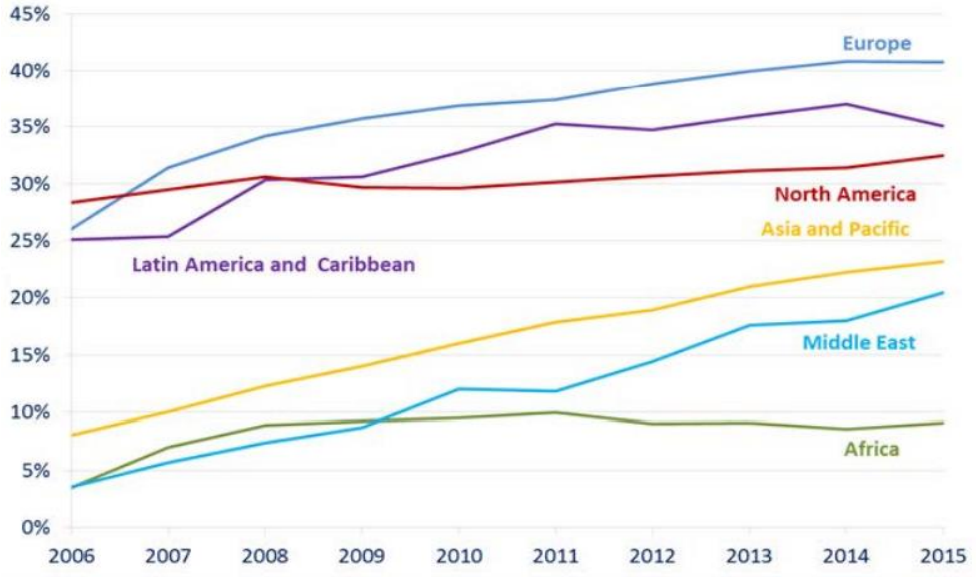
Obviously, this precludes that rivalry between LCCs and FSCs is not global homogeneous and, consequently, structural change is not worldwide uniform. In fact, world market share of RPK according to the business model was considerably unbalanced in 2015. Low-cost carriers represented 19% of the world RPK, and legacy operators had a 78% market share (IATA, 2016). The remaining value relates to the leisure airlines.

Although, there are some regions where the initiatives deployed have been acting by producing significant developments (see Figure **5**). From 2006 to 2015, the market share of available seats offered by LCCs in Asia Pacific, Europe, and the Middle East had the largest increases across the globe. In Europe, after 15 percentage points (pp) rise between 2006 and 2015, 41% of the available seats are being supplied by low-fare airlines which is the largest regional low-cost market share in the world. The Middle East market

[2] For a detailed introduction of air transport deregulation, check https://www.icao.int/Meetings/a39/Documents/Overview_of_Regulatory_and_Industry_Developments_in_International_Air_Transport.pdf .

share grew from 4% to 20% during the same period, and Asia Pacific's increased from 8% to 23%. Although North America was the world leader in 2006, its growth was only four pp to 32% becoming the third low-cost global market share in 2015. Latin America and the Caribbean with a growth of 10 pp to 35% and Africa increment of 6 pp to 9% were intermediate growth performances between the previously analysed. Thus, the world market share of available seats provided by LCCs has grown from 21% to 30% during this period.

Figure 5: *Percentage of Available Seats Offered by LCCs*



Source: ICAO Secretariat (2016:27)

Turning now specifically to the world airline industry as a whole (see Table **5**), in 2015 world airlines transported 3.561 billion passengers and 52.2 million freight tonnes (IATA, 2016). This record followed the significant positive trend registered in the previous years since in 2005, ten years before, airline operation only covered 2.139 billion passengers and 40.8 million tonnes (IATA, 2017). In this year, Asia Pacific airlines were the world leaders of air passenger and freight transportation. They moved around 1.214 billion passengers and 19,977 million freight tonnes that, together with Europe and North America operators, made available more than 82% of world seat-kilometres, and represent more than 80% of the world FTK and RPK.

Table 5: *World Scheduled Systemwide Passenger and Freight Traffic by Region of Airline Domicile in 2015*

Systemwide	Africa	Asia Pacific	Europe	Latin America	Middle East	North America
Passengers Carried (thousands)	79,492	1,214,366	935,460	267,630	188,224	883,177
Freight Tonnes Carried (thousands)	817	19,977	8,107	2,163	5,972	15,180
Revenue Passenger-Kilometres (millions)	145,726	2,141,317	1,795,585	352,639	614,645	1,628,783
Available Seat-Kilometres (millions)	213,540	2,717,301	2,183,037	442,899	806,353	1,942,076
Freight and Mail Tonne-Kilometres (millions)	3,456	81,715	48,749	6,446	28,399	45,428
Available Freight Tonne Kilometres (millions)	10,381	145,529	94,540	16,644	60,449	124,662

Source: Adapted from IATA (2016:35)

Air traffic was mainly concentrated within these regions, and in the links between them since more than 75% of the total RPK and FTK arose from flights in and across these regions (IATA, 2016). The Hartsfield-Jackson Atlanta International, the Beijing Capital, and the Dubai International were the airports handling more passengers, around 270 million passengers. Also, 12 million tonnes were moved in the top 3 cargo airports: the Hong Kong International, the Memphis International and the Pudong International (IATA, 2016). Naturally, the most prominent world operators, with the highest RPK and FTK were mainly originated in these regions. From Table **6**, we can highlight that both tops are dominated by FSCs, although there are also two low-cost operators on the world RPK top-10, Southwest Airlines, and Ryanair.

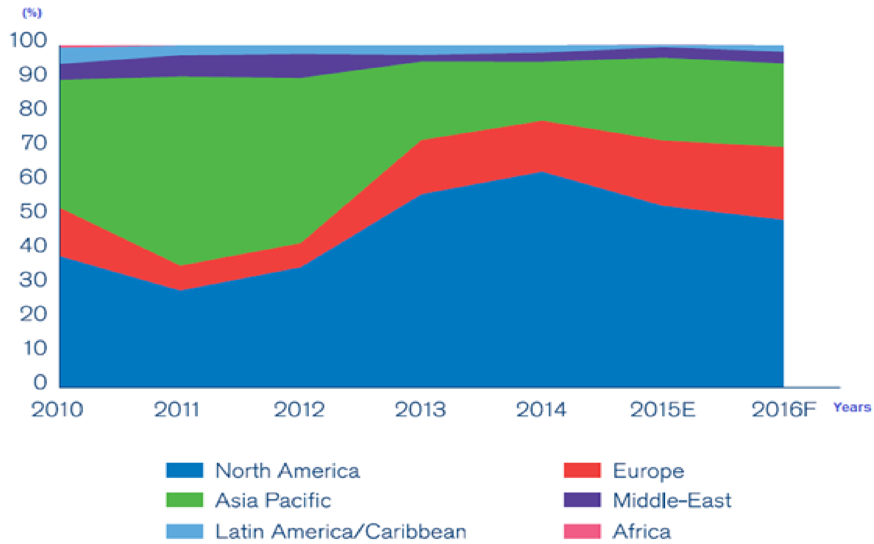
Table 6: *Top 10 according to FTK and RPK (2015)*

Rank	Airline	Millions of FTK	Rank	Airline	Millions of RPK
1	Federal Express	15,799	1	American Airlines	320,813
2	Emirates	12,157	2	Delta Air Lines	302,512
3	United Parcel Service	10,807	3	United Airlines	294,970
4	Cathay Pacific Airways	9,935	4	Emirates	251,190
5	Korean Air	7,761	5	China Southern Airlines	189,186
6	Qatar Airways	7,660	6	Southwest Airlines	189,097
7	Lufthansa	6,888	7	Lufthansa	145,904
8	Cargolux	6,309	8	British Airways	140,780
9	Singapore Airlines	6,083	9	Air France	139,217
10	Air China	5,718	10	Ryanair	125,194

Source: Adapted from IATA (2016:55-63)

The distribution of the regional operating profit, between 2010 and 2015, described in Figure **6**, followed the conclusions derived above since the significant three regions concentrate at least 90% of the world operating profit (IATA, 2017). In 2015, the highest share was from North American airlines, around 50% of the world amount. This positive signal for the North American industry is particularly interesting since it had a difficult time between 2001-2005 with a net aggregate loss of US$40 billion. The 9/11 attacks, the SARS virus and the emergence of LCCs triggered this crisis and forced US Airways, United Airlines, Delta, and Northwest to adopt cost-cutting measures and downsizing operations (Lee and Worthington, 2014). During the same period, Asia Pacific airlines had a 25% share in the same year, followed by European with a 20% share.

Figure 6: *Distribution of Operating Profit by Region 2010–2015*



Source: Adapted from IATA (2016:28)

It is important to note that, between 2010 and 2015, the world operating profit grew from 27.6 billion US$ to 61.1 billion US$ (IATA, 2017). During this period, the revenue of world airlines increased 28% achieving 720 billion US$ in 2015. Passengers transportation has been taking a leading role to generate income and, in 2015, represented 70% of the total amount, with cargo flights corresponding to 7% (IATA, 2017). On the expenditure side, we can denote a 22% increase reaching 659 billion US$ in 2015. Spending on fuel has been the most significant part of airline budget, and it raised 15% for this period, even with an average decrease of the crude oil price around 32% (IATA, 2017). In 2015, planes consumed 81 billion gallons, 175 billion US$, accounting for 26.5% of total expenses. Finally, fuel consumption, in the year concerned, produced 773 million tonnes of CO_2 emissions (IATA, 2017).

3. Related Literature

3.1. Efficiency of the airline industry

As a result of the intense competition in this industry, where the growth of low- cost carriers is taking a serious role, and also of the current instabilities on the macroeconomic environment[3] (Pearson and Merkert, 2014), studying efficiency is getting very attractive to the academic community. This curiosity is no less valid for full-service airlines, as a survival need, which have been adopting strategies to adapt to the recent low-cost growth, such as mergers and acquisitions (M&A), (Merkert and Morrell, 2012), and the creation of subsidiary airlines (Pearson and Merkert, 2014). However, it is nonetheless valid that studying airline efficiency is not new.

The first studies focused on the efficiency of the airline industry were based on the named Stochastic frontier analysis (SFA), the "*econometric approach to efficiency analysis*"(Greene, 2008). SFA was introduced by Aigner, Lovell and Schmidt (1977); Meeusen and Broeck (1977) and its application in the study of airline efficiency has become popular with Good, Nadiri and Sickles (1993). Good, Nadiri and Sickles (1993) used a Cobb-Douglas single output technology to carry out technical efficiency and productivity growth comparisons among the four most significant European carriers and eight American airlines using three alternative estimators: the generalised least square (GLS), the efficient instrumental variables (IV) and the within estimator. Data between 1976 and 1986 were analysed to identify potential efficiency gains of the European market liberalisation since this period coincided with the starting of a deregulation process in the US industry (see Section **2**) and ends just prior the introduction of the first steps to deregulate the European market. Based on the geographical assessment, they concluded that European operators were nearly 15% less efficient than the American

[3] affected the price of airlines' key raw material, fuel.

carriers and if the gap was eliminated, European airlines would save $4.5 billion per year and reduce its employees by 42,000.

Coelli, Perelman and Romano (1999) used a translog production frontier to measure the efficiency of 32 international airlines between 1977 and 1990. The analysis was conducted under two alternative approaches. The first method assumed that shape of the production frontier was affected by environmental factors while the second accounted for direct environmental impact on the efficiency scores. The chosen environmental variables were representative of network conditions and geographical differences: the average stage length, the average load factor and the average aircraft size. Both approaches classified Asian-Oceanic airlines as being more technically efficient than European and North American airlines, and such disparities seemed to be the result of more favourable environmental conditions. Concerning to the methodology, both methods provided similar rankings, but with different technical efficiency scores.

Inglada et al. (2006) proceeded with the use of SFA by focusing their analysis between 1996–2000. This particular period reflected worldwide heterogeneous processes of liberalisation since it took into account a full-liberalised North American market, an almost entirely open European business and the Asian industry starting to deregulate. Two stochastic frontiers were estimated for cost and production functions to calculate economic (price) and technical efficiency scores. The evidence suggested very curious results on Asian airlines. Although they were operating in the less open market, these companies were the most efficient operators, which is in line with Coelli, Perelman and Romano (1999). It was therefore concluded that Asian industry was benefiting from the recent deregulation process.

More recently, Assaf (2009) executed a study focused on the technical efficiency of US airlines using a Bayesian random stochastic frontier model. The focus of this analysis was in 2003, 2005 and 2007 as an attempt to provide insights for private and public policy makers due to a severe period for the international airline industry where the oil price and the long-term influence of September 11 had a great responsibility. Results revealed that American airlines were not operating at the optimum level of scale and, at the same time, the average technical efficiency was decreasing to reach 69.02% in 2007.

Nowadays, Data Envelopment Analysis (DEA) is the most used approach to study efficiency in the airline industry. Unlike SFA, DEA is a non-parametric method whereby does not assume any functional form on the data to calculate efficiency estimations. Alternatively, efficiency is measured through a benchmarking process where a frontier, based on the efficient performers, is estimated, and the degree of inefficiency is measured according to the distance to the estimated efficient frontier. This method either assumes an input or output orientation that is, with the available technology, a firm is inefficient if, can increase its output level without increasing its input quantities, or may reduce its input levels without decreasing output (Coelli et al., 2005).

Barbot, Costa and Sochirca (2008) conducted an input-oriented efficiency, effectiveness and productivity comparison between low-cost and full-service airlines. With 2005 data, this study focused on 49 International Air Transport Association (IATA) members, from various regions around the world, and attempted to suggest which factors were responsible for efficiency differences among airlines. Main discoveries outlined that the vast majority of low-cost carriers were more efficient than full-service airlines and geography, as well the type of business model, might explain such disparities. Similarly, authors concluded that the most efficient airlines were operating in the US and Europe, although it seemed clear that North American carriers had lower efficiency inequalities than European operators.

In line with Barbot, Costa and Sochirca (2008), Barros and Peypoch (2009) focused on the efficiency gains of the low-cost model by using a two-stage DEA. The two-stage approach includes a first step which calculates traditional efficiency scores by solving a DEA model and, in the second stage, first step estimates are regressed against many hypothesised covariates to study efficiency drivers (Coelli et al., 2005). Thus, authors implemented an investigation to evaluate the operating performance of 27 airlines of the Association of European Airlines. Using data between 2000 and 2005, the authors estimated technical efficiency scores for both CRS, airlines operate at an optimal scale, and VRS, only compares airlines of similar sizes, scenarios by using physical and financial variables. In the second step, they looked for determinants of CRS efficiency scores with a bootstrap truncated regression. The second stage regression focused on the role of geographical and demographical factors, as well on the relevance of being an alliance member (Star Alliance, OneWorld, and SkyTeam), a low-cost carrier and a long-established carrier, to the technical efficiency of airlines. Primary conclusions revealed significant efficiency differences on the sample despite accepting that European airlines were working at a notable scale efficiency and, by looking at the trend and its square, authors observed an efficiency improvement at a diminishing rate. From the second stage, it was concluded that the demographic dimension of the airline's home country, belonging to an alliance (Star Alliance and OneWorld) and the adoption of a low-cost model were significant variables for the technical efficiency of air transporters.

Following the two-stage Data Envelopment Analysis (DEA), Greer (2009) implemented a study on the impact of unionisation on the technical efficiency of 17 US legacy airlines between 1999 and 2008. In the first stage, efficiency scores were estimated through an input-based measure, under constant returns, with inputs representing labour force, fuel consumption in gallons, as well seating capacity to produce Available Seat Miles. A Tobit regression analysis was undertaken in the second stage to assess sources of technical efficiency. On this basis, the average size of aircraft, the scale of hubs in the routes of airlines and the average stage length - the average distance travelled by each aircraft - were significant for the technical efficiency. Thus, unionised employees appeared to be not significant to the performance of airlines.

Also applying a two-stage model, Merkert and Hensher (2011) scrutinised the impact of fleet planning and strategic management decisions. In the first stage, bootstrapped and non-bootstrapped efficiency scores were calculated on 58 international airlines over the two fiscal years of 2007-2008 and 2008-2009. This approach followed an input orientation, under CRS and VRS since, according to the authors, output highly depends on the macroeconomic context. In the second phase, a series of random effects Tobit regressions investigated determinants of technical, allocative and cost efficiency using first-stage VRS DEA scores as a dependent variable. From these results, it was concluded that airline management should focus less on the distance travelled and the age of each aircraft, and more on other factors such as the number of different manufacturers in the fleet. Methodologically, in one hand, bootstrapping provided more accurate efficiency scores but, on the contrary, during the subsequent stage did not change the significance of explanatory variables, just changing results marginally.

