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Evaluating airline operational performance: A Luenberger-Hicks-Moorsteen productivity indicator

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Keywords: Data envelopment analysis, airlines, by-production, emissions, Luenberger-Hicks-Moorsteen.

JEL Classification: D21, C61, Q53

1. Introduction

The US Environmental Protection Agency (EPA) stated recently that 'greenhouse gas emissions from airplanes are dangerous to human life', and therefore should be subject to further emission-reducing regulations (EPA, 2015, p. 1). In addition to the immediate threat to human lives, the Intergovernmental Panel on Climate Change (IPCC) has forecast that aviation emissions will make an important contribution to the build-up of greenhouse gases (GHGs) in the atmosphere, heavily contributing to global warming in the next few decades (IPCC, 2007). Consequently, over the past few years, national and international attempts to curb climate change have forced governments to implement strategies to reduce anthropocentric CO_2 (carbon dioxide) emissions in general, and by the aviation industry in particular. As significant users of fossil fuels, airline industries have been included in planned and operational emission trading schemes (ETSs) in several jurisdictions across the world. They were considered for inclusion in the first phase of the European ETS in January 2005. In January 2012 it became the first trading scheme to cover CO_2 emissions from air travel, quickly followed by Australia and New Zealand in July 2012. In China, the Shanghai ETS included six major airlines, making them subject to a price on carbon from November 2013 onwards. In January 2015, another Asian country, South Korea, started its ETS covering six GHGs with a 30 per cent reduction target until 2020 and planned to put a price on emission from airlines. In the US, the mandatory trading under the RGGI (Regional Greenhouse Gas Initiative) founded in 2009 has, since 2013, included in the voluntary trading within the Western Climate Initiative (WCI) with the potential inclusion of airlines in British Columbia, California, Manitoba, Ontario and Quebec. In 2012, the US EPA also announced that market-based measures (MGMs) against aviation emissions need to be taken, but left the design of such measures to the International Civil Aviation Organization (ICAO).[1] Currently, several other countries (such as Brazil, Chile, Japan, Mexico, Russia, Turkey, Ukraine and Vietnam) have also considered an ETS as a viable solution to reduce their carbon footprint, indicating a substantial growth in ETSs worldwide that put a price on GHGs emission and require airlines to surrender permits equivalent to their footprint (ICAP, 2015). Coinciding with the establishment of ETSs, increases in fuel prices have provided additional incentives for airlines to reduce their carbon footprints, because fuel is among the top three cost items faced by airlines, accounting on average for up to one-third of their operating costs in 2013 and 20 per cent in 2016 depending on the price of Jet A/A-1 fuel (IATA, 2013; 2016). Airlines may respond to these new higher cost regulatory and economic environments by upgrading their fleet and introducing more fuel-efficient models, and adjusting operating practices to reduce fuel consumption and thus ease the financial burden (Sgouridis et al., 2011). In this context, it is pertinent and timely to produce a precise measure of airline performance. This study proposes a novel productivity indicator to measure airline pollution-adjusted operational efficiency and productivity changes. This measure can provide crucial findings and help policy makers to better understand the environmental performance of their national carriers (vis-à-vis their rivals) and gain a deeper insight into the effectiveness of ETSs in reducing airline emissions in different regions. This new indicator can also assist airlines understand their relative pollution-adjusted performance in order to eliminate existing shortcomings. Moreover, eco-conscious travelers may find our findings helpful to help them select services from more environmentally friendly airlines and so reduce their own carbon footprint.

In the non-parametric framework of data envelopment analysis (DEA), a common approach to analysing the relationships between multiple inputs and outputs and evaluating the relative efficiency of decision-making units (here, airlines), many models have been developed to account for undesirable outputs.[2] In these models, pollution has commonly been treated as an output under the weak disposability assumption, WDA (Färe et al., 1986; 1989). Although this approach has been widely used in both energy (Zhou et al., 2008; Chen, 2013a) and airline efficiency literature (e.g., Fukuyama et al., 2011; Chang et al., 2014; Li et al., 2016a), clear limits of this approach have been put forward in several studies (Førsund, 2009; Chen, 2013b). Among others, the WDA violates the materials balance principle which ensures every physical process occur within the limits of the laws of thermodynamics (Coelli et al., 2007). The by-production approach, introduced by Murty et al. (2012), is considered in the literature as a better alternative for avoiding such drawbacks (Chambers et al., 2014; Serra et al., 2014). This approach posits that complex systems are made of several independent processes (Frisch, 1965) and the global technology can be separated into sets of sub-technologies: one for the production

[1] We would like to thank the anonymous reviewer for pointing out that non-market based solutions, e.g. technology standards, aircraft engine and technology improvements measures, had already been adopted by the US Government (FAA, 2012).

[2] DEA was first introduced by Charnes et al. (1978), after Farrell (1957) proposed the original idea of efficiency evaluation.

of good outputs and one for the generation of bad outputs. In other words, the by-production approach draws on an explicit representation of the process that generates each type of output (good and detrimental outputs in this case). Then, the global technology implies interactions between several separate sub-technologies. Førsund (2017) has recently classified the by-production approach among the multi-equation modelling approaches and argued that an important advantage of this approach over other approaches (such as WDA, the strong disposability assumption and the slack-based models) is that it represents pollution-generating technologies by accounting for materials balance and therefore satisfies the physical laws. Discussing the limits of pollution-generating technologies, Dakpo et al. (2016) also confirmed that the by-production method offers some very promising opportunities, such as treating multiple types of outputs, in comparison to other existing approaches. Therefore, this study employs the by-production approach and also contributes to the efficiency analysis literature by offering a new by-production model which deals with the inclusion of undesirable outputs to provide a comprehensive analysis of operational performance of 33 major international airlines for the period 2007 to 2013.