Merkert and Morrell (2012) also interested in the competitive environment between full-service and low-cost operators, focused their paper to review literature and management perspectives in one of the strategies adopted by the FSCs to fight the growth of the low-cost model: airline mergers and acquisitions (M&A). The overall conclusion of the study was that M&A benefits appeared to outweigh their potential cons. The authors pointed out, in one hand, that the main advantages of M&A were increases in efficiency and profitability, as well higher access to airports and aircraft which contributes to higher market share. On the other hand, it was clear that vital disadvantages came from different cultures of several companies, different IT systems and the risk of becoming too large to operate cost-efficiently (diseconomies of scale). Since diseconomies of scale were a disadvantage, this study also included an assessment of the scale efficiency of 66 international airlines during two fiscal years: 2007-2008 and 2008-2009. Results from bootstrapped efficiency scores pointed that optimal airline size ranges between 34 and 52 billion Available Seat Kilometres, and operating above 100 billion ASK, and surely over 200 billion ASK, was cost inefficiently.

The following year, Wu, He and Cao (2013) strived for the impact of wage levels and the share of international and cargo operations in the operational process of Chinese and non-Chinese airlines. In line with Barros and Peypoch (2009), input-based technical efficiency scores, under CRS, were regressed in a bootstrapped truncated regression. Outcomes pointed to the negative impact of internationalisation, and the positive significance of the level of salaries. However, the most innovative conclusion revealed an "*inverted U-shaped relationship*" (Wu, He and Cao, 2013:38) between cargo operation and technical efficiency, that is, at some level, increasing cargo revenue declined the performance of airlines.

Chang et al. (2014) promoted an innovative analysis by combining a slacks-based DEA measure (SBM-DEA) to study economic and environmental efficiency, with 2010 data, of 27 worldwide airlines. The authors used ATK with fuel consumption as inputs, and RTK as output to study input and output based CRS and VRS efficiency slacks, "*additional improvements (increase in outputs and/or decrease in inputs) needed for a unit to become efficient*"(Emrouznejad, 2011), in two different models. In one hand, the first model assumed an independent relation between the improvement of slacks and fuel consumption. On the other hand, the second model introduced a weak disposability assumption to better describe reality since the improvement of output slacks increased undesirable output usage, carbon emission. Thus, airlines were faced with a trade-off between improving output slacks and consuming fuel which affected environmental efficiency. Results of this paper considered Asian airlines to be more economic and environmental efficient than American and European operators, in line with Coelli, Perelman and Romano, (1999); Inglada et al. (2006), with fuel consumption and diversified revenue structure, were inefficiency drivers.

Tavassoli, Faramarzi and Saen (2014) also draw, for the first time, a theoretical model combining the Slacks-based measure and the Network DEA: Slacks-based Network Data Envelopment Analysis (SBM-NDEA). The Network DEA has come about to incorporate the "*internal structures*" (Tavassoli et al., 2014:147) of airlines on the study of technical efficiency and service effectiveness. Their motivation came from the fact that shared input also takes a relevant role in the production process taken by airlines which is why it is pertinent to represent the transformations that occur in the network (processes and sub-processes), and not exclusively the traditional approach which only deals with initial inputs and final outputs. A case study was implemented to apply the proposed model to 2010 data of 11 Iranian airlines. Two different processes were considered: one for cargo, the other for passengers, and the number of employees was the shared input. Within both, it took place two distinct sub-processes: production and consumption. The aggregation of processes and sub-processes resulted in a single overall efficiency measure, through which it was concluded that Mahan Air was the most efficient airline.

The same approach was performed by Lozano and Gutiérrez (2014) to calculate input and output slacks of European airlines. This model attempted to better describe the production process of airlines, linking activities between the transformation of initial inputs in final outputs, where inputs are not all consumed. This process of airlines was divided into two: production and sales, and included fuel costs, wages and salaries, non-current assets and other operating expenses as inputs to produce Available Seat Kilometres (ASK) and Available Tonne Kilometres (ATK). On the other side, sales process used as inputs the production outcomes plus selling costs to obtain Revenue Passenger Kilometres (RPK) and Revenue Tonne Kilometres (RTK). Results reflected two distinct groups, one with high-level efficiency and another with slightly lower performance. In general, inefficiency came from sales and the efficiency improvement should focus on non-current assets, other operating costs and wages-salaries. On the side of outputs, RPK was considered the target variable. The authors concluded that airlines with the most significant possible improvements, mainly on wages and salaries, non-current assets, other operating expenses and RPK, were the same that were considered as inefficient. Concerning to the methodology, it was confirmed that SB-NDEA had more discriminative power than the traditional technique.

In line with Barbot, Costa and Sochirca (2008); Barros and Peypoch (2009); Merkert and Morrell (2012), Pearson and Merkert (2014) continued with studies on the competition between FSCs and LCCs. Following Merkert and Morrell (2012), the study focused its analysis on a strategy taken by FSCs to the growth of the low-cost business model: airlines within airlines (see Table **3**). The authors reviewed literature and airline data to analyse the creation of 67 subsidiary airlines. Conclusions revealed that 27 airlines did not work, and in the US, where this concept emerged, there were no airlines of this nature. Unlike in the US, subsidiary airlines had been successful in Asia-Pacific. Based on the Asian success, authors suggested a set of factors for effective subsidiary companies including the need for autonomy from its FSC, do not diverge from the low-cost model and more significant market presence. The focus in these recommendations would combat some problems that had been leading to the failure of these operators: lower operating revenue per RPK and load factor compared to the corresponding FSC.

Similarly, Lee and Worthington (2014) analysed the impact of the business model and the ownership on the technical efficiency of 42 international airlines. The authors used a two-stage procedure to estimate bootstrapped efficiency scores under VRS, and then regress them against a set of environmental variables to look for sources of technical efficiency. The second step allowed to conclude, by using two different dummy variables, that privately owned airline were better managed than public carriers, as well the positive impact of being a low-cost carrier due to the adoption of quality management and operations to remain competitive.

Merkert and Pearson (2015), in line with Lee and Worthington (2014), followed the two-stage DEA approach by assuming variable returns to scale to calculate bootstrapped efficiency scores and regress them against a set of covariates in a bootstrapped truncated regression. The authors innovated with a combined overall efficiency measure which included measures of the profitability of airlines, customer satisfaction, as well the RPK. The first phase settled that on average LCCs efficiency and charter operators were higher than the efficiency grades of full-service carriers in line with Barbot, Costa and Sochirca (2008). For its part, the subsequent step attempted to measure the impact of service level and profitability on the efficiency scores by applying four distinct models: original or bootstrapped efficiency scores combined with input or output orientations. Results revealed, in one hand, that the projected efficiency measure was meaningful for both model orientations since they provided very similar efficiency ratings and, on the other hand, the bootstrap procedure allowed to have a more reliable efficiency measurement. Concerning the second-step, the ratio of the cabin workers to the total number of employees, representing the service level, was the single significant variable to positively explain the overall efficiency. Other variables such as the average fleet age were not considered significant given it represented the trade-off between customer satisfaction and profitability that is, investing in new aircraft positively affects customer satisfaction, and negatively the profitability of airlines.

To conclude, taking a closer look at each paper, it is easy to understand that DEA has been having a more critical task to perform recent efficiency studies in the airline industry. However, it does not seem to be consensual which orientation is most appropriate, as well as the returns to scale assumption which is more in line with the reality of this industry. Also, some contradictory conclusions emerge in the classification of the most efficient geographies. Nevertheless, there are some common facts. One of them is the most common inputs representing capacity, capital, labour, and fuel, while the most regular outputs characterise movements, revenues, and profits. Another fact is that recent approaches had been including a two-step technique with bootstrapping to identify efficiency sources, or the network DEA to increase the discriminatory power, in line with DEA studies in other industries (Emrouznejad and Yang, 2017). A large part of the studies investigate periods relating to market deregulation processes, with a more recent trend focusing on the competitive environment between low-cost and full-service carriers. However, there appears to be no evidence of an investigation focused on the direct impact of low-cost on FSC efficiency, except considering specific reactions taken by FSCs such as M&A and subsidiary airlines. In this way, it appears that a study with a broad sample would allow gauging some of the conclusions drawn on geographical comparisons, as well to answer some of the uncertainties presented about the scale in which companies operate. Similarly, the application of a two-stage DEA with the market share of low-cost, in a given region, being an independent variable would make it possible to fill a gap in the literature by verifying if the concentration of low-cost operators in a given region influences the technical efficiency of FSCs domiciled in that region.

3.2. Developments in Data Envelopment Analysis

DEA, a frontier method, was inspired by the non-parametric technique developed by Farrell (1957) to evaluate the overall productive efficiency of firms accounting for several inputs and a single output of all sorts. This technique was particularly innovative since did not merely restricted to a specific share of business processes, such as the average productivity of labour, and evaluated performance by not imposing any functional form on data. Alternatively, this measure proposed a comparative efficiency assessment directly from calculated information by estimating a fully efficient frontier based on the detected efficient entities and that therefore ranking inefficient units according to the distance to the efficient frontier. Farrell's (1957) pointed three different sorts of efficiency (Coelli et al., 2005): 1) The technical efficiency which focuses on the capacity of a firm to maximise its output; 2) the price (also know as allocative) efficiency which translates the optimal use of inputs, given their prices and the productive technology; 3) the overall (also know as economic) efficiency which represents a combination of both measures.

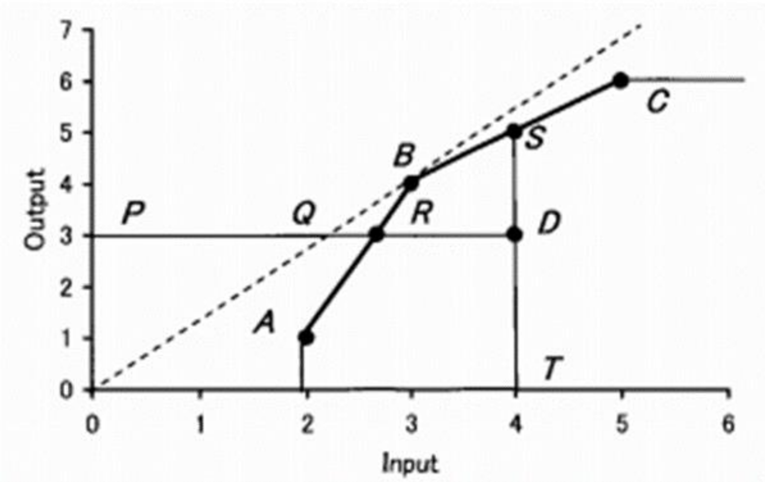
On the basis of Farrell (1957), Charnes, Cooper and Rhodes (1978) introduced DEA, a non-parametric linear programming procedure, through the commonly denominated CCR model which takes into account multiple inputs and outputs to measure the overall technical efficiency of Decision-Making Units (DMUs). This model adopted a constant returns to scale hypothesis (CRS) by assuming that DMUs are operating at an optimal scale and explains technical efficiency as the ratio of weighted outputs to weighted inputs by providing an efficiency score between 0 and 1 for all DMUs in the sample. Besides, this measure was hand-in-hand with Pareto optimality since "*none of its inputs can be decreased without either decreasing some of its outputs, or increasing some of its other inputs*" and vice-versa (Emrouznejad, 2011). Thus, an efficiency score equals to one indicates that a DMU is allocated on the efficient frontier and it is "*weak*" technical efficient. In the case of having no slacks - extra output increases and/or inputs decreases required to be efficient - a DMU is considered strong/Pareto technical efficient (Coelli et al., 2005). An efficiency measure below 1 indicates technical inefficiency since the unit is under the efficient frontier.

Later Banker, Charnes and Cooper (1984) upgraded the CCR model by proposing the BCC model which relaxed the CRS hypothesis, assuming that DMUs might be not operating at an optimal scale to be efficient. Instead, they suggested a variable returns to scale hypothesis (VRS) which allows for increasing returns to scale (IRS) and decreasing returns to scale (DRS). This hypothesis was implemented through an extra convexity condition on the efficient frontier which envelops more the data set than the CCR efficient frontier (Thanassoulis, 2001). By introducing the VRS hypothesis, this model suggested an efficiency measure which only compares DMUs of similar sizes relying on the impact of scale efficiency.

Thereby, it is clear to understand that both measures focus on two distinct specific sorts of Farrell's (1957) technical efficiency (Coelli et al., 2005). CCR efficiency provides Farrell's (1957) technical efficiency score (TE) - pure technical efficiency and scale efficiency - and measures inefficiency by the relation of inputs and outputs as also the size of the DMU which means that a CCR efficient unit must operate with an efficient input-output mix as also with the optimal size. With regards to the BCC efficiency, it is a measure of Farrell's (1957) pure technical efficiency (PTE) without scale efficiency incorporated which betokens that a DMU can be BCC efficient without being scale efficient. A combination of both allows calculating scale efficiency (SE). Thus, scale efficiency is $\frac{CCR-\,Technical\ efficiency}{BBC-Pure\ technical\ efficiency} \leq 1$ and represents how close is a DMU from its optimal size (Coelli et al., 2005).

To illustrate the difference between the two efficiency measures, we can look to DMUs B, D and S cases in Figure **7**. The CCR efficient frontier is represented by the dotted line which passes through B from the origin, and the BCC model frontier comprises the bold line connecting A, B and C. So, it is feasible to claim that both models might present different efficiency scores for the same DMU if its relative location changes from one model to other. At the same time, it is no less valid that both models can present the same efficiency score for the same DMU.

***Figure 7**: CCR and BCC models*



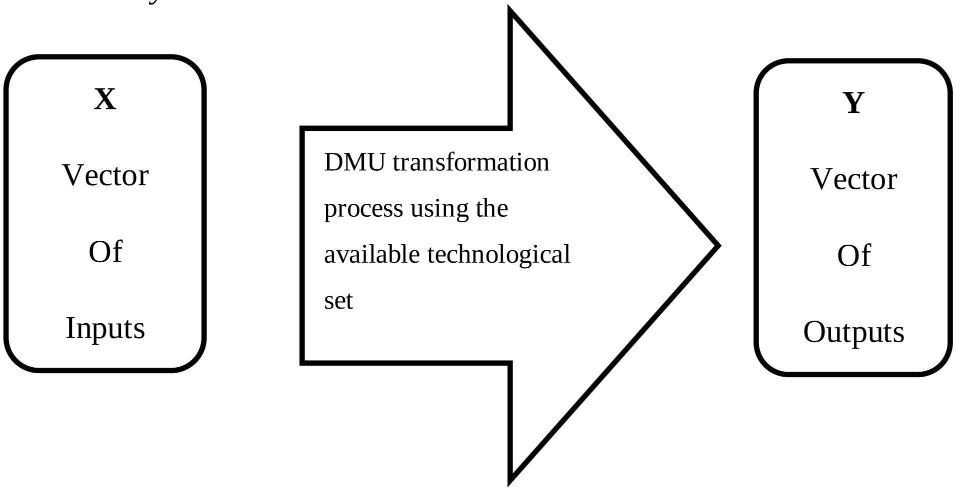
Source: Cooper, Seiford and Tone (2007:90)

From Figure **7**, it is feasible to draw the following relations between both models:

- DMU B has the same efficiency score under both measures. Under this equality, we can state it is pure technical efficient (BCC-efficient) and is also technical efficient, operating with the optimal size (CCR-efficient);
- DMU D is not allocated in any efficient frontier, so it is CCR and BCC inefficient. Although, is further from CCR than the BCC given: $\frac{PR}{PD} \geq \frac{PQ}{PD}$. Under this inequality, we can claim that DMU is less pure technical inefficient (BCC-inefficient) than technical inefficient (CCR-efficient);
- DMU S is pure technical efficient, although it is not technical efficient. Given these circumstances, we can claim that DMU S it is technical inefficient since it is not operating scale efficiently.

Following Banker et al. (1984), Charnes et al. (1978) and Farrell (1957), Thanassoulis (2001) provides a more general definition of DEA. The author describes DEA as an attempt to understand how efficiently each decision-making unit (DMU) is processing its business (see Figure **8**) by performing a transformation process using resources and getting outcomes. It compares each DMU to other homogeneous entities which produce the same outputs using the same inputs although in different quantities.

***Figure 8**: Data Envelopment Analysis Traditional Logic for a DMU performing its Activity*



Source: Own production

In most of DEA models, efficiency is calculated using a scalar measure, achieved through a linear programming model, which ranges between zero and one, or from one to positive infinity.

Following Farrell's (1957) contribution, a DMU performs its activity, i.e. its transformation process, by having control over resources or outcomes, either with an input orientation or output orientation (Cooper et al., 2007). Input-orientation checks whether a DMU can improve its performance by reducing its input levels, not dropping outputs, and maintaining its input mix. Output-based technical efficiency investigates if a DMU's operation could be improved through the expansion of output levels while using the same level of resources and preserving its output mix. In the airline industry literature, there is no clear consensus about which orientation should technical efficiency follow. Studies as Assaf (2009), Barros et al.(2009) and Merkert et al. (2011) followed an output-orientation arguing airlines do not have so much flexibility to adjust inputs in the short-term, considering its as quasi-fixed. On the other side, Barbot et al. (2008) and Merkert et al. (2011) used an input-orientation rooted in the trust that output is significantly dependent on economic factors and often predetermined by long-term slot allocations contracts.