In the area of productivity analyses, the Malmquist index is by far the most popular index for assessing the productivity of decision-making units (DMUs) over time, though it has several shortcomings (Arjomandi, 2011; Arjomandi & Seufert, 2014; Kerstens & Van de Woestyne, 2014; Arjomandi et al., 2015). O'Donnell (2008) argues that an adequate productivity index must be multiplicatively or additively complete. That is, a total factor productivity index (TFP) should be written as the ratio of an aggregate output to an aggregate input (multiplicative completeness) or as the difference of these aggregate values (additive completeness). Besides, TFP indices must satisfy a certain number of axioms and tests; monotonicity, homogeneity, identity, dimensionality, proportionality, time-reversal, factor-reversal and circularity tests are among the 20 key tests listed by Diewert (1992). However, the Malmquist index fails to satisfy these conditions. The Hicks-Moorsteen (HM) index, discussed in Bjurek (1996) and Lovell (2003), is proven to be a complete index (O'Donnell, 2008; 2010; 2012).[3] In this study, in addition to the above-mentioned contribution, we extend the Luenberger-Hicks-Moorsteen (LHM) productivity indicator of Briec and Kerstens (2004) to account for undesirable outputs in the framework of the by-production approach. The directional distance function (DDF) used in this study has the advantage of allowing for simultaneous changes in both good and bad outputs (Chung et al., 1997). Moreover, unlike the Malmquist index, our difference-based indicator possesses the advantage of dealing with zero and negative variables and also inherits of the translation invariance property.

In sum, this study develops a novel approach that incorporates undesirable outputs in the production technology modelling to measure DMU inefficiency and productivity changes in general, and airline

[3] This HM index is based on the ratios of Malmquist output and input productivity indices.

performance in particular. This new indicator is inspired by the environmental performance index of Färe et al. (2004) which was presented as a ratio of a Malmquist good output quantity index over a Malmquist bad output quantity index. Our approach, however, is difference-based and we use the by-production approach to model pollution-generating technologies and also avoid theoretical and practical issues of the WDA and the Malmquist productivity index as discussed above. Our developed by-production LHM productivity indicator also allows us to decompose the pollution-adjusted TFP more comprehensively into the good and the bad output components providing further insight into our understanding of airline operational performance.

The paper is structured as follows: Section 2 outlines existing institutional and regulatory frameworks relevant to the study. Section 3 reviews the literature. The methodology and data are presented in Section 4. Section 5 discusses the results, followed by some concluding remarks in Section 6.

2. Regulatory framework: international emission trading schemes

On an international scale the ICAO (International Civil Aviation Organization) is in sole authority for setting out measures to reduce aviation emissions in a globally consistent and binding way. Directly after the ICAO rejected the Europeans' attempts to put a price on emissions of the flights from and to Europe, the 38th assembly decided to introduce a cap-and-trade-based scheme for the aviation industry by 2020 in line with its voluntary goal to reduce aviation emissions by 50 per cent by 2050 (IATA, 2016). The European emission trading scheme (EU ETS) included emissions from flights starting or landing in Europe including those beyond the EU territory, from 2012 onwards. However, opposition from China, India, Russia and the US amongst others forced the EU, in April 2013, to constrain the ETS operation to the flights within European countries only.

In the US, there had been a voluntary trading program from 2003 to 2010, named the Chicago Climate Exchange. Besides this voluntary emission trading program, airlines faced mandatory inclusion in an ETS in 2007 when the Lieberman-Warner Climate Security Bill was approved by the US Senate Committee of Environment and Public Works. Although this Bill aimed to create an ETS across the country and included aviation industry emissions, it was aborted under pressure from the Republicans (Gössling et al., 2008). In November 2012, the then US President Obama signed a law opposing the EU-ETS with bilateral support as both parties considered the EU ETS an unilateral and illegitimate tax . Since the failure of the climate actions at a national level, regional cap and trade mechanisms were implemented in the US. Thus, the RGGI (Regional Greenhouse Gas Initiative) was founded in 2009 as a mandatory ETS membered by Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New York, Rhode Island and Vermont. In addition, the Western Climate Initiative was founded as a voluntary ETS by California in 2007 and brings together British Columbia, California, Manitoba, Ontario and Quebec, and implemented an ETS in 2012 which started 2013. Even though the members of the WCI have high reduction goals, emissions from airlines have so far been excluded in their schemes. In 2015, the Environmental Protection Agency (EPA) announced that greenhouse gas emissions from airplanes are a health hazard and should be regulated under the *Clean Air Act*. The EPA has not yet determined the design of an American ETS, but has deferred to ongoing deliberations by ICAO on the issue (EPA, 2015). At the same time the EPA has established domestic standards and limitations on exhaust emissions for any aircraft engines in the US which are enforced by the US Federal Aviation Administration (FAA).

In the Asia-Pacific region, Australia introduced an ETS in July 2012 which also applied to domestic flights. But the change to a Liberal government also opened the way for legislation to abolish a price on carbon in July 2014 (Australian Government, 2014). China, currently the largest CO_2 emitter, implemented an ETS in five cities and two provinces as pilot areas before the planned nationwide ETS comes into force in 2017. Out of these seven pilot ETSs, only the Shanghai ETS includes emissions from aviation sectors, which makes six major airlines subject to a price on CO_2 (Yang & Zhao, 2015; Zhang, 2015). Japan also chose to implement an ETS in 2010. Initially, the Tokyo Metropolitan Government launched a mandatory ETS preceded by two phases of voluntary trading spanning 2002–2009. This ETS covers transportation emissions but until now it has not included the aviation sector, however, a national voluntary ETS aims to familiarise companies with emission trading (Bureau of Environment Tokyo Metropolitan Government, 2012). Finally, in January 2015, Korea introduced an ETS covering six GHGs and again, the aviation sector is not included (Cho, 2012; Reklev, 2015). A summary of the above-mentioned ETSs are provided in Table 1.