Nowadays, after significant developments, we can classify DEA models into radial and non-radial measures (Jahanshahloo et al., 2010). The radial models follow

Farrell (1957) and are the commonly known CCR and BCC representations. The non-radial representations include four types: the additive model, the multiplicative model, the range adjusted measure (RAM), and the slack-based measure (SBM).

Some studies have been performed by implementing SBM in the airline industry. Since this measure is based on the additive model, we will explain it beforehand. The additive model proposed by Charnes, Cooper, Golany, Seiford and Stutz (1985) combines input and output orientations in a single efficiency measure by simultaneously studying output shortfalls and input excesses. Nevertheless, this method does not provide an efficiency score, as also does not measure the depth of inefficiency. Instead, it only distinguishes between efficient and inefficient DMUs by the existence of slacks. Despite, this model has not frequently been used to study airlines' efficiency.

Tone (2001) introduced the slacks-based measure (SBM) of efficiency. Contrary to the additive model, SBM calculates the depth of inefficiency through the measurement of slacks, under CRS or VRS, and provides a measure which varies between 0 and 1 where the one value is attributed to DMUs with no slacks. The most relevant studies using this technique to the airline industry were performed by Chang et al. (2014) with an SBM measure on the economic and environmental efficiency of 27 international airlines.

More recently, Färe and Grosskopf (2000) also provided new developments on DEA. Their Network DEA (NDEA) method adds to the traditional DEA logic, represented in Figure **8**, the existence of several stages in DMUs' transformation processes, not treating them as "*black boxes*" (Färe and Grosskopf, 2000:34). According to the authors, there are several stages, each of which consumes its set of inputs and originates its set of outputs aside from consuming and producing intermediate goods, which need to be part of the efficiency study. These intermediate goods can be inputs for some stages and can be outputs for others. Thus, the main advantage of this approach is that "*it has more discriminating power than the single-process DEA approach and that the targets and efficiency scores computed are thus more valid*" (Emrouznejad et al., 2014:75). Recently, this approach has been one of the most used to implement studies in airlines' efficiency. Lozano et al. (2014) implemented an SBM network DEA to investigate the efficiency of production and sales processes of 16 European airlines. Tavassoli et al. (2014) used it to study the technical efficiency of 11 Iranian airlines decomposing their operational process as a combination of production and consumption.

Mallikarjun (2015) measured the operational efficiency based on a three-stage operational process strive for operations, services and sales arranged by US airlines.

Similarly, since DEA does not explain efficiency disparities, a need for identifying inefficiency drivers introduced a two-stage procedure (Coelli et al., 2005). This method includes a first step which consists of calculating efficiency scores through solving DEA including only traditional inputs and outputs. In the second stage, efficiency scores are regressed against many hypothesised explanatory variables to study efficiency sources:

$$\theta_i = a + \delta Z_i + \varepsilon_i \, , i = 1, \ldots, n, \tag{1}$$

$where\ \theta_i\ is\ the\ 1st\ stage\ estimated\ efficiency\ score\ for\ DMU_i$

$a\ is\ the\ constant\ term,$

$Z_i is\ a\ vector\ of$ hypothesised explanatory variables to explain θ_i,

δ is the vector of parameters,

$\varepsilon_i\ is\ statistical\ noise.$

Such method has been attempting to explain efficiency through environmental variables which can be considered as influences that are not traditional inputs and are not under management control (Coelli et al., 2005). According to Coelli et al. (2005), main advantages of this approach include the possibility of using more than one variable, either continuous and categorical, the ease and simplicity of calculation, the fact that it is not necessary to establish prior assumptions on the direction of the hypothesised influence, as also the implementation of hypothesis tests to check if covariates are significant to describe efficiency. Second stage approaches are usually implemented through OLS linear regressions or the censored/Tobit model in efficiency studies. More specifically to the airline industry, in Table **7** it is conceivable to understand which studies have been made to analyse technical efficiency with a two-stage procedure where Tobit and truncated regression models have been the critical methods in the second-step.

Table 7*: Two Stage Efficiency Studies in the Airline Industry*

Authors	Airline/Geography /Time Period	Methodology (1st and 2nd stages)	Inputs	Outputs	Second Stage Variables	Statistical Signifiance Level	Direction
Scheraga (2004)	38 International airlines (1995 and 2000)	1st: SBM DEA 2nd: Tobit regression	ATK, operating cost, non-flight assets.	RPK, non-passenger RTK.	Percentage state ownership	Not significant	-
					% International operations	5%	Negative
					Load Factor	1%	Negative
					% International operations*Load Factor	5%	Positive
					Non-flight assets per ATK	1%	Positive
					Passenger revenues/ Total operating revenues	Not significant	-
Barros and Peypoch (2009)	27 European airlines (2000 - 2005)	Simar and Wilson (2007) 1st: Farrell/Debreu-type technical efficiency 2nd: Truncated bootstrap regression	Number of planes, operational cost and the number of employees.	RPK, EBIT.	Trend	1%	Postive
					Square Trend	1%	Negative
					Population	1%	Postive
					Star Alliance member dummy	1%	Postive
					Low-cost airline dummy	1%	Postive
					Oneworld member dummy	1%	Postive
					SkyTeam member dummy	Not significant	-
					National airlines dummy	Not significant	-
Greer (2009)	17 US airlines (1999 - 2008)	1st: CCR efficiency 2nd: Tobit regression analysis	Full-time equivalent employees, millions of fuel gallons and fleet-wide seating capacity.	ASM	Union density	Not significant	
					Avarage age of fleet	Not significant	-
					Avarage size of aircraft	5%	Negative
					Extent of hubbing	1%	Postive
					Average stage length	10%	Negative
					% of passengers flying internationally	Not significant	-
					Legacy carrier dummy	Not significant	-
Merkert and Hensher (2011)	58 international airlines (2007 - 2009)	1st: Bootstrapped CCR efficiency 2nd: Partially bootstrapped random effects Tobit regression	Full-time equivalent employees, ATK, FTE unit price, ATK unit price.	RPK, RTK.	ASKs	1%	Positive
					Average size of aircraft	10%	Positive
					Average stage length	5%	Negative
					Number of different manufacturers	10%	Negative
					Avarage age of fleet	Not significant	-
Wu et al. (2013)	12 Chinese and non-Chinese airlines (2006 - 2010)	1st: CCR and BCC efficiencies 2nd: Truncated bootstrapped regression	Full-time employees, operational costs and number of aircraft.	RTK and Operating Revenue.	% International RPK	1%	Negative
					Cargo revenue/Total operating revenue	1%	Positive
					(Cargo revenue/Total operating revenue)^2	1%	Negative
					The average level of salaries	1%	Positive
					Chinese nationality dummy variable	Not significant	-
					Logarithm of respective population	Not significant	-
					Load Factor	1%	Positive
					Fuel cost per ATK	1%	Negative
Lee and Worthington (2014)	42 international airlines (2006)	Simar and Wilson (2007) 1st stage: BCC bootstrapped efficiency 2nd stage: Bootstrap truncated regresion	Kilometres flown, number of employees and total assets.	ATK	State/quasi-state ownership dummy variable	5%	Positive
					Low-cost dummy variable	5%	Positive
					Number of departures	5%	Negative
					Load Factor	5%	Positive
Merkert and Pearson (2015)	107 (SKYTRAK) or 116 (CUSTOM) international airlines (2011)	Simar and Wilson (2007) 1st: Bootstrap BCC efficiency 2nd: Bootstrap truncated regression	ASK, full-time equivalent staff.	RPK, operating margin and CUSTOM _RANK.	Avarage age of fleet	1% and 5%	Negative
					% Crew	Not significant	-
					Low-cost dummy	10% and Not significant	Negative
					Load Factor	Not significant	-

Source: Own production based on the existing literature

Although some investigations have been exploring efficiency through censored/Tobit approach, it was proved that this approach has been contributing to inconsistent inference. Simar and Wilson (2007) demonstrated, through Monte Carlo experiments, how censored/Tobit models do not account for serial correlation and bias complications in the estimation of efficiency scores, as well as between the error term and the covariates in the second stage model. According to the authors, there exists strong correlation among efficiency scores originating biased efficiency estimations in the first stage, due to the fact they are jointly estimated by a comparative method as DEA. Consequently, if it is ignored, this bias can be incorporated in the error term of the second stage regression and given the fact that it is correlated with inputs and outputs, the error term and the explanatory variables would also be correlated. Similarly, the Tobit model was not considered appropriate due to its standard dependent variable truncation below zero that does not coincide with estimated efficiency scores boundary that varies between zero and one or above one (Barros and Peypoch, 2009). Also, the fact of none of these techniques' applications described its data-generating process (DGP) was also criticised given it creates some doubt in what are the two-stage estimation approaches precisely estimating.

Alternatively, Simar and Wilson (2007) suggested two bootstrap procedures to offer accurate conclusions in the search for efficiency determinants: a single or a double bootstrap. The critical difference between both lies on the estimation of the efficiency scores since the double procedure additionally estimates non-bias bias efficiency scores before matching them to the bootstrap truncated model, in the second stage, where both produce standard errors and confidence intervals for the estimated parameters. Thus, it is reliable to investigate the impact of environmental variables in explaining DMUs' efficiency by applying this procedure. In fact, some papers have been using it as we can depict from Table **7**.

Besides DEA, stochastic frontier analysis (SFA), introduced by Aigner, Lovell and Schmidt (1977); Meeusen and Broeck. (1977), is also appropriate to study efficiency, but it has been having a significant minor role when compared to DEA in airline industry efficiency' investigations. The "*econometric approach to efficiency analysis*" (Greene, 2008), it is also a frontier method although parametric which means that requires a specification of the functional form of the data to calculate efficiency estimations. Besides, it econometrically estimates, usually trough Cobb-Douglas or Translog functions (Merkert and Pearson, 2015), parameters for the whole dataset and splits the error term into stochastic and inefficiency terms (Aigner et al., 1977). Similarly, this method does not provide specific information on the existence of slacks for specific output increases and input reductions, just as it does not decompose technical efficiency into pure technical efficiency and scale efficiency (Tandon, Tandon and Malhotra, 2014). Moreover, it can be said that in contrast to DEA – used without additional procedures such as Simar and Wilson (2007) - SFA incorporates noise as part of the efficiency scalar measure. However, if an inappropriate functional form or distributional assumption is utilised, it is known that the parametric frontiers will suffer from wrong misspecification (Emrouznejadet al., 2014).

4. Database description

To implement this analysis, we use cross-sectional data of the global airline industry's performance in 2015. The database was obtained from the World Air Transport Statistics (WATS) 2016 provided by The International Air Transport Association (IATA), and includes statistical information for 119 full-service and 18 low-cost passenger airlines (see Table **11** and Table **12**). Our focus lies on the scheduled flights of passenger airlines which transport: passengers, freight and mail. For this reason, cargo airlines were excluded from this investigation since they do not perform passenger transportation.

Apparently, there is no evidence in the literature that any study, with many such observations for one year, has ever been performed. This study covers all world geographical regions, and it is based on more than 65% of the total 2015 airline industry operations as it is presented in Table **8**. For this reason, we believe that our scrutiny conveys a very close efficiency measure to the recent reality in this industry since it delivers an extensive basis for the implementation of DEA. Considering the relative nature of DEA, performing an investigation with many observations will allow obtaining a more precise perception of an airline positioning in the international industry context, especially comparing to minor samples focus on niche markets where benchmarking is considerably more restricted. Consequently, robust conclusions will be set on regional realities, as also on the international competition between low-cost and full-service operators.

***Table 8**: Measuring Database Coverage*

Indicator/Region	Africa	Asia Pacific	Europe	Latin America	Middle East	North America	**Total**
ASK_{sample}	157,307	1,933,121	1,335,020	324,553	651,730	1,320,593	5,722,324
$ASK_{industry}$	213,540	2,717,301	2,183,037	442,899	806,353	1,942,076	8,305,206
$ASK_{coverage}$	74%	71%	61%	73%	81%	68%	69%
RPK_{sample}	109,136	1,519,024	1,082,928	260,409	501,392	1,111,992	4,584,881
$RPK_{industry}$	145,726	2,141,317	1,795,585	352,639	614,645	1,628,783	6,678,695
$RPK_{coverage}$	75%	71%	60%	74%	82%	68%	69%
ATK_{sample}	24,341	292,023	178,799	44,845	115,510	181,466	836,984
$ATK_{industry}$	31,579	394,927	304,532	57,833	137,342	310,381	1,236,594
$ATK_{coverage}$	77%	74%	59%	78%	84%	58%	68%
RTK_{sample}	14,059	201,062	129,112	29,242	73,746	115,181	562,402
$RTK_{industry}$	17,900	278,237	220,727	39,201	87,100	196,741	839,906
$RTK_{coverage}$	79%	72%	58%	75%	85%	59%	67%
in millions							

Source: Own production based on IATA's (2016) statistical information

ICAO (2017) was adopted to identify LCCs in our sample (see Table **9**) which represent 13% of the total number of observations. We follow IATA regional classification (IATA, 2016) which is subdivided into six regions - Africa, Asia-Pacific, Europe, Latin America, Middle East and North America – to identify airlines region of domicile.

***Table 9**: Database according to the Business Model and Regional Characteristics*

Business Model / Region	Africa	Asia Pacific	Europe	Latin America	Middle East	North America	**% Total**	**Total**
Low-cost carriers	1	5	8	3	0	1	13%	18
Full-service carriers	11	34	46	10	12	6	87%	119
Total	12	39	54	13	12	7	100%	137
% Total	9%	29%	39%	10%	9%	5%	100%	

Source: Own production based on ICAO (2017) classification

5. Methodology

This study strives on the airline industry performance in 2015. It includes cross-sectional data of 137 passenger airlines and attempts to carry out an international efficiency comparison between low-cost and full-service operators. Its relevance lies in the innovative research about the impact of low-cost carriers on the technical efficiency of full-service airlines, as also on the extensive geographical coverage that it provides. Therefore, we attempt to deliver accurate conclusions on the modern reality of the airline industry given the high discriminatory power implemented. To perform this analysis, we follow a two-step procedure proposed by Simar and Wilson (2007). In the first stage, we calculate non-bias technical efficiency scores for each airline by using a comparative method named Data Envelopment Analysis. In its second step, 1st stage estimates are regressed against some hypothesised explanatory variables, using a bootstrapped truncated regression, to detect efficiency drivers.

5.1. Research question, hypotheses and objectives

Given the competitive environment that is taking place in this industry (see Section **2**) where low-cost operators are raising their worldwide and continental presence forcing full-service carriers to adapt, it is a matter of great importance to understand how are low-fare companies influencing full-service airlines efficiency. Thus, this paper arises from the following question:

Does low-cost regional market share impact on full-service airlines' technical efficiency based in the same region?

Thus, it is the aim of this study to achieve the following objectives:

1. Provide a technical efficiency measure for each airline;
2. Rank airlines considering technical efficiency;
3. Understand if there exist significant differences between low-cost and full-service carriers' technical efficiency;
4. Compare airlines' efficiency in the different regions of the world;
5. Identify the drivers of technical efficiency;

6. Perceive whether the local low-cost market share affects the technical efficiency of full-service airlines domiciled in the same region.

By the primary research question and the objectives outlined in this paper, as also with Sections **2** and **3**, it is feasible to draw the following set of hypotheses:

1. Low-cost air transporters are, on average, more efficient than full-service operators;
2. The passenger load factor and the share of cargo in total operation have positive impacts on technical efficiency;
3. Low-cost carriers have a positive impact on the efficiency of FSCs based in the same region;
4. Alliance membership (Star Alliance, OneWorld, and SkyTeam) has a positive impact on technical efficiency of FSCs;
5. The low-cost business model contributes to technical efficiency advantages;
6. The number of different manufacturers in the fleet has a negative impact on the technical efficiency of airlines;
7. The average duration of each flight has a negative impact on the technical efficiency of air transporters.

Additionally, a set of weighted averages will be calculated to understand if there are significant efficiency differences between many world regions.

5.2. Inputs, outputs and explanatory variables

The choice of inputs and outputs follows the observed literature and, simultaneously, considers data availability constraints. Since we want to preserve the largest possible sample to draw accurate regional and business model comparisons, we confined the estimation of efficiency scores to the choice of physical inputs and outputs. The lack of data forced us to exclude financial measures from the input-output mix, in line with many other studies that only use physical measures such as Arjomandi and Seufert (2014); Barbot (2006); Greer (2009); Inglada et al. (2006); Lee and Worthington (2014). At the same time, efficiency scores are likely to be more reliable than the ones using financial measures, since they do not depend on any foreign exchange or different international accounting requirements distortions (Merkert and Hensher, 2011).

For the inputs, we attempt to represent the trade-off between labour and capital in airlines' operation (Merkert and Pearson, 2015). For this reason, we chose the number of employees, in line with Arjomandi and Seufert (2014); Barros and Peypoch (2009); Chang et al. (2014); Wu, He, and Cao (2013), as a proxy for labour. The total number of aircraft (Barbot, 2006; Lee and Worthington, 2014), as well the Available Tonne Kilometres (ATK) to characterise capital (Chang et al., 2014; Lozano and Gutiérrez, 2014; Merkert and Hensher, 2011).

On the side of outputs, the Revenue Tonne Kilometres (RTK) is our choice in line with Barbot (2006); Chang et al. (2014); Lee and Worthington (2014); Lozano and Gutiérrez (2014); Merkert and Hensher (2011); Wu, He and Cao (2013). Furthermore, the input-output combination (see Figure **9**) complies with endorsements proposed by Boussofiane, Dyson and Thanassoulis (1991) that advice a minimum number of DMUs equal to the product of the number of inputs and outputs (137>3).

Figure 9*: Description of the Variables used during the First and Second Stages*

Stage/Function	Title	Description	Type	Unit/Coding
First Stage				
Input	tna	Total number of aircraft	Quantitative	Number of aircraft
Input	tne	Total Employees at 31 December 2015	Quantitative	Number of employees
Input	satkts	Scheduled Available tonne-Kilometres - Systemwide	Quantitative	Thousand tonne-km
Output	srtkts	Scheduled Revenue Tonne-km Performed - Systemwide	Quantitative	Thousand tonne-km
Second stage				
Dependent	non_bias_i_TE	Non bias input-based efficiency scores	Quantitative	-
Dependent	non_bias_o_TE	Non bias output-based efficiency scores	Quantitative	-
Independent	scargo	Scheduled freight and mail (non-passenger) tonne-km performed as a percentage of scheduled tonne-km performed	Quantitative	%
Independent	hpf	The average duration of each fight	Quantitative	Hours per flight
Independent	splfts	Scheduled Passenger Load Factor - Systemwide	Quantitative	%
Independent	lccic	ICAO airline type classification	Quantitative	1: LCC 0: Other
Independent	mslcas	Low-cost regional market share as the ratio of LCCs' available seats to the total number of available seats in the same region	Quantitative	%
Independent	am	Alliance member (Star Alliance or OneWorld, or SkyTeam)	Quantitative	1: Alliance Member 0: Other
Independent	ndam	Number of different aircraft manufacturers in the fleet	Quantitative	Number of manufacturers

Source: Own production

As it was previously explained in Section **4**, this sample accounts for a significant share of the airline industry in 2015. For this reason, it represents operations of varying scope. Considering these differences, it was applied a mean normalised process on the selected inputs and outputs to ensure there was not much imbalance in the dataset (Sarkis, 2007). This procedure was implemented by dividing each input and output by the mean of the data set for each variable. In Table **13** and Figure **20** is presented a summary of mean normalised inputs and outputs.

Finally, in the second stage, we will study the significance of seven different variables (see Figure **9**) for the technical efficiency of airlines.

The descriptive statistics of inputs, output and second stage variables are presented in Figure **10**.

***Figure 10**: Descriptive Statistics*

Variable	Obs	Mean	Std. Dev.	Min	Max
tna	137	93.06569	148.7959	2	951
tne	137	10954.88	19506.42	43	120652
satkts	137	6109364	1.06e+07	37	5.52e+07
srtkts	137	4154725	7143117	8	3.63e+07
Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
non_bias_i~s	137	.7200098	.1426721	.1855378	.9717363
non_bias_o~s	137	1.484376	.5422986	1.035787	5.474552
mslcas	137	30.20438	10.60115	9	41
lccic	137	.1313869	.3390627	0	1
ndam	137	2.321168	1.200088	1	6
hpf	137	2.607109	1.413483	.490099	9.038012
splfts	137	75.1742	8.568901	22	92
am	137	.3722628	.4851819	0	1
scargo	137	13.01429	13.63719	0	62.38771

Source: Own production by using Stata

5.3. Efficiency scores estimation and sources of technical efficiency

To perform this analysis, we use a two-step procedure based on Simar and Wilson (2007). In the first stage, we calculate technical efficiency scores for each airline by using Data Envelopment Analysis based on Farrell (1957) technical efficiency measure. Then, a smooth bootstrap procedure is applied to estimate non-bias efficiency scores, and in a second stage, non-bias estimates are regressed against some explanatory variables by using bootstrapped truncated regressions.

The choice for this approach follows the recent trend on two-step studies in airline industry's efficiency (see Table **7**). This technique has been the most used in two-step studies since the authors proved, through Monte Carlo experiments, how vital DEA second stage approaches, like censored/Tobit regressions and OLS regression models, had been contributing to inconsistent and biased inference, especially in small samples. According to Simar and Wilson (2007), measuring efficiency through non-parametric methods originates strong correlation among efficiency scores: "*The correlation arises in finite samples from the fact that perturbations of observations lying on the estimate frontier will in many, and perhaps all, cases cause changes in efficiencies estimated for other observations*" (Simar and Wilson, 2007:33). Consequently, if it is not estimated, the bias is incorporated in the error term of the second stage regression and, given the fact that it is correlated with inputs and outputs, there would be a correlation between the error term and the covariates.

Alternatively, Simar and Wilson (2007) provide a Data Generating Process (DGP) in which environmental variables explain DMUs' efficiency scores through a bootstrapped truncated (not censored) linear regression which ensures conceivable consistent inference. In one hand, the truncation considers that the error term is left-truncated (right-truncated) and the dependent variable, first stage estimated efficiency scores, is bounded above (below) one. On the other hand, the bootstrap procedure produces standard errors and confidence intervals for the estimated parameters to solve correlation problems. Simar and Wilson (2007) presented two bootstrapping alternatives: a single or a double bootstrap, defined in Simar and Wilson (2007:13-14) as Algorithm#1 and Algorithm#2, respectively. The main difference between both lies in the estimation of the efficiency scores since the second procedure additionally estimates non-bias efficiency scores before matching them to the bootstrapped truncated regression. In the second stage, they both produce standard errors and confidence intervals for the estimated parameters. Besides, the second procedure also offers a quicker root-mean-square-error reduction of the intercept and slope estimators than the single bootstrap, being the preferred choice of the authors.

Despite it is mentioned in Simar and Wilson (2007:40) that " *this correlation, as well as the bias itself, disappears asymptotically*" which could lead us to merely apply the Algorithm#1 given our sample size, this investigation follows the Algorithm#2 for robustness in the estimation of first and second stages' parameters. Although, since there was no available command in Stata to specifically perform Simar and Wilson's (2007) Algorithm#2, we follow Tauchmann's (2017) suggestion to calculate corrected efficiency scores based on teradicalbc Stata command. This command provides a bootstrap procedure based on Simar and Wilson (1998, 2000) to estimate non-bias efficiency scores used as dependent variable in Simar and Wilson's (2007) bootstrapped truncated regression.

5.3.1. Estimation of non-bias efficiency scores

This section attempts to demonstrate all the steps taken to estimate non-bias efficiency scores. To perform this intermediate step, we use Data Envelopment Analysis based on Farrell's (1957) technical efficiency which represents "*the ability of a firm to obtain maximal output from a given set of inputs*" (Coelli et al., 2005:51).

Next, we briefly detailed this procedure by following Badunenko and Mozharovskyi (2016):

For each airline k there exists a vector of N inputs, x_k , and a vector of M outputs, y_k. The relationship between inputs and outputs is defined by T , the production frontier, which represents the maximum output attainable from each input level or the minimum input requirement needed to produce each output level (Coelli et al., 2005). Under the production frontier a transformation process (see Figure **8**) occurs where:

$$T\ \{(x, y): y\ are\ producible\ by\ x\} \qquad \textbf{(2)}$$

The distance from the frontier for each airline k represents its efficiency. For an output-oriented measurement, T is defined by the upper boundary of the production possibility set, P, and the technical efficiency measure is given by "*the maximal proportional increase in output possible given the technology and the input vector"* (Färe, Grosskopf and Lovell, 1985:83).

$$P(x) \equiv \{y : (x, y)\ \epsilon\ T\} \qquad \textbf{(3)}$$

As for the case of input-based measure, T is defined by the lower boundary of the input requirement, L, and the technical efficiency represents the maximal amount by which x_k can be proportionally decreased while keeping the same level of output (Badunenko and Mozharovskyi, 2016).

$$L(y) \equiv \{x : (x, y) \epsilon T\} \qquad \textbf{(4)}$$

Conditions **3** and **4** ensure that available inputs and outputs are feasible.

Based on the description provided it can be therefore stated that airlines which are technically inefficient operate at points in the interior T, and technically efficient airlines perform their activity somewhere along T (Badunenko and Mozharovskyi, 2016).

To empirically estimate Farrell's (1957) technical efficiency we use Data Envelopment Analysis which implements a linear programming method to estimate a piece-wise frontier over the data to represent the true (unobserved) best-practice frontier (Coelli et al., 2005; Badunenko and Mozharovskyi, 2016). The frontier is given by "*the smallest convex free-disposal hull that envelops the observed data*" (Badunenko and Mozharovskyi, 2016:3), and from the distance to the estimated frontier, a technical efficiency measure, $\widehat{\delta_k}$, for each airline is calculated.

Under input-oriented DEA, airline k attempts to reduce its input levels by as much as possible while not decreasing output amounts:

$$\begin{gathered} \widehat{\delta_k}\,(y_k x_k\,, y, x) = \ min_{\theta,z}\theta \\ s.t. \sum_{k=1}^{K} z_k x_{kn} \leq x_{kn}\theta_n, n = 1, \dots, N, \\ \sum_{k=1}^{K} z_k y_{km} \geq y_{km}, m = 1, \dots, M, \\ z_k \ \geq 0 \end{gathered} \qquad \textbf{(5)}$$

Where z_k is a non-negative "*intensity variable used to scale individual observed activities for constructing the piecewise linear* " frontier (Emrouznejad et al., 2014:364).

Consequently,

If $\widehat{\delta_k} = 1$, the airline k is input-technical efficient, since it is allocated somewhere along the estimated best-practice frontier.

If $\widehat{\delta_k} < 1$, the airline k is input-technical inefficient, since it is allocated below the estimated best-practice frontier. $1 - \widehat{\delta_k}$ is the percentage by which all inputs need to be reduced to achieve technically efficient production frontier, without a reduction in output (Coelli et al., 2005:52).

Under output-oriented DEA, airline k attempts to increase its output levels by as much as possible while not increasing input amounts:

$$\begin{gathered}\widehat{\delta_k}(y_k x_k, y, x) = max_{\theta,z}\theta \\ s.t. \sum_{k=1}^{K} z_k y_{km} \geq y_{km}\theta_m, m = 1, \dots, M, \\ \sum_{k=1}^{K} z_k x_{kn} \leq x_{kn}, n = 1, \dots, N, \\ z_k \geq 0\end{gathered} \quad \textbf{(6)}$$

Consequently,

If $\widehat{\delta_k} = 1$, the airline k is output-technical efficient, since it is allocated somewhere along the estimated best-practice frontier.

If $\widehat{\delta_k} > 1$, the airline k is output-technical inefficient, since it is allocated below the estimated best-practice frontier. $\widehat{\delta_k} - 1$ is the percentage by which all outputs need to be increased to achieve technically efficient production frontier, without an increase in input.

Equations **5** and **6** represent technical efficiency measures under CRS assumption which means that airlines operate at an optimal scale. To relax this assumption, an additional convexity condition on the efficient frontier can be added to allow for VRS (Thanassoulis, 2001):

$$\sum_{k=1}^{K} z_k = 1 \quad \textbf{(7)}$$

Under VRS, efficiency measurements are performed within airlines with the same size relying on the impact of scale efficiency: Farrell's (1957) pure technical efficiency.

Moreover, replacing it with $\sum_{k=1}^{K} z_k \leq 1$ allows for non-increasing returns to scale (NIRS) where $\widehat{\delta_k}$ is obtained based on comparisons of airlines with not very different sizes.

Data Envelopment Analysis is a deterministic method since efficiency is measured relative to an estimate of the true (unobserved) production frontier (Simar and Wilson, 1998). Consequently, it considers the entire deviation of an observation from the technology as inefficiency (Färe, Grosskopf and Lovell, 1985), as well does not reflect the existence of noise in the data (Coelli et al., 2005). Particularly, Simar and Wilson (1998, 2000, 2007) have warned about the sensitive of these measures to sampling variations of the estimated frontier. To take into account the sensitivity, these authors developed a bootstrap procedure which consists of generating large numbers of pseudo-observations (Førsund, 2016) to correct for bias and calculating confidence intervals for bootstrapped estimates.

Thus, a bootstrap estimator of bias can, in turn, be used to calculate a non-bias estimator:

$$\widehat{\widehat{\delta_k}} = \widehat{\delta_k} - BIAS\,\widehat{\delta_k} \tag{8}$$

Next, we provide the smoothed homogeneous proposed by Simar and Wilson (1998) to the output-based efficiency measure, based on Barros, Assaf and Sá-Earp (2010):

1) Compute the efficiency scores $\widehat{\delta_k}\,(x_k, y_k)$ k=1, … 137; by solving DEA in equation **6;**

2) Use the kernel density estimation and the reflection method to generate a random sample of size *n* from $\{\widehat{\delta_k}\,; k = 1, \dots, 137\}$, providing $\{\widehat{\delta_{1_b}^{*}}\,; \dots, \widehat{\delta_{n_b}^{*}}\}$;

3) Compute a pseudo data set $\{(x, y_{kb}^{*}), \mathrm{k} = 1, \dots\ 137\}$ to form the reference bootstrap production frontier;

4) Using this pseudo data, compute the bootstrap estimate of efficiency $\widehat{\delta_{n_b}^{*}}$ of $\widehat{\delta_k}$ for each k=1, … 137;

5) Repeat steps 2-4 B (1000) times to obtain a set of bootstrapped efficiency estimates $\{\widehat{\delta_{k_b}^{*}}\,; b = 1, \dots, \mathrm{B}\}$.

For the input-based measure, the pseudo data set is given by (x_{kb}^{*}, y).

However, the application of bootstrapping varies according to an independence assumption (Wilson, 2003). On the one hand, the homogeneous bootstrap can be used if input-based (output-based) measures of technical efficiency are independent of the mix of inputs (outputs), as well of the output (input) levels (Simar and Wilson 1998, 2000; Wilson, 2003). On the other hand, the heterogeneous bootstrap (Simar and Wilson, 2000) allows for the possibility of dependence. To decide whether to apply homogeneous or heterogeneous, a test proposed by Wilson (2003) is applied under the following hypothesis:

H0: There is independence – Homogeneous bootstrap.
H1: There is no independence - Heterogeneous bootstrap. (I)

This test is performed by using nptestind Stata command developed by Badunenko and Mozharovskyi (2016). We follow Wilson (2003:367) by using 1000 replications “*Since B will typically be at least 1,000*”.

With regards to the shape of T, there are some studies which point that the main source of inefficiency does not come from the size of airlines (Barros and Peypoch, 2009; Lee and Worthington, 2014). Although, it is equally true that some literature listed a set of factors such as regulation and public/private ownership to state that airlines are not operating at their optimal size and, consequently, adopt a VRS assumption (Merkert and Pearson, 2015). As there is no clear consensus in the shape of T in the airline industry, we implement a test to assess the scale efficiency of the airlines in our sample with the aim to understand which type of returns to scale shall we assume. This test was developed by Simar and Wilson (2002) under the following hypotheses:

H0: T is globally CRS.
H1: T is VRS. (II)

This test is introduced by using nptestrts Stata command developed by Badunenko and Mozharovskyi (2016).

Based on the conclusions of tests **I II**, we have all the information necessary to estimate equation **8** for each airline. We follow Tauchmann's (2017) recommendation to obtain non-bias estimates by using teradialbc command developed by Badunenko and Mozharovskyi (2016).

In a second stage, estimated non-bias efficiency scores will be regressed against some explanatory variables to assess their impact on technical efficiency. However, we also intend to draw a set of evaluations based on weighted averages. Our weights are given by the RTK (output-based), and the ASK (input-based) as we believe that are proper measures to evaluate the whole operation of an airline since including passengers, mail and freight. Thus, weighted technical efficiency average allows to understand how much these airlines can proportionally reduce (increase) its inputs (outputs) to become technical efficient. Simultaneously, weighted technical efficiency average to each business model (LCCs vs FSCs) is set with the objective of understanding which business model is the most efficient. Finally, we will focus on the regional technical efficiency weighted average to perceive if there are significant efficiency differences across the globe.

5.3.2. Determinants of technical efficiency

This section corresponds to the use of Simar and Wilson's (2007) bootstrapped truncated regression (Algorithm#1) to study the impact of hypothesised environmental variables on the technical efficiency of carriers considering that $\widehat{\widehat{\delta_k}}$ is equal to or bounded above (output-based), or below (input-based), one.

Coelli et al. (2005) described environmental variables as influences in technical efficiency which are not traditional inputs and are not under management control. According to Simar and Wilson (2007:34) these variables "*constrain their choices of inputs x and outputs y*". Thus, the choice of environmental variables looks, primarily, to our research question which attempts to provide innovation to the literature, to the observed literature (see Table **7**) and to the available data. In this way, we intend to analyse which factors explain the inefficiency of the airlines through the variables presented in Table **10**.