Table 1. Summary of the planned and established ETSs

Jurisdiction	Milestones	Obligation
Europe (all 28 EU countries plus Iceland, Liechtenstein and Norway)	▪ Phase 1 (2005−2007), during 2007 considerations to include aviation emission.	Mandatory
	▪ Phase 2 (2008−2012), beginning of 2012 inclusion of aviation emission from domestic (within Europe) and international (start or landing in Europe) flights.	Mandatory
	▪ Phase 3 (2013−2020), due to pressure from other nations, in April 2013, the EU limits the ETS to flights with start and landing in Europe.	Mandatory
USA/North America	▪ 2003 to 2010, Chicago Climate Exchange	Voluntary
	▪ 2007 Lieberman-Warner Climate Security Bill – airlines face inclusion into an ETS; aborted in 2008	Mandatory
	▪ 2012 President Obama signs a law opposing the EU-ETS	
	▪ 2009 RGGI (Regional Greenhouse Gas Initiative) was founded (Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New York, Rhode Island and Vermont). Included the power sector only.	Mandatory
	▪ 2013 Western Climate Initiative, (British Columbia, California, Manitoba, Ontario and Quebec,)	Voluntary
	▪ 2015, the EPA announced that GHG emissions from airplanes are a health hazard and should be regulated under the Clean Air Act.	
Australia	▪ 2012 introduction of an ETS, also covering airlines	Mandatory
	▪ 2014 repeal of ETS	
China	▪ 7 pilot ETSs, only the Shanghai ETS includes emissions from aviation sectors	Mandatory
Japan	▪ 2010 introduction of an ETS not covering airlines	Mandatory
South Korea	▪ 2015 introduction of an ETS not covering airlines	Mandatory
Internationally	▪ 2020 introduction of an ETS, mandated by ICAO	To be confirmed

Overall, there is a mix of mandatory and voluntary ETSs promoting airlines' CO_2 emissions reduction or waiting for an international solution by the ICAO. Depending on the respective national or regional context, there is also diverging pressure on airlines to either reduce or bear the cost of CO_2 emissions. Consequently, it can be questioned whether airlines from different regions have improved their performance accordingly.

3. Literature Review

There exists a number of previous studies on airline efficiency and productivity which utilise different approaches to investigate airline performance. We first summarise the literature on analysing airline efficiency and then review studies on airline productivity.

Most of the early studies on airline efficiency applied quantitative methods such as regression models (Morrell & Taneja, 1979), cost functions (e.g., Caves et al., 1981, 1984; Windle, 1991; Baltagi et al., 1995) and stochastic frontier models (e.g., Schmidt & Sickles, 1984; Cornwell et al., 1990; Good et al., 1993; Coelli et al., 1999). DEA-based methods became relatively more common in analysing airline performance after Schefczyk (1993) used a standard DEA for evaluating the efficiency of 15 international airlines during period 1989–1992 (Cui et al., 2016b). Few airline studies, such as Capobianco and Fernandez (2004), Bhadra (2009), Hong and Zhang (2010), Ouellette et al. (2010) and Wang et al. (2011), directly applied such standard DEA models in their analyses of efficiency. A number of studies however employed DEA models along with other techniques to examine airline efficiency. Examples include Good et al. (1995) and Alam and Sickles (1998; 2000) which combined DEA with stochastic frontier approach, free disposal hull and full disposal hull, respectively. Chiou and Chen (2006), Barros and Peypoch (2009), Greer (2009; 2016), Merkert and Hensher (2011) and Lee and Worthington (2014) were also among the studies which used DEA analysis with a regression in the second stage to explain efficiency drivers.[4]

In recent years, network DEA models of Li et al. (2015), Mallikarjun (2015), Li et al. (2016a), Cui and Li (2016) and Cui et al. (2016c), and dynamic models of Cui et al. (2016a; 2016b), Li et al. (2016b) and Wanke and Barros (2016) have been the core methods of assessing airline performance. With regard to network studies, Mallikarjun (2015) and Li et al. (2015) divided the network structure of airline efficiency into three stages: operations, services and sales. Mallikarjun (2015) applied a radial unoriented DEA network method to assess US airline performance in 2012. Li et al. (2015) applied the idea of virtual frontier to the network model and proposed a non-radial virtual frontier slack-based

[4] An extended survey of airlines' studies can be found in Table 1 in Li et al. (p.3, 2015) where the authors have also summarized the number of observations along with the methodology used.

measure to evaluate energy efficiency of 22 international airlines from 2008 to 2012. Li et al. (2016a) and Cui et al. (2016c) adopted the network slack based measure (SBM) and network range-adjusted measure, respectively, to investigate the impact of EU policies on airline performance. Cui and Li (2016) studied airline energy efficiency with network structure and divided the efficiency process into two operations and carbon abatement stages. They built a network SBM to evaluate these efficiencies. In the most recent study of network DEA models, Xu and Cui (2017) focused further on the internal process of the airline operation system using a four-stage network structure of airline energy efficiency (i.e. Operations Stage, Fleet Maintenance Stage, Services Stage and Sales Stage). They employed a new integrated approach with network epsilon-based measure and network SBM to evaluate the overall energy efficiency and divisional efficiency of 19 international airlines in period 2008 to 2014. With regard to dynamic models, Li et al. (2016b) developed the virtual frontier dynamic range adjusted measure (VDRAM) upon the classic DEA models and considered the capital stock as the dynamic factor or the carryover effect to be used. Wanke and Barros (2016) adopted the VDRAM of Li et al. (2016b) to measure efficiency of Latin American airlines. They also assessed the impact of different contextual variables related to cargo type, ownership type, and fleet mix on their efficiency levels. Cui et al. (2016a) improved the VDRAM of Li et al. (2016b) and introduced virtual frontier dynamic slack-based measure in order to measure airline energy efficiency and discuss the impacts of some external factors. Cui et al. (2016b) proposed two dynamic environmental DEA models to discuss the impacts of the emission limits on airline performance under circumstances that emissions are either regulated or unregulated.

Among the previous studies on airline efficiency very few have taken aviation emissions into account. Arjomandi and Seufert (2014) used carbon dioxide equivalent (CO_2-e) emission as an undesirable output in their DEA models to examine environmental efficiency of the world's major airlines between 2007 and 2010. They employed bootstrapped DEA models with a strong disposability assumption to rank the airlines. Chang et al. (2014) examined the environmental efficiency of 27 global airlines in 2010 using a slacks-based measure DEA model with the weak disposability assumption. Cui and Li (2015), proposed the virtual frontier benevolent DEA cross efficiency model (VFB-DEA) to calculate the energy efficiencies of 11 airlines in period 2008 to 2012 They used a CO_2 emissions decrease index as a proxy for undesirable output in their VFB-DEA model assuming strong disposability. Using the network SBM and network range-adjusted measure with both weak and strong disposability assumptions and considering greenhouse gas emissions as an undesirable output, Cui et al. (2016c) and Li et al. (2016a) found weak disposability results more reasonable in the aspect of distinguishing airline efficiency and establishing airlines ranking. Therefore, in their two-stage operating framework, Cui and Li (2016) used weak disposability to examine airline energy efficiency employing the network SBM. Cui et al. (2016b) also followed the finding of Cui et al. (2016c) and Li et al. (2016a) and utilised the weak disposability assumption in their new dynamic environmental

DEA models. However, the weak disposability assumption, as underlined earlier, has been criticised by several studies for its disadvantages.[5]

Early analyses on airline productivity applied approaches such as the multilateral TFP index (Caves et al., 1981; Windle, 1991; Oum and Yu, 1995), decompositions/developments of TFP growth (Bauer, 1990; Ehrlich et al., 1994) and Fisher productivity index (Ray and Mukhrejee, 1996). The Malmquist TFP index, which is a DEA-based approach allowing for the measurement of changes in productivity of decision making units over time has been by far the most popular method adopted in the literature on airlines' TFP. Distexhe and Perelman (1994) were the first who employed the Malmquist TFP index and reported the productivity change and its two decompositions (efficiency change and technological change) for 33 US and European airlines over period 1977−1988. Subsequently, the Malmquist index was employed by Sickles et al (2002) and Greer (2008) to examine productivity change of 16 European airlines and eight US airlines, respectively. In addition, Chow (2010) used the Malmquist index to measure productivity changes in Chinese private and state-owned airlines and Cui and Li (2015) adopted this index to calculate the civil aviation safety efficiency of ten Chinese airlines. Assaf (2011) employed the bootstrapped Malmquist index for measuring the changes in efficiency and productivity of 18 major UK airlines between 2004 and 2007. Recently, Yang and Wang (2016) also applied the bootstrapped Malmquist index to assess airlines in four different regions in Europe. Barros and Couto (2013) used Malmquist TFP index as well as the Luenberger productivity indicator to evaluate productivity changes of European airlines from 2000 to 2011. Lee et al. (2015) has measured productivity growth of airlines when undesirable output production is incorporated into the model using the Malmquist–Luenberger productivity index. They argued that "pollution abatement activities of airlines lowers productivity growth, which suggests that the traditional approach of measuring productivity growth, which ignores CO_2 emissions, overstates 'true' productivity growth" Lee et al. (2015, p.338). More recently, Lee et al. (2016) have used the Luenberger indicator to measure and decompose productivity of 34 worldwide airlines companies in the presence of CO_2 emissions. Bad outputs are considered under the WDA in this latter study.

Yu (2016, p.11) conducted a survey of alternative methodologies and empirical analyses for airline performance and concluded that "environmental efficiency now becomes an important area of airline productivity and efficiency studies, focusing on CO_2 emission as a negative or undesirable output." This paper builds upon this body of literature by offering additional insights on the inclusion of undesirable output in the efficiency and productivity measurement of airlines. For this aim we propose a by-production Luenberger-Hicks-Moorsteen productivity indicator. The Hicks-Moorsteen TFP index is proven to be more accurate than the popular Malmquist TFP index which is widely used in the literature. In a comprehensive comparison of the Malmquist index and Hicks–Moorsteen index,

[5] See Dakpo et al. (2016) for a thorough discussion on these limits.

Kerstens and Van de Woestyne (2014, p.756) clearly state: "As to the question whether the Malmquist and Hicks–Moorsteen indices are empirically indistinguishable or not, the differences between both primal productivity indices turn out to be significantly different for all flexible returns to scale technology specifications." Kerstens and Van de Woestyne (2014, p.756) also state that "if one wants to be on the safe side, then one conclusion is that in case the interest centers on TFP measurement it is probably wise to immediately opt for the Hicks–Moorsteen index." In regard to modelling pollution-generating technologies, the by-production method of including undesirable output is also argued to be better and more reliable than those methods which are assuming strong or weak disposability assumptions. This study is the first applying such a comprehensive indicator which is a combination of both the by-production approach and the Hicks-Moorsteen productivity index using Luenberger directional distance functions.

Overall, this study contributes to the efficiency and productivity literature in general, and airline performance analysis in particular, by introducing a new indicator and including an undesirable output in the Hicks–Moorsteen TFP index. In addition, we have decomposed this indicator into good and bad output components which allow us to measure the combined effect of good and bad efficiency change. Therefore, in this paper, instead of focussing on classical decomposition of TFP indicators into technical and efficiency change, our decomposition stresses the changes in the different outputs, the goods and the bads. This choice is guided by the aim at providing a direct decomposition of a pollution-adjusted productivity indicator. The good output component provides information on the managerial ability of DMUs (here airlines) in producing more desirable outputs given their input consumption, and the bad output provides insights into the possibility of decreasing detrimental outputs like pollution based on inputs and states of the environment (in terms of policy for instance). Practically this decomposition can help us identifying companies that take advantage of both or only one of the components.

4. Methodology and data

4.1. Methodology

Formally, let x represents a vector of inputs ($x \in \mathbb{R}_{+}^{K}$), y a vector of good outputs ($y \in \mathbb{R}_{+}^{Q}$), b denotes a vector of bad outputs $b \in \mathbb{R}_{+}^{R}$, and N the number of DMUs. To work it out, Murty et al. (2012) split the input vector into two groups: non-pollution causing inputs (x_1) and pollution-generating inputs (x_2).