***Table 10**: Description of Second Stage Explanatory Variables*

Title	Description	Type	Unit/Coding
scargo	Scheduled freight and mail (non-passenger) tonne-km performed as a percentage of scheduled tonne-km performed	Quantitative	%
hpf	The average duration of each fight	Quantitative	Hours per flight
splfts	Scheduled Passenger Load Factor - Systemwide	Quantitative	%
lccic	ICAO airline type classification	Quantitative	1: LCC 0: Other
mslcas	Low-cost regional market share as the ratio of LCCs' available seats to the total number of available seats in the same region	Quantitative	%
am	Alliance member (Star Alliance or OneWorld, or SkyTeam)	Quantitative	1: Alliance Member 0: Other
ndam	Number of different aircraft manufacturers in the fleet	Quantitative	Number of manufacturers

Source: Own production

The descriptive statistics of second stage variables are presented in Figure **11**.

***Figure 11**: Descriptive Statistics of Second Stage Variables*

Variable	Obs	Mean	Std. Dev.	Min	Max
non_bias_i~s	137	.7200098	.1426721	.1855378	.9717363
non_bias_o~s	137	1.484376	.5422986	1.035787	5.474552
mslcas	137	30.20438	10.60115	9	41
lccic	137	.1313869	.3390627	0	1
ndam	137	2.321168	1.200088	1	6
hpf	137	2.607109	1.413483	.490099	9.038012
splfts	137	75.1742	8.568901	22	92
am	137	.3722628	.4851819	0	1
scargo	137	13.01429	13.63719	0	62.38771

Source: Own production by using Stata

Several studies have focused on the impact of the low-cost business model for the technical efficiency of airlines. Usually, this is implemented through a dummy variable which distinguishes if the airline is low-cost (see Table **7**). In this study, we do the same to verify the hypothesis. However, an analysis of the impact of LCCs on the technical efficiency of FSCs has never been provided. Thus, we aim to assess whether the concentration of low-cost airlines in a specific region affects the technical efficiency of the FSCs that are domiciled there. Thus, we consider the following hypotheses:

(i) In what concerns to the number of different manufacturers in the fleet of an airline, it is assumed a negative impact on technical efficiency of airlines. We believe that a limited number of different aircraft makes it simpler for its employees to be able to operate on any of its flights in an industry where there are strong work regulations and collective agreements affecting the assigning of crew members (Zanin and Lillo, 2013; Dobruszkes, 2006);

(ii) The regional low-cost market share has a positive influence on the technical efficiency of FSCs which can be the result of important strategies adopted by FSCs to answer to the emergence and increasing competition of LCCs. Such strategies are mainly implemented to reduce costs and increase staff productivity and aircraft utilisation to compete with low-fare carriers in short-haul flights;

(iii) The adoption of the low-cost business model is positive for the technical efficiency since the goal of a low-cost is to enjoy economies of density by maximising the use of its aircraft, using a single/few type of aircraft, reducing turnaround times and providing on-board budget service (Francis et al., 2006; Dobruszkes, 2006);

(iv) Regarding the average number of hours per flight, our hypothesis predicts a negative impact on the technical efficiency since longer flights require more crew to operate and, at the same time, affect the use of its employees who need more rest periods. The very significant positive correlation between the total number of aircrafts, the total number of employees, the number of departures, as well the number of hours flown reinforces this suggestion (see Figure **21**);

(v) For the alliance membership is also assumed a positive impact on the technical efficiency of airlines due to the enjoyment of economies of density (see Section **2.1**) which may have positive consequences on the transformation of inputs into outputs;

(vi) The scheduled passenger load factor and the share of cargo in the total operation complete our set of variables with an expected positive sign. These hypotheses may seem a little trivial, but we assume a positive impact given the fact that airlines have available more seats and cargo capacity than the ones that are sold.

Next, we formally outline the second stage econometric model, which follows an output-orientation, based on Simar and Wilson (2007):

$$\widehat{\widehat{\delta_k}} = d_k\beta + \varepsilon_k \geq 1$$

$$\text{where } k = 1,2, \ldots ,137 \qquad \textbf{(9)}$$

where $\widehat{\widehat{\delta_k}}$ represents the non-bias estimated efficiency score for airline k, $\mathrm{d_k}$ is a vector of environmental variables which are expected to be related to $\widehat{\widehat{\delta_k}}$ and ε_k is statistical noise following a normal distribution N $(0,\sigma_\varepsilon^2)$, and it is left-truncation at $1 - \hat{\beta}d_k$. In the case of $\widehat{\widehat{\delta_k}}$ is input-based, and consequently ≤ 1, the left-truncation is replaced by a right truncation at $1 - \hat{\beta}d_k$ (Tauchmann, 2015).

Equation **9** is estimated L times by using the maximum likelihood estimator. Bootstrapped estimates $\hat{\beta}$ and $\widehat{\sigma_\varepsilon}$ are calculated to construct confidence intervals for each β and σ_ε and, consequently "*improve(s) on inference estimates*" (Simar and Wilson, 2007:34). This process can be described as follows (Simar and Wilson, 2007):

(1) Use of the maximum likelihood method to obtain $\hat{\beta}$ and $\widehat{\sigma_\varepsilon}$, β and σ_ε estimates, in the truncated regression **9** using non-bias efficiency scores from equation **8** as the dependent variable**.**

(2) Loop over the next three steps L (2000) times to get bootstrap estimates for β and σ_ε:

   (i) For each k = 1, . . ., 137, draw ε_k from the N $(0,\sigma_\varepsilon^2)$ with left-truncation at $1 - \hat{\beta}d_k$ for an output-based measure or with a right -truncation at $1 - \hat{\beta}d_k$ for an input-based analysis

   (ii) Compute the bootstrapped regression **9** for each k = 1, . . ., 137

   (iii) Estimate the bootstrapped truncated regression **9** by using the maximum likelihood technique, yielding bootstrapped $\hat{\beta}$ and $\widehat{\sigma_\varepsilon}$

(3) Finally, estimated confidence intervals are constructed for each element of β and for σ_ε using their bootstrapped values.

This stage is implemented by using simarwilson command (Tauchmann, 2015) in Stata with and L = 2000 (bootstrap replications) as it is suggested by (Simar and Wilson, 2007:44).

To assess if the explanatory variables are individually significant to explain technical inefficiency, the usual t-tests are implemented, as well the F-test to study the global significance of the model.

6. Empirical Results

This section represents the application of the steps listed in Sections **5.3.1** and **5.3.2**, so a careful reading of it is recommended before analysing any further.

It is therefore intended to disseminate the results obtained with the application of Simar and Wilson (1998, 2000, 2002, 2007); Wilson (2003) so that raised hypotheses can be tested and the research question answered.

In a first part, the results of Simar and Wilson (2002) and Wilson (2003) hypothesis tests, to obtain non-bias efficiency scores, are presented. Based on these, a set of weighted averages is completed to understand if there are significant geographical differences, as well disparities between FSCs and LCCs.

In the second stage, a set of bootstrap truncations are estimated to study the impact of environmental variables on the technical efficiency of airlines. Since in the literature, there is no clear consensus about which orientation should technical efficiency follow, and for the sake of robustness, efficiency scores are calculated assuming input and output orientations. Studies as Assaf (2009), Barros et al.(2009) and Merkert et al. (2011) followed an output-orientation arguing that airlines do not have so much flexibility to adjust inputs in the short-term, considering its as quasi-fixed. On the other side, Barbot et al. (2008) and Merkert et al. (2011) used an input-orientation rooted in the trust that output is significantly dependent on economic factors and often predetermined by long-term slot allocations contracts.

To empirically estimate non-bias Farrell's (1957) technical efficiency scores for each airline, we implement Data Envelopment Analysis which solves a linear programming model for each airline based on a smooth bootstrap procedure as it as previously explained in Section **5.3.1**. However, bootstrapping depends on whether if the input-based (output-based) measures of technical efficiency are independent of the mix of inputs (outputs), as well of the output (input) levels (Simar and Wilson, 1998, 2000; Wilson, (2003), therefore we implemented **I** hypothesis test. This test was performed by using nptestind Stata command (Badunenko and Mozharovskyi, 2016) with 1000 replications (see Figure **12**).

Figure 12: *Independence Tests P-values*

```
testsindpv[2,2]
                  CRS    VRS
output-based        0   .003
 input-based        0   .006
```

Source: Own production by using Stata results

It is then possible to conclude from Figure **12** that the null hypothesis is rejected for input-based and output-based measures of technical efficiency under CRS and VRS since the respective p-values were lower than the significance level 0.01. By this test, we conclude that under CRS and VRS, input-based (output-based) technical efficiency scores are dependent on the mix of inputs, as well of the output (input) levels. The "*rejection of the null hypothesis of independence clearly indicates that the heterogeneous bootstrap should be used instead of the homogeneous bootstrap*" (Wilson, 2003:387).

As explored in Section **5.3.1**, our measure of technical efficiency depends on the assumption assumed for the shape of the technology frontier - CRS and VRS or NIRS. Since there is no clear consensus on the scale at which airlines operate, the test **II**, developed by Simar and Wilson (2002), was applied (see Figure **13** and Figure **14**) to enlighten us about the best assumption to take. The test was implemented using nptestrts Stata command (Badunenko and Mozharovskyi, 2016) and accounting for a heterogeneous bootstrap on the reference set.

Figure 13: *Test of Returns to Scale in Input-based Technical Efficiency*

```
. nptestrts srtkts_mn = satkts_mn tne_mn tna_mn, base(i) het a(0.05) reps(1000) nodots se(non_bias_scale_efficiency_o)

Radial (Debreu-Farrell) input-based measures of technical efficiency under assumption of CRS, NIRS, and VRS technology are
computed for the following data:

   Number of data points (K) = 137
   Number of outputs     (M) = 1
   Number of inputs      (N) = 3

Reference set is formed by 137 data points, for which measures of technical efficiency are computed.
------------------------------------------------------------------------------------------------------------------------
        Test #1

Ho: mean(F_i^CRS)/mean(F_i^VRS) = 1
  and
Ho: F_i^CRS/F_i^VRS = 1 for each of 137 data point(s)

Bootstrapping reference set formed by 137 data points and computing radial (Debreu-Farrell) input-based measures of technical
efficiency under assumption of CRS and VRS technology for each of 137 data points relative to the bootstrapped reference set

Smoothed heterogeneous bootstrap (1000 replications)


p-value of the Ho that mean(F_i^CRS)/mean(F_i^VRS) = 1 (Ho that the global technology is CRS) = 1.0000:
```

Source: Own production by using Stata results

Figure 14: *Test of Returns to Scale in Output-based Technical Efficiency*

```
nptestrts srtkts_mn = satkts_mn tne_mn tna_mn, base(o) het a(0.05) reps(1000) nodots se(non_bias_scale_efficiency_o)

Radial (Debreu-Farrell) output-based measures of technical efficiency under assumption of CRS, NIRS, and VRS technology are
computed for the following data:

   Number of data points (K) = 137
   Number of outputs     (M) = 1
   Number of inputs      (N) = 3

Reference set is formed by 137 data points, for which measures of technical efficiency are computed.
------------------------------------------------------------------------------------------------------------------------
        Test #1

Ho: mean(F_i^CRS)/mean(F_i^VRS) = 1
  and
Ho: F_i^CRS/F_i^VRS = 1 for each of 137 data point(s)

Bootstrapping reference set formed by 137 data points and computing radial (Debreu-Farrell) output-based measures of technica
efficiency under assumption of CRS and VRS technology for each of 137 data points relative to the bootstrapped reference set

Smoothed heterogeneous bootstrap (1000 replications)


p-value of the Ho that mean(F_i^CRS)/mean(F_i^VRS) = 1 (Ho that the global technology is CRS) = 1.0000:
```

Source: Own production by using Stata results

Through obtained results, we concluded that the null hypothesis is not rejected for both orientations since p-values were higher than the significance level 0.01. Consequently, we concluded that on average airlines are input-based and output-based scale efficient since T is globally CRS. For this reason, the implemented technical efficiency measure assumes CRS, otherwise “*if one assumes variable returns to scale* *when returns are actually constant everywhere, there may be a loss of statistical efficiency*" (Simar and Wilson, 2002:16).

According to the results obtained in tests **I** and **II**, non-bias efficiency scores were estimated (see Table **14** and Table **15**) for each airline through Stata command teradialbc (Badunenko and Mozharovskyi, 2016). As expected, the correction of efficiency scores decreased the technical efficiency for all airlines (Simar and Wilson, 2000, 2007). In Figure **15**, we can verify that on average the maximum proportional reduction of inputs that each airline would have, producing the same level of output, if it was operating at the efficient frontier was underrated by about 2.36 percentage points. On the side of the output-based measure, on average the maximum proportional increase of outputs that each airline would have, using the same level of inputs, if it was operating at the efficient frontier was undervalued by about 5.1 percentage points.

***Figure 15**: Bootstrap bias estimate for original (non-corrected) technical efficiency scores*

Variable	Obs	Mean	Std. Dev.	Min	Max
bias_o	137	-.0515811	.034425	-.3148399	-.0146138
bias_i	137	.023585	.0188265	.0057703	.1425104

Source: Own production using Stata

To complete the first phase, a set of weighted averages was calculated (see Figure **16** and Figure **19**). Our hypotheses pointed to higher average technical efficiency in regions where the market is more deregulated due to the increase of competition (see Figure **5**). The regional market share of low-cost seems to be a good proxy for measuring the level of regulation given the degree of implementation of low-cost companies is linked to the deregulation processes carried out in each region (see Section **2.1**). As far as the business model is concerned, our hypothesis assumes low-cost airlines being more efficient than FSCs due to its business model focus on the core activity of air transport (see Section **2.2**), as well on some conclusions drawn from previous results (Barbot, 2006; Barros and Peypoch, 2009; Lee and Worthington, 2014).

Figure 16: *Weighted Averages according to the Business model adopted and the Region of Domicile*

Variable	Obs	Mean
Africa_TE_i	12	.6670277
AsiaPacifi~i	39	.8137475
Europe_TE_i	54	.8247091
LatinAmeri~i	13	.7680989
MiddleEast~i	12	.8384246
NorthAmeri~i	7	.736278
LCC_TE_i	18	.732003
FSC_TE_i	119	.7999578
TE_i	137	.7959859
Africa_TE_o	12	1.505163
AsiaPacifi~o	39	1.234555
Europe_TE_o	54	1.216961
LatinAmeri~o	13	1.303262
MiddleEast~o	12	1.20433
NorthAmeri~o	7	1.359723
LCC_TE_o	18	1.3456
FSC_TE_o	119	1.257284
TE_o	137	1.262643

Source: Own production using Stata

The conclusions drawn from weighted averages are mixed. In one hand, African airlines, where LCCs have the lowest market share, are the least technical efficient under both orientations and European airlines, where low-cost has the highest regional market share, address our hypothesis which positively links the level of geographic deregulation and technical efficiency. On the other hand, Middle East is, on average, the most input and output-based technical efficient region, although it is the second world region with the lowest low-cost market share. One possible justification for this record might be the fact that Emirates, which is one of the most efficient companies in our dataset (see Table **14** and Table **15**), has a significant influence in the total ASK (48%) and the total RTK (49%) generated in the Middle East. Similarly, North America has one of the highest low-cost market shares, although it is, on average, the second-worst technical efficient region. This value may be related to the fact that our sample does not include one of the world best performers which is based in North America: Southwest Airlines. This airline registered a weighted load factor around 81.6% (IATA, 2016) which is a variable highly positively correlated with technical efficiency – negatively with output-based efficiency scores and positively with input-based – and it is clearly above the mean in our sample 65.19%. Therefore, the absence of this airline might have affected the average efficiency of North America.

Concerning the business model, obtained conclusions are contrary to the hypothesis considered since FSCs seemed to be, on average, more technical efficiency than LCCs, so we will try to address this issue by analysing the dummy variable (lccic) in the second phase regressions.

Finally, through the 137 efficiency scores, it is feasible to set some conclusions which might reflect a close reality to 2015 airline operations since our sample represents a significant share of it. Therefore, it can be concluded that, on average, the proportional increase in output that airlines would have, for the same level of inputs, if they were operating at the efficient frontier is 26.2% (Färe, Grosskopf and Lovell, 1985). Simultaneously, concerning to the input-based measure, on average the maximum possible proportional reduction of inputs that airlines would have, with the same level of output, if they were operating at the efficient frontier is 21% (Coelli et al., 2005).

Turning now to the second stage bootstrapped truncated regressions, we intend to verify the impact of some environmental variables on the technical efficiency of airlines by using simarwilson (Tauchmann, 2015) Stata command with 2000 replications. Consequently, the following hypotheses will be tested:

I. Strategies implemented by FSCs have resulted in technical efficiency increases through the presence of LCCs in the same region;

II. Passenger load factor is significantly decisive to the technical efficiency of airlines;

III. Share of cargo in total operation positively impacts on the technical efficiency of airlines;

IV. Being an alliance member (Star Alliance, OneWorld, and SkyTeam) has a positive impact on technical efficiency of FSCs;

V. The adoption of the low-cost business model contributes to technical efficiency gains. However, considering contradictory results which revealed higher technical efficiency of full-services compared to low-cost operators, it might not be the case;

VI. The number of different manufacturers in the fleet has a negative impact on the technical efficiency of airlines;

VII. The average duration of each flight has a negative impact on the technical efficiency of air transporters.

Before addressing our hypotheses, it is crucial to observe correlation between covariates to exclude potential multicollinearity. From Figure **17**, there seems to be no evidence of perfect correlation or either strong (above 0.6) correlation between any environmental variable.

Figure 17*: Matrix of Correlations between Covariates*

	mslcas	splfts	scargo	am	lccic	ndam	hpf
mslcas	1.0000						
splfts	0.0236	1.0000					
scargo	-0.3305	0.2203	1.0000				
am	-0.0220	0.2238	0.5765	1.0000			
lccic	0.0927	0.1242	-0.3038	-0.2995	1.0000		
ndam	0.1040	0.0736	0.1632	0.2730	-0.2671	1.0000	
hpf	-0.1794	0.4107	0.4326	0.1053	-0.1279	-0.0786	1.0000

Source: Own production by using Stata

Concerning to the truncated regressions, we started by including all hypothesised environmental variables in the model to study their significance as a source of technical efficiency under input and output orientations (see Figure **23**).

As demonstrated in Figure **23** both models are globally significant since Prob > Chi2(7) is below the significance level of 1% which lead us to reject the null hypothesis, since there is at least one $\beta_k \neq 0$. However, there is a set of variables which are not individually significant to explain the technical efficiency of aviation companies. The associated p-values for am, ndam, hpf (under both orientations), mslcas and scargo (output-based), and lccic (input-based) are higher than the significance level of 10% and, consequently, we do not reject the null hypothesis of individual insignificance to explain the technical efficiency of airlines. Thus, hypotheses raised on the alliance membership, on the average duration per flight, as well on the number of different aircraft manufacturers did not occur. One possible justification may be the fact that joining an alliance, as well as reducing the average time for each flight and have less aircraft manufacturers in the fleet, only impact in cost minimisation of airlines not reflecting in the transformation process of airlines.

The p-values of ndam, am and hpf are much higher than the significance level of 10% which may affect the individual significance of other variables. For this reason, a new model was estimated, for both orientations, without these variables. However, we chose to keep lccic (input-based), as well scargo and mslcas (output-based) to check if they were individually insignificant, or if their significance was being affected by the excluded covariates (ndam, am, hpf). Both models (see Figure **24**) were globally significant to explain the technical efficiency of airlines at 1% significance level.

Concerning the input-oriented measure, in one hand, adopting a low-cost model is not significant to the technical efficiency of airlines – Null hypothesis is not rejected since p-value >10%. On the other hand, passenger load factor, the share of cargo - under a significance level of 1% - and the regional market share of low-cost – under a significance level of 10% - are statistically significant to positively explain technical efficiency. By following Coelli et al. (2005) is feasible to conclude that:

- An increase of one percentage point in the passenger load factor is associated with a one percentage point decrease in the maximum possible proportional reduction of inputs that an airline would have, with the same level of output and technology, if it was operating at the efficient frontier;

- A one percentage point increase in the share of cargo is linked to a decrease of 0.32 percentage points in the maximum possible proportional decrease in input that an airline would have, with the same outputs and technology, if it was operating at the efficient frontier;

- The increase of one percentage point of the market share of LCCs in a region contributes to the reduction by 0.14 percentage points of the maximum proportional decrease in inputs that an airline, based in the same region, would have, producing the same output and using the same technology, if it was operating at the efficient frontier;

Turning now to the output-based model (see Figure **24**), the null hypothesis of the individual insignificance of the regional market share is not rejected since 0.11>10%. Thus, the local low-cost market share is not significant to explain the reduced output production of airlines domiciled in that region, considering the maximum possible output that they could achieve, with the same level of inputs and technology, if they were operating at the efficient frontier. However, passenger load factor, the share of cargo, as well the low-cost business model are significant to explain the technical inefficiency of an air carrier. So, by following Färe, Grosskopf and Lovell (1985), it can be stated that:

- An increase in the passenger load factor of one percentage point is associated with a decrease of 8.4 percentage points in the proportional increase in output that an airline would have, with the same inputs and technology, if it was operating at the efficient frontier;

- A one percentage point increase in the share of cargo is linked to a decrease of 3.5 percentage points in the proportional increase in output an airline firm would have, with the same inputs and technology, if it was operating at the efficient frontier;

- On average, the proportional increase in output that low-cost carriers could have for the same level of inputs if they were operating at the efficient frontier is 98 percentage points higher than for full-service carriers.

The results presented in Figure **24** allowed to draw essential conclusions on factors which influence the levels of technical efficiency. However, it is necessary to estimate the last model to answer the research question. Thus, to ascertain the hypothesis that assumes a significant positive sign of the regional low-cost market share as a driver of technical efficiency, an interaction term could be used. This strategy would allow differentiating the impact of mslcas according to the business model of the airline: lccic*mslcas: Interaction term between lccic and mslcas where lccic is a dummy variable to indicate (=1) if the airline is classified as low-cost by ICAO. However, this option was excluded since its introduction would cause perfect collinearity in the output-based model, and in the case of input-based, we would consider a non-significant variable (lccic) in our model. Alternatively, low-cost efficiency scores were dropped and we estimated two models with 119 FSCs' observations (see Figure **18**).

Figure 18: *The Impact of Low-Cost Market Share on the Technical Efficiency of FSCs*

```
Simar & Wilson (2007) eff. analysis      Number of obs            =        119
                                         Number of efficient obs  =          0
                                         Number of bootstr. reps  =       2000
inefficient if non_bias_i_TE_scores < 1  Wald chi2(3)             =     180.39
twosided truncation                      Prob > Chi2(3)           =     0.0000
```

efficiency	Observed Coef.	Bootstrap Std. Err.	z	P>|z|	Percentile [95% Conf.	Interval]
non_bias_i~s						
mslcas	.001653	.0007493	2.21	0.027	.0002186	.0031862
splfts	.0096802	.0009489	10.20	0.000	.0078401	.0115144
scargo	.0032715	.0006555	4.99	0.000	.0020095	.0045768
_cons	-.0930826	.0714519	-1.30	0.193	-.2307362	.0430812
/sigma	.0817445	.0056996	14.34	0.000	.0693636	.0914461

```
Simar & Wilson (2007) eff. analysis      Number of obs            =        119
                                         Number of efficient obs  =          0
                                         Number of bootstr. reps  =       2000
                                         Wald chi2(3)             =     127.05
inefficient if non_bias_o_TE_scores > 1  Prob > Chi2(3)           =     0.0000
```

efficiency	Observed Coef.	Bootstrap Std. Err.	z	P>|z|	Percentile [95% Conf.	Interval]
non_bias_o~s						
mslcas	-.0049665	.0032716	-1.52	0.129	-.0114785	.0012065
splfts	-.0432278	.0041216	-10.49	0.000	-.0510008	-.0353071
scargo	-.0087542	.0034125	-2.57	0.010	-.0161268	-.0027173
_cons	4.815503	.3131347	15.38	0.000	4.206711	5.417429
/sigma	.2882247	.0265182	10.87	0.000	.2329138	.3365255

Source: Own production by using Stata

As previously concluded for the whole sample (see Figure **24**), passenger load factor and the share of cargo positively affect the ability of an airline to efficiently transform inputs into outputs with both orientations since we reject the nulls of individual insignificance (p-values < 1%). This conclusion follows the existing literature (see Table **7**), and reinforces the relevance of demand factors in the technical efficiency of airlines (Lee and Worthington, 2014). Thus, our suggestions are in line with Barros and Peypoch (2009); Lee and Worthington (2014) by pointing to the critical role of management to create/reformulate marketing and advertising strategies to get more passengers and cargo.

As far as the regional low-cost market share is concerned, results are mixed.

On the one hand, the regional low-cost market share is statistically significant, with a significance level of 5%, for the input-based technical efficiency of FSCs. This result allows us to conclude that the maximum level of input reduction that an FSC can achieve while maintaining the same output and technology, depends negatively on the regional low-cost market share in the same region. Thus, our hypothesis holds since the increase of one percentage point in the regional low-cost market share is associated with a 0.1 percentage point decrease in the maximum possible proportional reduction of inputs that an FSC, based in the same region, would have, without using additional output and technology, if it was operating at the efficient frontier (Coelli et al., 2005).

In contrast, there is no evidence of a positive and significant relationship between the regional low-cost market share and output-based technical efficiency of FSCs, since we do not reject the null of individual insignificance (0.12>10%).

Concerning to the input-based measure, the result confirms our hypothesis and answers positively to our research question. This means that competition imposed by the expansion of low-cost operators has a positive impact on the level of technical efficiency of FSCs operating in the same region. In practice, larger low-cost market shares are associated with lower input uses for identical FSCs' output levels based in that region. Thus, some of the recent measures adopted by the full-service carriers, especially in short-haul flights, which are making FSCs more hybridised to compete with LCCs, may have some relation to this result (Dennis 2007; Tomová and Materna 2017):

- Outsourcing some services like catering, ground and handling (Dennis, 2007) might reduce the number of employees per RTK;

- Changes in on-board service. For instance: not providing food, or offering the same, and abandon business class allows to have the minimum staff per flight and avoids frequent cleaning and loading, as well replacing space for food storage by seats (Dennis, 2007);

- Reducing turnaround times through increases in regional aircraft utilisation and converting into seats the old galley space (Dennis, 2007) might reduce the number of aircraft per RTK.

7. Conclusion

The aviation industry has been indispensable to ensure the numerous worldwide movements daily occurring in our lives. In its field, low-cost carriers led to a new era by combining the focus on the core business and providing increased access to low-fare air transport (Dobruszkes, 2006). The growing competitive environment which they have implemented, driven by global market liberalisations, has been forcing full-service airlines to adapt to remain competitive (see Section **2**). In the literature, there are several studies focus on reviewing and comparing the efficiency of low-cost and full-service operators. However, there seems to be non-existent literature focused on the direct impact of LCCs on the technical efficiency of traditional carriers. Therefore, this study offers a pioneering analysis on the influence of low-cost carriers on the technical efficiency of full-services based in the same region and, at the same time, provides one of the largest geographical coverages to study airlines' efficiency (see Table **8**).

To answer the research question, a two-step method based on Simar and Wilson (1998, 2000, 2007); Wilson (2003) has been implemented. In a first step, we applied Data Envelopment Analysis based on Farrell's (1957) technical efficiency to obtain a scalar measure for each airline either with input and output orientations. Simar and Wilson's (2002) test was implemented to assess the shape of the efficient frontier on this sample and, based on the results, we implemented a technical efficiency measure assuming CRS, that is, airlines operate at an optimal scale. Following Wilson (2003), a hypothesis test was executed to study the use of a bootstrap procedure to estimate non-bias efficiency scores. The outcome led us to implement a smooth heterogeneous bootstrap method to correct for bias in original efficiency scores.

Using non-bias estimates, weighted averages were calculated to check for differences in technical efficiency between geographies and the two dominant business models. On average, African airlines were the least technical efficient performers and Europe, as well the Middle East were the regions with the best players. Simultaneously, low-cost carriers were, on average, less technically efficient than full-service airlines.

To find the primary drivers of technical efficiency on a global scale, we have come to different conclusions. The alliance membership, as well as the number of different aircraft manufacturers in the fleet and the average flight duration, were not explanatory factors for the technical efficiency of air transporters. Conversely, the significance of the low-cost model seems to depend on the orientation used. If on the one hand, it is significantly positive for output-based technical inefficiency, that is, on average, with the same level of inputs and technology available, the proportional increase in output that low-cost carriers could have for the same level of inputs if they were operating at the efficient frontier is 98 percentage points higher than for full-service carriers. On the other hand, with an input orientation, being an LCC is not significant to the technical efficiency of airlines.

As expected, passenger load factor and the share of cargo positively affect technical efficiency which reinforces the need for management to attract more passengers and cargo to counter-act factors outside their control (Barros and Peypoch, 2009; Lee and Worthington, 2014).

As for the influence of low-cost market share on the technical efficiency of full-service airlines, conclusions are not uniform. On the one hand, larger low-cost market shares are associated with lower input uses for the same FSCs' output levels based on that region. A possible justification could be on the actions taken by FSCs to converge their business models, mainly in regional flights, to a hybrid model (Dennis, 2007; Tomová and Materna, 2017). Thus, we can highlight recent trends of FSCs such as the focus on the cost reduction and the increase of staff and aircraft productivity FSCs which allow them to operate with less input (employees and aircraft) by RTK, i.e. being more technical efficient, On the other hand, there seems to be no relation between output-based technical efficiency of FSCs and the low-cost market share of the region where they are domiciled.

Since we wanted to preserve the largest possible sample to have the closest efficiency measure to the 2015 airline industry reality, we confined our research to a physical input-output mix. Therefore, further investigation may also want to carry a similar analysis with other measures, such as fuel, financial, or even using panel data since it describes the increasing market-share of LCCs (see Figure **5**), instead of looking to a specific year which reflects its growth trend.

One of the conclusions drawn is somewhat contradictory to recent results (see Table **7**), that is, the adoption of the low-cost business model has a negative impact on the (output-based) technical efficiency of airlines. Since there is no evidence of an analysis looking to such a wide set of airlines, one possible explanation might be the raising of worldwide disparities between LCCs. For instance, Comair is the best worldwide technical efficient airline in our sample and, in contrast, Air Do, Solaseed Air and Sky Airline are on the top-5 worst performers (see Table **14** and Table **15**). Thus, we also suggest future research to compare between technical and allocative efficiency with a large sample, since LCCs might be less disparate in what concerns cost minimisation and, consequently, on average more allocative efficient than FSCs.

8. References

Aigner, Dennis, C.A.Knox Lovell, and Peter Schmidt. 1977. "Formulation And Estimation Of Stochastic Frontier Production Function Models." *Journal of Econometrics* 6 (1): 21–37.

Arjomandi, Amir, and Juergen Heinz Seufert. 2014. "An Evaluation of the World's Major Airlines' Technical and Environmental Performance." *Economic Modelling* 41: 1–12.

Assaf, A. 2009. "Are U.S. Airlines Really in Crisis?" *Tourism Management* 30 (6): 916–21.

Badunenko, Oleg, and Pavlo Mozharovskyi. 2016. "Nonparametric Frontier Analysis Using Stata." *Stata Journal* 16 (3): 550–89.

Banker, R. D., A. Charnes, and W.W. Cooper. 1984. "Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis." *Management Science* 30 (9). Management Science: 1078–92.

Barbot, Cristina. 2006. "Low-Cost Airlines, Secondary Airports, and State Aid: An Economic Assessment of the Ryanair-Charleroi Airport Agreement." *Journal of Air Transport Management* 12 (4): 197–203.

Barbot, Cristina, Álvaro Costa, and Elena Sochirca. 2008. "Airlines Performance in the New Market Context: A Comparative Productivity and Efficiency Analysis." *Journal of Air Transport Management* 14 (5): 270–74.

Barros, Carlos Pestana, and Nicolas Peypoch. 2009. "An Evaluation of European Airlines' Operational Performance." *International Journal of Production Economics* 122 (2): 525–33.

Barros, Carlos Pestana, and Peter Wanke. 2015. "An Analysis of African Airlines Efficiency with Two-Stage TOPSIS and Neural Networks." *Journal of Air Transport Management* 44–45: 90–102.

Boussofiane, A., R.G. Dyson, and E. Thanassoulis. 1991. "Applied Data Envelopment Analysis." *European Journal of Operational Research* 52 (1): 1–15.

Chang, Young Tae, Hyo soo Park, Jae beom Jeong, and Jin woo Lee. 2014. "Evaluating Economic and Environmental Efficiency of Global Airlines: A SBM-DEA Approach." *Transportation Research Part D: Transport and Environment* 27: 46–50.

Charnes, A., W. W. Cooper, B. Golany, L. Seiford, and J. Stutz. 1985. "Foundations of Data Envelopment Analysis for Pareto-Koopmans Efficient Empirical Production Functions." *Journal of Econometrics* 30 (1–2): 91–107.

Charnes, A., W. W. Cooper, and E. Rhodes. 1978. "Measuring the Efficiency of Decision Making Units." *European Journal of Operational Research* 2 (6): 429–44.

Coelli, Tim, Sergio Perelman, and Elliot Romano. 1999. "Accounting for Environmental Influences in Stochastic Frontier Models : With Application to International Airlines." *Journal of Productivity Analysis* 11: 251–73.

Coelli, Timothy, Dodla Sai Prasada Rao, Christopher O'Donnell, and George Edward Battes. 2005. *An Introduction to Efficiency and Productivity Analysis*. *Biometrics*. Vol. 41. doi:10.2307/2531310.

Cook, Gerald N., and Jeremy Goodwin. 2008. "Airline Networks : A Comparison of Hub-and- Spoke and Point-to-Point SystemsAirline Networks : A Comparison of Hub-and-Spoke and Point-to-Point Systems." *The Journal of Aviation/Aerospace Education & Research* 17 (2): 51–60.