The by-production technology

The global technology is the intersection of the following two sub-technologies: production of good outputs and generation of bad outputs.

$$\Psi = \Psi_1 \cap \Psi_2 \tag{1}$$

In the non-parametric framework of DEA the different sub-technologies can be represented under variable returns to scale (VRS) as:

$$\Psi_1 = \left[(x_1, x_2, y, b) \in \mathbb{R}^{K+Q+R} \mid \sum_{n=1}^{N} \lambda_n x_{1n} \leq x_1; \sum_{n=1}^{N} \lambda_n x_{2n} \leq x_2; \sum_{n=1}^{N} \lambda_n y_n \geq y\, ; \sum_{n=1}^{N} \lambda_n = 1 \right] \tag{2}$$

and

$$\Psi_2 = \left[(x_1, x_2, y, b) \in \mathbb{R}^{K_1+K_2+Q+R} \mid \sum_{n=1}^{N} \mu_n x_{2n} \geq x_2\, ; \sum_{n=1}^{N} \mu_n b_n \leq b\, ; \sum_{n=1}^{N} \mu_n = 1 \right] \tag{3}$$

Then Murty et al. (2012) propose to represent the global technology as follows:

$$\Psi = \left[(x_1, x_2, y, b) \in \mathbb{R}^{K_1+K_2+Q+R} \mid \sum_{n=1}^{N} \lambda_n x_{1n} \leq x_1; \sum_{n=1}^{N} \lambda_n x_{2n} \leq x_2\, ; \sum_{n=1}^{N} \lambda_n y_n \geq y\, ; \sum_{n=1}^{N} \lambda_n = 1\, ; \sum_{n=1}^{N} \mu_n x_{2n} \geq x_2\, ; \sum_{n=1}^{N} \mu_n b_n \leq b\, ; \sum_{n=1}^{N} \mu_n = 1 \right] \tag{4}$$

In model (4) the two sub-technologies are represented with two distinct intensity (structural) variables $(\lambda,\ \mu)$. These variables are the weights assigned to each DMU in the benchmark (reference set) of a DMU under evaluation. For global technology, the good outputs and the non-pollution-causing inputs verify the free (strong) disposability assumption; that is, if any non-pollution-causing input is increased (whether proportionally or not), (good) outputs do not decrease. On the good outputs side, the strong disposability states that it is possible to produce less with the same levels of inputs. The bad outputs satisfy the assumption of "costly disposability", which implies that it is possible to pollute more with the same levels of polluting inputs.[6]

Luenberger-Hicks-Moorsteen (LHM) pollution-adjusted productivity indicator

Given the particular nature of the by-production approach, we need to adapt the LHM index to properly fit with the existence of two independent sub-technologies. Following the work of Briec and Kerstens (2004), we propose an indicator that is output oriented and measures the difference between two Luenberger quantity indicators. For the period t we have

$$LHM_t = LG_t - LB_t \tag{5}$$

In Equation (5) we define the pollution-adjusted LHM indicator as the difference between the Luenberger productivity indicator for the good outputs (LG) and the Luenberger productivity indicator for the bad outputs (LB).

LG_t is defined in Equation (6) as the changes in good outputs production from year t to $t+1$ using the inputs and bad outputs levels of period t. When $LG_t > 0$, it means that from t to $t+1$, using the inputs and bad outputs levels of period t, the DMU under evaluation has improved its efficiency:

$$LG_t = D^t\left(x^t, y^t, b^t; (0, g_G^t, 0)\right) - D^t\left(x^t, y^{t+1}, b^t; (0, g_G^{t+1}, 0)\right) \tag{6}$$

Similarly, on the bad output side we have

$$LB_t = D^t\left({x_2}^t, y^t, b^{t+1}; (0, 0, g_B^{t+1})\right) - D^t({x_2}^t, y^t, b^t; (0, 0, g_B^t) \tag{7}$$

Here, values greater than zero expresses productivity losses, while values lower than zero corresponds to productivity gains.

In Equations (6) and (7) g_G^t , g_B^t are directional vectors used to assess the inefficiency.

Similarly, the LMH can also be estimated for period $t+1$:

[6] See Murty (2010) for more discussion on this assumption.

$$LG_{t+1} = D^{t+1}\left(x^{t+1}, y^{t}, b^{t+1}; (0, g_O^{t}, 0)\right) - D^{t+1}\left(x^{t+1}, y^{t+1}, b^{t+1}; (0, g_O^{t+1}, 0)\right) \quad (8)$$

and

$$LB_{t+1} = D^{t+1}\left(x^{t+1}, y^{t+1}, b^{t+1}; (0, 0, g_B^{t+1})\right) - D^{t+1}(x^{t+1}, y^{t+1}, b^{t}; (0, 0, g_B^{t}) \quad (9)$$

From Equations (6) to (9) we can derive the total factor pollution-adjusted productivity change as an arithmetic mean of each period LHM quantity indicator. Thus, we have the following:

$$\begin{gathered} LHM_{t,t+1} = \frac{1}{2}(LHM_t + LHM_{t+1}) \\ LHM_{t,t+1} = \frac{1}{2}(LG - LB) \end{gathered} \quad (10)$$

where $LG = \frac{1}{2}(LG_t + LG_{t+1})$ and $LB = \frac{1}{2}(LB_t + LB_{t+1})$. LG is the good-output TFP change, while LB is the bad-output TFP change from t to $t+1$. LHM Values greater than zero express productivity gains, while values below zero reflect productivity losses.