Cooper, William W., Lawrence M. Seiford, and Kaoru Tone. 2007. *Data Envelopment Analysis: A Comprehensive Text with Models , Applications, References and DEA-Solver Software*. Edited by Springer Science+Business Media. Second. New York: Springer Science-i-Business Media. http://www.springer.com/gp/book/9780387452814.

Dennis, Nigel. 2007. "End of the Free Lunch? The Responses of Traditional European Airlines to the Low-Cost Carrier Threat." *Journal of Air Transport Management* 13 (5): 311–21.

Dobruszkes, Frédéric. 2006. "An Analysis of European Low-Cost Airlines and Their Networks." *Journal of Transport Geography* 14 (4): 249–64.

Dobruszkes, Frédéric, Moshe Givoni, and Timothy Vowles. 2017. "Hello Major Airports, Goodbye Regional Airports? Recent Changes in European and US Low-Cost Airline Airport Choice." *Journal of Air Transport Management* 59: 50–62.

Emrouznejad, Ali. 2011. "Ali Emrouznejad's Data Envelopment Analysis." http://deazone.com/en/pareto-efficiencypareto-koopmans-efficiency. Accessed on 2017-09-28.

Emrouznejad, Ali, Rajiv Banker, Susila M Doraisamy, and Behrouz Arabi. 2014. "Recent Developments in Data Envelopment Analysis and Its Applications." In *Proceedings of the 12th International Conference of DEA, April 2014, Kuala Lumpur, Malaysia*, 1–437.

Emrouznejad, Ali, and Guo liang Yang. 2017. "A Survey and Analysis of the First 40 Years of Scholarly Literature in DEA: 1978-2016." *Socio-Economic Planning Sciences*. Elsevier Ltd, 1–5.

European Union. 1995. "EUR-Lex-Access to European Union Law." http://eur-lex.europa.eu/legal-content/EN-PT/TXT/?uri=CELEX:51995PC0353&from=EN. Accessed on 2017-10-28.

Fageda, Xavier, Pere Suau-Sanchez, and Keith J. Mason. 2015. "The Evolving Low-Cost Business Model: Network Implications of Fare Bundling and Connecting Flights in Europe." *Journal of Air Transport Management* 42: 289–96.

Färe, Rolf, and Shawna Grosskopf. 2000. "Network DEA." *Socio-Economic Planning Sciences* 34: 35–49.

Färe, Rolf, Shawna Grosskopf, and C.A. Knox Lovell. 1985. *The Measurement of Efficiency of Production*.

Farrell, M. J. 1957. "The Measurement of Productive Efficiency." *Journal of the Royal Statistical Society. Series A (General)* 120 (3): 253–90.

Førsund, Finn R. 2016. "Economic Interpretations of DEA." *Socio-Economic Planning Sciences*, no. 1. Elsevier Ltd: 1–7.

Francis, Graham, Ian Humphreys, Stephen Ison, and Michelle Aicken. 2006. "Where next for Low Cost Airlines? A Spatial and Temporal Comparative Study." *Journal of Transport Geography* 14 (2): 83–94.

Fu, Xiaowen, Th Oum, and Anming Zhang. 2010. "Air Transport Liberalization and Its Impacts on Airline Competition and Air Passenger Traffic." *Transportation Journal* 49 (7): 24–41.

Good, David H., M. Ishaq Nadiri, and Robin C. Sickles. 1993. "Efficiency and Productivity Growth Comparisons of European and U.S. Air Carriers: A First Look at the Data." *Journal of Productivity Analysis* 4 (1–2): 115–25.

Greene, William H. 2008. "The Econometric Approach to Efficiency Analysis." In *The Measurement of Productive Efficiency and Productivity Change*, 92–250.

Greer, Mark. 2009. "Is It the Labor Unions' Fault? Dissecting the Causes of the Impaired Technical Efficiencies of the Legacy Carriers in the United States." *Transportation Research Part A: Policy and Practice* 43 (9–10): 779–89.

Gross, Sven, and Michael Lück. 2016. *The Low Cost Carrier Worldwide*. New York: Routledge.

IATA. 2016. "World Air Transport Statistics 2016."

———. 2017. "Fact Sheet: Industry Statistics." http://www.iata.org/NR/rdonlyres/8BDAFB17-EED8-45D3-92E2-590CD87A3144/0/FactSheetIndustryFactsDEC2008.pdf. Accessed on 2017-08-18.

ICAO. 2003. "The Impact of Low Cost Carriers in Europe."

———. 2014. "Glossary."

———. 2017. "List of Low-Cost-Carriers (LCCs)." https://www.icao.int/sustainability/Documents/LCC-List.pdf. Accessed on 2017-07-15.

ICAO Secretariat. 2016. "Overview of Trends and Developments in International Air Transport."

Inglada, Vicente, Belen Rey, Ana Rodríguez-Alvarez, and Pablo Coto-Millan. 2006. “Liberalisation and Efficiency in International Air Transport.” *Transportation Research Part A: Policy and Practice* 40 (2): 95–105.

International Air Transport Association (IATA). 2006. “Airline Cost Performance.” http://www.iata.org/whatwedo/Documents/economics/airline_cost_performance.pdf. Accessed on 2017-08-19.

Ito, Harumi, and Darin Lee. 2003. “Low Cost Carrier Growth in the U.S. Airline Industry: Past, Present, and Future.” *SSRN Electronic Journal*, no. 401: 1–30.

Jahanshahloo, G. R., F. Hosseinzadeh Lotfi, V. Rezaie, and M. Khanmohammadi. 2010. “Ranking DMUs by Ideal Points in DEA.” *International Journal of Mathematical Analysis* 3 (17–20). Elsevier Inc.: 919–29.

Lee, Boon L., and Andrew C. Worthington. 2014. “Technical Efficiency of Mainstream Airlines and Low-Cost Carriers: New Evidence Using Bootstrap Data Envelopment Analysis Truncated Regression.” *Journal of Air Transport Management* 38: 15–20.

Lozano, Sebastián, and Ester Gutiérrez. 2014. “A Slacks-Based Network DEA Efficiency Analysis of European Airlines.” *Transportation Planning and Technology* 37 (7): 623–37.

Mallikarjun, Sreekanth. 2015. “Efficiency of US Airlines: A Strategic Operating Model.” *Journal of Air Transport Management* 43: 46–56.

Meeusen, Wim, and Julien van Den Broeck. 1977. “Efficiency Estimation from Cobb-Douglas Production Functions with Composed Error.” *International Economic Review* 18 (2): 435–44.

Merkert, Rico, and David A. Hensher. 2011. “The Impact of Strategic Management and Fleet Planning on Airline Efficiency - a Random Effects Tobit Model Based on Dea Efficiency Scores.” *Transportation Research Part A: Policy and Practice* 45 (7): 686–95.

Merkert, Rico, and Peter S. Morrell. 2012. “Mergers and Acquisitions in Aviation - Management and Economic Perspectives on the Size of Airlines.” *Transportation Research Part E: Logistics and Transportation Review* 48 (4): 853–62.

Merkert, Rico, and James Pearson. 2015. “A Non-Parametric Efficiency Measure Incorporating Perceived Airline Service Levels and Profitability.” *Journal of Transport Economics and Policy* 49 (April): 261–75.

O’Connell, John F., and George Williams. 2005. “Passengers’ Perceptions of Low Cost Airlines and Full Service Carriers: A Case Study Involving Ryanair, Aer Lingus, Air Asia and Malaysia Airlines.” *Journal of Air Transport Management* 11 (4): 259–72.

OECD. 2010. “Globalisation, Transport and the Environment.” *Globalisation, Transport and the Environment*. Paris: OECD Publishing. doi:10.1787/9789264072916-en.

Pearson, James, and Rico Merkert. 2014. “Airlines-within-Airlines: A Business Model Moving East.” *Journal of Air Transport Management* 38: 21–26.

Sarkis, Joe. 2007. "Preparing Your Data for DEA." In *Modeling Data Irregularities and Structural Complexities in Data Envelopment Analysis*, 305–20.

Simar, Léopold, and Paul W. Wilson. 1998. "Sensitivity Analysis of Efficiency Scores: How to Bootstrap in Nonparametric Frontier Models." *Management Science* 44 (1): 49–61.

———. 2000. "A General Methodology for Bootstrapping in Non-Parametric Frontier Models." *Journal of Applied Statistics* 27 (6): 779–802.

———. 2002. "Non-Parametric Tests of Returns to Scale." *European Journal of Operational Research* 139 (1): 115–32.

———. 2007. "Estimation and Inference in Two-Stage, Semi-Parametric Models of Production Processes." *Journal of Econometrics* 136 (1): 31–64.

Tan, Alan Khee Jin. 2010. "The ASEAN Multilateral Agreement on Air Services: En Route to Open Skies?" *Journal of Air Transport Management* 16 (6): 289–94.

Tandon, D, K Tandon, and N Malhotra. 2014. "An Evaluation of the Technical, Pure Technical and Scale Efficiencies in the Indian Banking Industry Using Data Envelope Analysis." *Global Business Review* 15 (3): 545–63.

Tauchmann, Harald. 2015. "Simarwilson : DEA Based Two-Step Efficiency Analysis." In *2015 German Stata Users Group Meeting*. Nuremberg. https://www.stata.com/meeting/germany15/abstracts/materials/de15_tauchmann.pdf. Accessed on 2017-09-25.

———. 2017. "SIMARWILSON: Stata Module to Perform Simar & Wilson Efficiency Analysis." https://ideas.repec.org/c/boc/bocode/s458156.html. Accessed on 2017-09-25.

Tavassoli, Mohammad, Gholam Reza Faramarzi, and Reza Saen. 2014. "Efficiency and Effectiveness in Airline Performance Using a SBM-NDEA Model in the Presence of Shared Input." *Journal of Air Transport Management* 34: 146–53.

Thanassoulis, Emmanuel. 2001. *Introduction To the Theory and Application of Data Envelopment Analysis*. Edited by Springer Science+Business Media New York. Second. New York: Springer-Verlag New York. http://www.springer.com/cn/book/9780792374299.

The World Bank. 2017a. "Air Transport, Freight (Million Ton-Km)." https://data.worldbank.org/indicator/IS.AIR.GOOD.MT.K1. Accessed on 2017-08-17.

———. 2017b. "Air Transport, Passengers Carried." https://data.worldbank.org/indicator/IS.AIR.PSGR?name_desc=false. Accessed on 2017-08-18.

Tomová, Anna, and Matúš Materna. 2017. "The Directions of On-Going Air Carriers' Hybridization: Towards Peerless Business Models?" In *Procedia Engineering*, 192:569–73.

Wilson, Paul W. 2003. "Testing Independence in Models of Productive Efficiency." In *Journal of Productivity Analysis,* 20:361–90.

Wu, Yongqiang, Changzheng He, and Xuefei Cao. 2013. "The Impact of Environmental Variables on the Efficiency of Chinese and Other Non-Chinese Airlines." *Journal of Air Transport Management* 29: 35–38.

Zanin, Massimiliano, and Fabrizio Lillo. 2013. "Modelling the Air Transport with Complex Networks: A Short Review." *The European Physical Journal Special Topics* 215 (1): 5–21.

9. Annexes

Table 11*: List of Low-cost Carriers in the sample*

Airline	Region
Air Do	Asia-Pacific
Atlasjet Airlines	Europe
Comair Limited (Kulula.com)	Africa
Condor	Europe
flybe	Europe
Gol Airlines	Latin America
Hong Kong Express	Asia-Pacific
Jet Lite (India) Ltd	Asia-Pacific
JetBlue	North America
Meridiana fly	Europe
Onur Air	Europe
Pegasus Airlines	Europe
Ryanair	Europe
Sky Airline	Latin America
Solaseed Air	Asia-Pacific
Sun Express	Europe
Virgin Australia	Asia-Pacific
Volaris	Latin America

Source: Own Production

***Table 12**: List of Full-service Airlines in the sample*

Airline	Region	Airline	Region
Adria Airways	Europe	British Airways	Europe
Aegean Airlines	Europe	Brussels Airlines	Europe
Aeroflot Russian Airlines	Europe	Bulgaria Air	Europe
Aerolineas Argentinas	Latin America	Cathay Pacific Airways	Asia-Pacific
Aeromexico	Latin America	China Airlines	Asia-Pacific
Aeromexico Connect	Latin America	China Eastern Airlines	Asia-Pacific
Air Astana	Asia-Pacific	China Southern Airlines	Asia-Pacific
Air Baltic	Europe	Corsair	Europe
Air Cairo	Africa	Croatia Airlines	Europe
Air Canada	North America	Czech Airlines	Europe
Air China	Asia-Pacific	Delta Air Lines	North America
Air Europa	Europe	Dniproavia	Europe
Air India	Asia-Pacific	Donavia	Europe
Air Koryo	Asia-Pacific	Dragonair	Asia-Pacific
Air Mauritius	Africa	Egyptair	Africa
Air Moldova	Europe	El Al Israel Airlines	Middle East
Air Nostrum	Europe	Emirates	Middle East
Air Seychelles	Africa	Ethiopian Airlines	Africa
Air Tahiti Nui	Asia-Pacific	Etihad Airways	Middle East
Air Transat	North America	EVA Air	Asia-Pacific
Air Vanuatu	Asia-Pacific	Finnair	Europe
Alitalia	Europe	Garuda Indonesia	Asia-Pacific
All Nippon Airways	Asia-Pacific	Germania	Europe
American Airlines	North America	Globus	Europe
Arkia Israeli Airlines	Middle East	Gulf Air	Middle East
Asiana Airlines	Asia-Pacific	Hahn Air	Europe
Austral	Latin America	Hainan Airlines	Asia-Pacific
Austrian	Europe	Hawaiian Airlines	North America
AVIANCA	Latin America	Insel Air	Latin America
Azerbaijan Airlines	Europe	Iran Air	Middle East
Belavia	Europe	Israir	Middle East
Binter Canarias	Europe	Japan Airlines	Asia-Pacific
BMI Regional	Europe	Jet Airways	Asia-Pacific

Airline	Region	Region	Airline
Kenya Airways	Africa	Siberia Airlines	Europe
KLM	Europe	SilkAir	Asia-Pacific
Korean Air	Asia-Pacific	Singapore Airlines	Asia-Pacific
Lan Airlines	Latin America	South African Airways	Africa
LOT Polish Airlines	Europe	SriLankan Airlines	Asia-Pacific
Lufthansa	Europe	SWISS	Europe
Luxair	Europe	TAAG Angola Airlines	Africa
Mahan Air	Middle East	TAM Airlines	Latin America
Malaysia Airlines	Asia-Pacific	TAM Mercosur	Latin America
Malmö Aviation	Europe	TAME	Latin America
Mandarin Airlines	Asia-Pacific	TAP Portugal	Europe
MIAT Mongolian Airlines	Asia-Pacific	TransAsia	Asia-Pacific
Middle East Airlines	Middle East	Tunis Air	Africa
Mistral Air	Europe	Turkish Airlines	Europe
Nordavia	Europe	Ukraine International Airlines	Europe
Nouvelair	Africa	United Airlines	North America
Okay Airways	Asia-Pacific	Ural Airlines	Europe
Olympic Air	Europe	Wamos Air	Europe
Oman Air	Middle East	Xiamen Airlines	Asia-Pacific
Pakistan International Airlines	Asia-Pacific	Yakutia Airlines	Europe
Philippine Airlines	Asia-Pacific	Yemenia Yemen Airways	Middle East
Qantas Airways	Asia-Pacific		
Qatar Airways	Middle East		
Rossiya - Russian Airlines	Europe		
Royal Air Maroc	Africa		
Royal Brunei Airlines	Asia-Pacific		
SAS Scandinavian Airlines	Europe		
SATA International	Europe		
SATA-Air Açores	Europe		
Shandong Airlines	Asia-Pacific		
Shenzhen Airlines	Asia-Pacific		

Source: Own Production

Figure 19: *Description of Weighted Averages*

Title	Description	Type	Unit/Coding
	Input-based Weighted Averages		
Africa_TE_i	The average input-based technical efficiency of African airlines	Quantitative	-
AsiaPacific_TE_i	The average input-based technical efficiency of Asia Pacific airlines	Quantitative	-
Europe_TE_i	The average input-based technical efficiency of Europe airlines	Quantitative	-
LatinAmerica_TE_i	The average input-based technical efficiency of Latin America airlines	Quantitative	-
MiddleEast_TE_i	The average input-based technical efficiency of Middle East airlines	Quantitative	-
NorthAmerica_TE_i	The average input-based technical efficiency of North America airlines	Quantitative	-
LCC_TE_i	The average input-based technical efficiency of low-cost airlines	Quantitative	-
FSC_TE_i	The average input-based technical efficiency of full-service airlines	Quantitative	-
TE_i	The average input-based technical efficiency of total airlines	Quantitative	-
	Output-based Weighted Averages		
Africa_TE_o	The average ouput-based technical efficiency of African airlines	Quantitative	-
AsiaPacific_TE_o	The average output-based technical efficiency of Asia Pacific airlines	Quantitative	-
Europe_TE_o	The average output-based technical efficiency of Europe airlines	Quantitative	-
LatinAmerica_TE_o	The average output-based technical efficiency of Latin America airlines	Quantitative	-
MiddleEast_TE_o	The average output-based technical efficiency of Middle East airlines	Quantitative	-
NorthAmerica_TE_o	The average output-based technical efficiency of North America airlines	Quantitative	-
LCC_TE_o	The average output-based technical efficiency of low-cost airlines	Quantitative	-
FSC_TE_o	The average output-based technical efficiency of full-service airlines	Quantitative	-
TE_o	The average output-based technical efficiency of total airlines	Quantitative	-

Source: Own Production

Table 13: *Description of Mean Normalised Input-Output Mix*

Title	Description	Type	Unit/Coding
	Inputs and Output mean normalised		
tna_mn	Total number of aircraft mean normalised	Quantitative	Number of aircraft
srtkts_mn	Scheduled Revenue Tonne-km Performed mean normalised - Systemwide	Quantitative	Number of employees
satkts_mn	Scheduled Available tonne-Kilometres mean normalised - Systemwide	Quantitative	Thousand tonne-km
tne_mn	Total Employees at 31 Dec 2015 mean normalised	Quantitative	Thousand tonne-km

Source: Own Production

Figure 20: *Descriptive Statistics of Mean Normalised Input-Output Mix*

Variable	Obs	Mean	Std. Dev.	Min	Max
tna_mn	137	1	1.598826	.0214902	10.21859
tne_mn	137	1	1.780615	.0039252	11.01354
satkts_mn	137	1	1.738277	6.06e-06	9.036981
srtkts_mn	137	1	1.719276	1.93e-06	8.730987

Source: Own production by using Stata

Figure 21*: Correlation matrix*

	shrsts	sdepts	tna	tne
shrsts	1.0000			
sdepts	0.9612	1.0000		
tna	0.9919	0.9779	1.0000	
tne	0.8968	0.8617	0.8928	1.0000

Source: Own production by sing Stata

***Table 14**: Airline Ranking according toTechnical Efficiency (non-bias input-based efficiency scores)*

Rank	cn	Score	Rank	cn	Score
1	Comair Limited (Kulula.com)	0.9733312	44	China Eastern Airlines	0.7921624
2	Corsair	0.9609848	45	Oman Air	0.790935
3	EVA Air	0.954717	46	AVIANCA	0.7901201
4	Alitalia	0.9518946	47	JetBlue	0.7893625
5	Hainan Airlines	0.9484119	48	Aerolineas Argentinas	0.780551
6	Air Europa	0.9298679	49	Air China	0.7785891
7	KLM	0.9293175	50	China Southern Airlines	0.7785469
8	Emirates	0.9186237	51	Jet Lite (India) Ltd	0.7746388
9	Korean Air	0.9158471	52	Japan Airlines	0.7707143
10	China Airlines	0.9073036	53	SAS Scandinavian Airlines	0.7682955
11	Sun Express	0.9058031	54	Dragonair	0.7668726
12	Cathay Pacific Airways	0.9024475	55	Siberia Airlines	0.7653035
13	TAM Airlines	0.9016767	56	Malaysia Airlines	0.7645708
14	Asiana Airlines	0.8991714	57	Austrian	0.7632133
15	Etihad Airways	0.8901469	58	Kenya Airways	0.7567207
16	Singapore Airlines	0.8871559	59	Yakutia Airlines	0.7524033
17	Lufthansa	0.8808765	60	El Al Israel Airlines	0.749611
18	Israir	0.8757775	61	All Nippon Airways	0.7449444
19	Qantas Airways	0.8722581	62	Mandarin Airlines	0.7428572
20	Air Tahiti Nui	0.8714918	63	Dniproavia	0.7360177
21	Volaris	0.8687074	64	Air India	0.7345808
22	Onur Air	0.8685802	65	Delta Air Lines	0.7322987
23	Okay Airways	0.8606618	66	flybe	0.7307851
24	Arkia Israeli Airlines	0.8574713	67	Qatar Airways	0.7260827
25	Ryanair	0.8518556	68	Ethiopian Airlines	0.7257243
26	British Airways	0.8486013	69	Luxair	0.7245035
27	Finnair	0.8415607	70	Air Canada	0.7238011
28	Bulgaria Air	0.836955	71	Aeroflot Russian Airlines	0.7232844
29	Shenzhen Airlines	0.8335716	72	Air Mauritius	0.7222313
30	Wamos Air	0.8232315	73	Shandong Airlines	0.7218971
31	Turkish Airlines	0.820347	74	Air Transat	0.7141805
32	Nouvelair	0.8181038	75	Olympic Air	0.7099169
33	United Airlines	0.8178206	76	Austral	0.706363
34	TAM Mercosur	0.8149553	77	Middle East Airlines	0.7062276
35	Jet Airways	0.8124167	78	Belavia	0.7061586
36	SWISS	0.8121931	79	Ural Airlines	0.706085
37	Condor	0.8112977	80	Air Moldova	0.7054385
38	Aegean Airlines	0.8101193	81	Croatia Airlines	0.701351
39	Globus	0.8095016	82	Ukraine International Airlines	0.700128
40	Lan Airlines	0.8066303	83	Aeromexico Connect	0.6978991
41	SriLankan Airlines	0.8025602	84	Xiamen Airlines	0.694354
42	Aeromexico	0.7938333	85	Brussels Airlines	0.6938193
43	Air Cairo	0.7921864	86	LOT Polish Airlines	0.6936395

87	TAP Portugal	0.6920775
88	Tunis Air	0.6878487
89	Air Nostrum	0.6871073
90	Hong Kong Express	0.6861244
91	Malmö Aviation	0.6858349
92	Air Koryo	0.680386
93	Rossiya - Russian Airlines	0.6800795
94	Virgin Australia	0.6782326
95	American Airlines	0.6769845
96	Germania	0.6753069
97	Royal Brunei Airlines	0.6727898
98	SATA International	0.6693337
99	South African Airways	0.666602
100	Atlasjet Airlines	0.663165
101	Philippine Airlines	0.6622574
102	Garuda Indonesia	0.6544645
103	Insel Air	0.651015
104	Czech Airlines	0.6470839
105	Binter Canarias	0.6463946
106	MIAT Mongolian Airlines	0.6436887
107	SATA-Air Açores	0.6407723
108	Donavia	0.6328217
109	SilkAir	0.6293443
110	Air Seychelles	0.6283957
111	Air Baltic	0.6192337
112	Pegasus Airlines	0.6172795
113	TAME	0.610619
114	Egyptair	0.59712
115	Iran Air	0.5932475
116	Hawaiian Airlines	0.5926234
117	Meridiana fly	0.589551
118	Gol Airlines	0.5841157
119	TAROM	0.5805098
120	Nordavia	0.5760976
121	Pakistan International Airlines	0.56394
122	Adria Airways	0.5637527
123	TransAsia	0.5629025
124	Royal Air Maroc	0.5487679
125	Gulf Air	0.5420445
126	BMI Regional	0.5410303
127	Air Astana	0.5361867
128	Azerbaijan Airlines	0.5198239
129	Air Vanuatu	0.484677
130	Yemenia Yemen Airways	0.4779244
131	Mistral Air	0.4692777
132	TAAG Angola Airlines	0.4322276
133	Air Do	0.4282277
134	Mahan Air	0.37282
135	Solaseed Air	0.2815352
136	Hahn Air	0.2262045
137	Sky Airline	0.1855938

cn denotes for Company name

Source: Own production

Table 15:*Airline Ranking according to Technical Efficiency (non-bias output-based efficiency scores)*

Rank	cn	Score	Rank	cn	Score
1	Comair Limited (Kulula.com)	1.036364	44	Oman Air	1.262156
2	Alitalia	1.050347	45	Air Cairo	1.262879
3	Hainan Airlines	1.053888	46	AVIANCA	1.264241
4	Corsair	1.062693	47	JetBlue	1.264881
5	EVA Air	1.064171	48	Aerolineas Argentinas	1.277705
6	Emirates	1.075222	49	China Southern Airlines	1.283223
7	Air Europa	1.083686	50	Air China	1.28629
8	KLM	1.090241	51	Jet Lite (India) Ltd	1.296033
9	Sun Express	1.10268	52	SAS Scandinavian Airlines	1.29987
10	Cathay Pacific Airways	1.105545	53	Dragonair	1.303264
11	TAM Airlines	1.106876	54	Austrian	1.307273
12	Korean Air	1.108857	55	Siberia Airlines	1.307863
13	China Airlines	1.124952	56	Japan Airlines	1.308524
14	Singapore Airlines	1.125307	57	Malaysia Airlines	1.314293
15	Asiana Airlines	1.132154	58	Kenya Airways	1.320135
16	Lufthansa	1.136562	59	El Al Israel Airlines	1.338314
17	Ryanair	1.138492	60	All Nippon Airways	1.340492
18	Etihad Airways	1.143444	61	Yakutia Airlines	1.341021
19	Qantas Airways	1.143649	62	Mandarin Airlines	1.35788
20	Volaris	1.149401	63	Air India	1.35811
21	Israir	1.151056	64	Delta Air Lines	1.365622
22	Onur Air	1.161173	65	Dniproavia	1.369088
23	Air Tahiti Nui	1.165095	66	flybe	1.380126
24	Okay Airways	1.171859	67	Aeroflot Russian Airlines	1.384957
25	Arkia Israeli Airlines	1.175474	68	Shandong Airlines	1.385044
26	British Airways	1.185099	69	Air Canada	1.389843
27	Finnair	1.188096	70	Ethiopian Airlines	1.391553
28	Bulgaria Air	1.200272	71	Luxair	1.392655
29	Shenzhen Airlines	1.200855	72	Qatar Airways	1.396257
30	Wamos Air	1.216129	73	Air Mauritius	1.397339
31	United Airlines	1.224196	74	Air Transat	1.410369
32	Jet Airways	1.228206	75	Ural Airlines	1.413496
33	TAM Mercosur	1.230524	76	Middle East Airlines	1.414371
34	Turkish Airlines	1.231923	77	Olympic Air	1.420201
35	Aegean Airlines	1.232312	78	Ukraine International Airlines	1.426828
36	Nouvelair	1.232312	79	Air Moldova	1.427552
37	Lan Airlines	1.238222	80	Austral	1.427634
38	SWISS	1.240293	81	Belavia	1.428738
39	Globus	1.240327	82	Aeromexico Connect	1.436024
40	Condor	1.247932	83	Croatia Airlines	1.438628
41	SriLankan Airlines	1.251337	84	Xiamen Airlines	1.439707
42	China Eastern Airlines	1.259024	85	LOT Polish Airlines	1.441449
43	Aeromexico	1.261033	86	Brussels Airlines	1.442349

87	TAP Portugal	1.446445
88	Hong Kong Express	1.456129
89	Tunis Air	1.4651
90	Air Nostrum	1.468454
91	Rossiya - Russian Airlines	1.470406
92	Virgin Australia	1.470691
93	Malmö Aviation	1.471192
94	American Airlines	1.476944
95	Air Koryo	1.481229
96	Germania	1.481746
97	Royal Brunei Airlines	1.487373
98	SATA International	1.492462
99	Atlasjet Airlines	1.508436
100	South African Airways	1.508548
101	Garuda Indonesia	1.529629
102	Philippine Airlines	1.532842
103	Czech Airlines	1.540796
104	Binter Canarias	1.541477
105	Insel Air	1.549595
106	MIAT Mongolian Airlines	1.555615
107	SATA-Air Açores	1.572624
108	SilkAir	1.583811
109	Donavia	1.585924
110	Air Seychelles	1.594615
111	Air Baltic	1.622939
112	Pegasus Airlines	1.623589
113	TAME	1.649876
114	Egyptair	1.670145
115	Meridiana fly	1.695306
116	Iran Air	1.699589
117	Hawaiian Airlines	1.708214
118	Gol Airlines	1.711595
119	TAROM	1.737075
120	Nordavia	1.751293
121	Pakistan International Airlines	1.769863
122	Adria Airways	1.780503
123	TransAsia	1.790617
124	Royal Air Maroc	1.820613
125	Gulf Air	1.849402
126	Air Astana	1.860488
127	BMI Regional	1.864438
128	Azerbaijan Airlines	1.937056
129	Air Vanuatu	2.081429
130	Yemenia Yemen Airways	2.094225
131	Mistral Air	2.147417
132	TAAG Angola Airlines	2.323137
133	Air Do	2.330893
134	Mahan Air	2.696791
135	Solaseed Air	3.545828
136	Hahn Air	4.453677
137	Sky Airline	5.47514

cn denotes for Company name

Source: Own production

Figure 22*: Correlation between Weighted Load Factor and Efficiency scores*

	n~i_TE~s	n~o_TE~s	swlfts
swlfts	0.9416	-0.8409	1.0000

Source: Own production by using Stata

Figure 23*: First Input and Output-based models*

```
Simar & Wilson (2007) eff. analysis         Number of obs              =       137
                                            Number of efficient obs    =         0
                                            Number of bootstr. reps    =      2000
inefficient if non_bias_i_TE_scores < 1     Wald chi2(7)               =    130.24
twosided truncation                         Prob > Chi2(7)             =    0.0000
```

efficiency	Observed Coef.	Bootstrap Std. Err.	z	P>|z|	Percentile [95% Conf.	Interval]
non_bias_i~s						
mslcas	.0015898	.0009262	1.72	0.086	-.000263	.0033822
splfts	.0106019	.0012742	8.32	0.000	.0082399	.0131339
scargo	.0031315	.0010664	2.94	0.003	.0009789	.0052102
am	.0019597	.0240741	0.08	0.935	-.0436774	.0487795
lccic	-.0472698	.0293847	-1.61	0.108	-.1055622	.0106466
ndam	-.0045372	.008148	-0.56	0.578	-.0204075	.0114929
hpf	.0040852	.0085875	0.48	0.634	-.0118033	.021963
_cons	-.1552445	.0905513	-1.71	0.086	-.3321515	.0237836
/sigma	.1007217	.0067561	14.91	0.000	.084492	.1110432

```
Simar & Wilson (2007) eff. analysis         Number of obs              =       137
                                            Number of efficient obs    =         0
                                            Number of bootstr. reps    =      2000
                                            Wald chi2(7)               =     25.96
inefficient if non_bias_o_TE_scores > 1     Prob > Chi2(7)             =    0.0005
```

efficiency	Observed Coef.	Bootstrap Std. Err.	z	P>|z|	Percentile [95% Conf.	Interval]
non_bias_o~s						
mslcas	-.0211301	.0134424	-1.57	0.116	-.0482764	.0057694
splfts	-.0807029	.0169652	-4.76	0.000	-.1124499	-.046982
scargo	-.0286213	.0199717	-1.43	0.152	-.0726797	.0077295
am	-.178069	.4069839	-0.44	0.662	-1.051735	.5903108
lccic	.9562107	.381508	2.51	0.012	.1868052	1.709923
ndam	.0090501	.1079169	0.08	0.933	-.218593	.2075175
hpf	-.1101121	.1555372	-0.71	0.479	-.4684857	.1546535
_cons	7.456966	1.158857	6.43	0.000	5.143018	9.769839
/sigma	.7674678	.1235007	6.21	0.000	.5232446	1.014638

Source: Own production by using Stata

***Figure 24**: Second Input and Output-based models*

Simar & Wilson (2007) eff. analysis	Number of obs = 137
	Number of efficient obs = 0
	Number of bootstr. reps = 2000
inefficient if non_bias_i_TE_scores < 1	Wald chi2(4) = 133.56
twosided truncation	Prob > Chi2(4) = 0.0000

efficiency	Observed Coef.	Bootstrap Std. Err.	z	P>|z|	Percentile [95% Conf.	Interval]
non_bias_i~s						
mslcas	.001483	.0008992	1.65	0.099	-.0002552	.0033292
splfts	.0108052	.0011467	9.42	0.000	.0085061	.0130237
scargo	.0032588	.0008502	3.83	0.000	.0016284	.0049809
lccic	-.0447754	.0282382	-1.59	0.113	-.09713	.010293
_cons	-.1685065	.0858577	-1.96	0.050	-.3367297	-.0001372
/sigma	.1009425	.0069176	14.59	0.000	.0857471	.1136731

Simar & Wilson (2007) eff. analysis	Number of obs = 137
	Number of efficient obs = 0
	Number of bootstr. reps = 2000
	Wald chi2(4) = 26.01
inefficient if non_bias_o_TE_scores > 1	Prob > Chi2(4) = 0.0000

efficiency	Observed Coef.	Bootstrap Std. Err.	z	P>|z|	Percentile [95% Conf.	Interval]
non_bias_o~s						
mslcas	-.0207201	.0132175	-1.57	0.117	-.0466295	.0046535
splfts	-.0843138	.0169617	-4.97	0.000	-.1186604	-.0527103
scargo	-.0357677	.0178471	-2.00	0.045	-.0753078	-.0061358
lccic	.9801433	.3655057	2.68	0.007	.2424592	1.71037
_cons	7.524937	1.174847	6.41	0.000	5.276884	9.699968
/sigma	.7574338	.1230347	6.16	0.000	.5236009	.9990715

Source: Own production by using Stata