Use of data envelopment analysis

All the previous quantity indicator indicators can be estimated using DEA. For simplicity and paper length issues, we will only present two of the eight models that need to be solved to compute TFP in Equation (10). The good-output inefficiency in period t given the other variable in the same period is presented in Equation (11).

$$\begin{gathered} D^{t}\left(x^{t}, y^{t}, b^{t}; (0, g_O^{t}, 0)\right) = \max_{\beta,\lambda,\mu} \beta_0^{t} \\ s.t.\ \sum_{n=1}^{N} \lambda_n^{t} x_{kn}^{t} \leq x_{k0}^{t}\ ;\ \sum_{n=1}^{N} \lambda_n^{t} y_{qn}^{t} \geq y_{q0}^{t} + \beta_0^{t} g_{qo}^{t}\ ;\ \sum_{n=1}^{N} \lambda_n^{t} = 1 \\ \sum_{n=1}^{N} \mu_n^{t} x_{k_2 n}^{t} \geq x_{k_2 0}^{t}\ ;\ \sum_{n=1}^{N} \mu_n^{t} b_{rn}^{t} \leq b_{r0}^{t}\ ;\ \sum_{n=1}^{N} \mu_n^{t} = 1 \end{gathered} \quad (11)$$

Similarly, the good output inefficiency in period $t+1$ using as reference inputs and bad outputs of period t can be assessed using model in Equation (12).

$$\begin{gathered} D^{t}\left(x^{t}, y^{t+1}, b^{t}; (0, g_O^{t+1}, 0)\right) = \max_{\beta,\lambda,\mu} \beta_0^{t} \\ s.t.\ \sum_{n=1}^{N} \lambda_n^{t} x_{kn}^{t} \leq x_{k0}^{t}\ ;\ \sum_{n=1}^{N} \lambda_n^{t} y_{qn}^{t} \geq y_{q0}^{t+1} + \beta_0^{t} g_{qo}^{t+1}\ ;\ \sum_{n=1}^{N} \lambda_n^{t} = 1 \end{gathered} \quad (12)$$

$$\sum_{n=1}^{N} \mu_n^t x_{k_2 n}^t \geq x_{k_2 0}^t \ ; \ \sum_{n=1}^{N} \mu_n^t b_{rn}^t \leq b_{r0}^t \ ; \ \sum_{n=1}^{N} \mu_n^t = 1$$

As discussed earlier, some of the recent studies in the literature have also considered the internal structure of these companies by focusing on different stages of their production system. Although in this paper a single-stage by-production model is presented for the sake of simplicity and consistency with the previous by-production models, our model can easily be extended to network and dynamic analyses as conducted in the previous studies. All the previous analyses of airline productivity change (such as Barros & Couto, 2013; Cui and Li, 2015; Yang & Wang, 2016; Lee et al., 2015; 2016) have also employed a single-stage analysis but with different views of the production system. This study focuses on the operation stage or the flight business only, which is a crucial stage of the production network system and can directly be affected by the inclusion of CO_2 emissions. Hence, we avoid airline behavioral adjustments (marketing functions) such as cost minimization or profit maximisation (Barros, 2008). As underlined in Mallikarjun (2015), the operation stage reflects the 'supply capacity' of an airline, as measured by available seat miles (ASM), available seat kilometer (ASK) or TKA in several studies, and corresponds to our primal quantity of technical production whereas other production stages, often measured by factors such as revenue passenger miles and operating revenues, represent the 'service demand' and 'revenue generation' of airlines (Mallikarjun, 2015). The latter stages in fact reflect the airline strategy to maximize revenues and profits by operating with some 'supply capacity'—an economic behavior rather than the technology of generating ASM, ASK or TKA which is the focus of this paper. In addition, given the sensitivity of non-parametric measures such as DEA to sample size and the number of variables, the discrimination power between different DMUs can be seriously affected (Daraio and Simar, 2007).

Our model discussed here does not account for a dynamic framework for different reasons. As described in the literature (Li et al., 2016b; Cui et al., 2016a; 2016b), the dynamic approach is based on the work of Färe and Grosskopf (1996) where some storable inputs and intermediate outputs used or produced in one period serve as inputs for the next period. In the airline literature, capital is treated as a storable input. This approach requires data describing investment levels and capital depreciation, which we do not have access to for this paper.[7]

4.2. Data

It is crucial for efficiency and productivity analyses to select the appropriate mix of inputs and outputs (Boussofiane et al., 1991; Dyson et al., 2001). Airlines face different prices on their inputs; for example, Asian countries have comparatively lower labour costs, Middle Eastern airlines likely benefit

[7] Depending on data availability, both network and dynamic approaches will be interesting leads for future research.

from lower costs on fuel and tax rates vary across jurisdictions. These different prices could produce different input units (Greer, 2009). To overcome these differences and ensure comparability, only physical inputs and outputs were considered for this study. RDC Aviation provided all data, which were cross-referenced with annual reports and other publicly available data to ensure accuracy.[8] The research period covers the years 2007 to 2013 which allows comparison with other recent similar studies and also avoids biases from including commercial flights using biofuels from 2014.

Cui and Li (2015 ; 2016), Li et al. (2016a) and Cui et al. (2016c) considered the period from 2008 to 2012 and Cui et al. (2016b) and Xu and Cui (2017) used the years 2008 to 2014 as reference period to evaluate performance of major international airlines from different aspects. There is a consensus among all these studies that our selected period can be seen as appropriate. Cui et al. (2016b, p.989) states “since the EU declared in 2008 that aviation will be included in the EU ETS in 2012, the years after 2008 can be considered a buffer period for global airlines. Although the policy is suspended for non-EU airlines, the EU firmly believes that the act can decelerate airline emissions and will continue to push it in future.” Li et al. (2016a), Cui et al. (2016c), Cui and Li (2016) also argue that it is meaningful to study the efficiencies of major international airlines during period 2008−2012 which is included in our selected period. In addition, as mentioned earlier, the first commercial flights fuelled by 50 per cent biofuels (such as Lufthansa) took place in 2014. This would place additional requirements on the model however the data on how much biofuel was used by each airline to estimate their CO_2-e was not available. Therefore, the period 2007−2013 is considered in this study.

Thirty-three full-service carriers (FSCs) are considered in this study with eight European, one Russian, four North American, one Latin American, twelve Chinese or North Asian, three Asia-Pacific and four Middle Eastern carriers. We focused on the world’s major FSCs (not low-cost carriers and so on) to ensure comparability of business models.

The selection of data is well grounded in the existing literature (for example, Barla & Perelman, 1989; Charnes et al., 1996; Greer, 2006; Inglada et al., 2006; Arjomandi & Seufert, 2014). We identified labour and capital as major inputs. As asserted by Coelli et al. (1999) and Greer (2008), labour is measured by the annual average of full-time equivalent, and can be divided into two categories: pilots and flight attendants, which directly relate to the core business of airlines. This paper focuses on the flight operations and we deliberately excluded auxiliary services using ground staff such as catering and maintenance as these can and are often outsourced. As such figures of staff other than FTE pilot and flight attendants are very likely to be distorted. This study follows the Coelli et al. (1999, p. 262) definition of capital, which is the “sum of the maximum take-off weights of all aircraft multiplied by the number of days the planes have been able to operate during a year (defined as the total number of

[8] RDC Aviation (www.rdcaviation.com) is one of the leading aviation advisory and data analysis providers.

flying hours divided by average daily revenue hours)". This definition avoids performance biases due to maintenance or other external impacts, and was also employed because of the high degree of complementarity between fuel consumption and capital (this correlation is above 0.95 in our case) when the consistency of fuel consumption data is a concern (Barla and Perelman,1989; Coelli et al., 1999; Ray 2008). We have considered the same inputs (capital and labour) under both sub-technologies.

To reflect the outputs of airlines, we chose tonne–kilometres available (TKA) and CO2-e emissions. TKA is the measure of desirable output for this study, following the logic of Barla and Perelman (1989), Coelli et al. (1999), Inglada et al. (2006) and Arjomandi and Seufert (2014) that TKA is not a marketing but capacity indicator (Greer, 2009). As Greer (2009, p. 779) asserts "the conversion of an airline's produced inventory of ASMs into revenue passenger-miles is a marketing function, not part of the airline's production process." As such this study uses TKA defined as the number of tonnes available for the carriage of revenue load (passengers, freight and mail) on each flight multiplied by the flight distance which includes ASMs as well. RDC provides estimated CO_2-e data based on specific airline-aircraft configurations and the served sector to translate the estimated fuel consumption into CO_2-e based on the widely accepted IPCC factor. These modelled CO_2-e data have specific benefits of CO_2-e extracted from annual reports or other publicly available sources: there is consistency of data because they come from one, rather than multiple sources. This is in line with the standardisation of external factors, weather, pilots' decisions on the choice of route, or airport-related factors that could impact CO_2-e emission. In this paper we assume that production technologies available to airlines are homogeneous and the differences in business environment lead to different choices in technology not to differences in the technologies available to them. Descriptive statistics for all the inputs and outputs and the list of selected airlines, ordered by the size of capital, are provided in Tables 2 and 3, respectively.

Table 2. Descriptive statistics of the inputs and outputs

Variable	Mean	Std. Dev.	Minimum	Maximum
The inputs				
Number of employees	9.78	6.79	1.66	32.9
Capital	8.55	6.50	1.91	38.70
The outputs				
TKA	105.10	78.41	22.84	458.86
CO_2-e	10.58	7.96	2.44	42.20

Notes: Number of Employees is measured as full time equivalent staff (in thousands). Capital is the sum of the maximum take-off weights of all aircraft multiplied by the number of days the planes have been able to operate during a year (defined as the total number of flying hours divided by average daily revenue hours) and is divided by 10^{12}. TKA is the number of tonnes available for the carriage of revenue load (passengers, freight and mail) on each flight multiplied by the flight distance and is divided by 10^{12}. Estimated CO_2-e represents the Carbon Dioxide equivalent (in millions of tonnes) emitted by each airline for their flight business. RDC employed the specified model to estimate CO_2-e which is a conversion from fuel, based on the IPCC's conversion factor.

Table 3. Selected airlines and regions

Airline	Region	Region Abbreviation
Delta Air Lines	US and Canada	USC
American Airlines	US and Canada	USC
United Airlines	US and Canada	USC
Emirates	Middle East	ME
Lufthansa	Europe and Russia	EURU
British Airways	Europe and Russia	EURU
Cathay Pacific Airways	China and North Asia	CHNA
Air France	Europe and Russia	EURU
Singapore Airlines	China and North Asia	CHNA
Korean Air	China and North Asia	CHNA
KLM Royal Dutch Airlines	Europe and Russia	EURU
Air Canada	US and Canada	USC
Air China	China and North Asia	CHNA
Qantas	Asia Pacific	AP
Thai Airways International	Asia Pacific	AP
China Southern Airlines	China and North Asia	CHNA
China Airlines	China and North Asia	CHNA
China Eastern Airlines	China and North Asia	CHNA
Japan Airlines International	China and North Asia	CHNA
Iberia	Europe and Russia	EURU
Turkish Airlines (THY)	Europe and Russia	EURU
Eva Air	Asia Pacific	AP
Virgin Atlantic Airways	Europe and Russia	EURU
Asiana Airlines	China and North Asia	CHNA
Etihad Airways	Middle East	ME
All Nippon Airways	China and North Asia	CHNA
Malaysia Airlines	China and North Asia	CHNA
TAM Linhas Aereas	Latin America	LA
Air India	China and North Asia	CHNA
Saudi Arabian Airlines	Middle East	ME
Qatar Airways	Middle East	ME
Aeroflot-Russian Airlines	Europe and Russia	EURU
Alitalia	Europe and Russia	EURU

5. Empirical results

For the empirical application, the directional vectors used are equivalent to the observed values of the different variables (Chung et al., 1997). For instance, $g_{qo}^{t} = y_{q0}^{t}$. We start with the efficiency results and thereafter discuss productivity changes. Table 4 lists several measures related to the by-production pollution-adjusted inefficiency (By-production inefficiency), good-output inefficiency (G.O. inefficiency) and bad-output inefficiency (B.O. inefficiency) of the individual airlines. For the sake of saving space, the inefficiency estimates of only three individual years (2007, 2010 and 2013) for all airlines are presented in Table 4. The table also includes each airline's ranking based on its by-production, good-output and bad-output inefficiencies.[9]

[9] The results of years 2008, 2009, 2011, and 2012 can be provided upon request.

Based on the results listed in Table 4, interested readers can identify the best and worst individual performers in the sample: United Airlines is consistently found to be the most efficient airline because its by-production, good-output and bad-output inefficiencies all equal zero in all years. Emirates is also found to be a top performer, because it is ranked among the top five performers based on its by-production inefficiency in all reported years. Air India was a 'fully' efficient airline in the period 2007 to 2010 as well, but lost this position to other airlines, such as Eva Air, Singapore Airlines, Alitalia and Emirates in 2011 to 2013. Delta Airlines, Qatar Airways and Korean Air also show considerable ranking improvements in terms of pollution-adjusted efficiency (by-production) in 2011 to 2013. In fact, Delta Airlines and Qatar Airways were among the worst performers in 2007 to 2010, but were among the top 10 performers in 2011 to 2013. All Nippon Airways and Air China consistently ranked among the five worst performers in 2007 to 2013.

Focusing on the regions, airlines from the Europe region, except Turkish Airlines, were found to be better ranked than the 10 least efficient airlines in the last five studied years (by not falling into this category in the period 2009 to 2013). Turkish Airlines is by far the most inefficient airlines of the region, and its by-production inefficiency is mainly attributable to its bad-output management.[10] Alitalia, Lufthansa and Air France can be seen as the region's most efficient airlines. It is worth mentioning that Alitalia was ranked 27th in the first year of our analysis, but managed to become one of the fully efficient airlines between 2011 and 2013. Airlines in China and northern Asia were found to be at very different stages of by-production efficiency: Air India and Singapore Airlines were among the world's most efficient airlines and All Nippon and Air China are positioned in the opposite position. None of the Chinese airlines were found to be in the top 10 most technically efficient airlines.[11] China Southern Airlines performed very well in terms of bad-output management; however, its very poor good output efficiency ranked it about 15 across different years. Some airlines' rankings, such as those of Japan Airlines and Asiana Airlines, substantially worsened over time. The Asia-Pacific region includes three airlines: Eva Air, a Taiwanese airline which was found to be in the world's top three most efficient airlines in all years (except for 2009 in which it was ranked the ninth); Qantas, which is not as efficient as Eva Air in terms of pollution-adjusted efficiency, but still among the top third of the best performers; and Thai Airways, which in this study never ranked better than 21st during the studied period. This was mainly because of its poor performance on bad output controlling. In fact, this airline was constantly among the five globally most pollution-adjusted inefficient airlines.

[10] It should be mentioned that although Turkish Airlines is classified by ICAO as part of the Europe region, Turkey itself is neither part of the European Union nor a participant in the EU ETS, and hence does not need to consider an imposed price on CO_2-e (ICAO, 2015).

[11] Note that China Airlines has its headquarters in Taiwan, and hence is not considered as a mainland China airline. China Airlines was in fact among the top ten best performers in 2007, 2011 and 2012.

Table 4. By-production, good-output and bad-output efficiency scores, 2007, 2010, and 2013

Airlines	Region	2007						2010						2013					
		By-prod. ineff.	**G.O. ineff.**	**B.O. ineff.**	**By-prod. rank**	**G.O. rank**	**B.O rank**	**By-prod. ineff.**	**G.O. ineff.**	**B.O. ineff.**	**By-prod. rank**	**G.O. rank**	**B.O rank**	**By-prod. ineff.**	**G.O. ineff.**	**B.O. ineff.**	**By-prod. rank**	**G.O. rank**	**B.O rank**
Delta Air Lines	USC	0.208	0.124	0.291	24	16	19	0.196	0.175	0.217	20	22	12	0.031	0.028	0.034	5	4	3
American Airlines	USC	0.050	0.101	0.000	6	13	1	0.235	0.118	0.353	28	18	23	0.024	0.049	0.000	3	7	1
United Airlines	USC	0.000	0.000	0.000	1	1	1	0.000	0.000	0.000	1	1	1	0.000	0.000	0.000	1	1	1
Emirates	ME	0.046	0.006	0.086	5	3	4	0.084	0.000	0.169	5	1	9	0.000	0.000	0.000	1	1	1
Lufthansa	EURU	0.093	0.061	0.124	10	11	7	0.118	0.066	0.170	10	14	10	0.025	0.050	0.000	4	8	1
British Airways	EURU	0.196	0.000	0.393	21	1	26	0.146	0.016	0.276	15	2	18	0.158	0.034	0.282	18	5	22
Cathay Pacific Airways	CHNA	0.101	0.034	0.169	11	6	9	0.148	0.038	0.258	16	6	16	0.088	0.066	0.111	8	13	7
Air France	EURU	0.029	0.058	0.000	4	10	1	0.115	0.067	0.164	9	15	7	0.064	0.040	0.088	6	6	5
Singapore Airlines	CHNA	0.088	0.000	0.176	9	1	10	0.069	0.000	0.139	4	1	5	0.013	0.003	0.023	2	2	2
Korean Air	CHNA	0.251	0.061	0.441	30	12	27	0.216	0.055	0.378	26	9	29	0.141	0.059	0.223	15	10	18
KLM Royal Dutch Airlines	EURU	0.107	0.027	0.188	12	4	12	0.141	0.032	0.250	13	3	15	0.120	0.061	0.179	13	12	14
Air Canada	USC	0.213	0.139	0.286	25	17	17	0.216	0.118	0.313	25	19	20	0.226	0.149	0.304	27	17	23
Air China	CHNA	0.238	0.146	0.331	29	18	23	0.241	0.153	0.329	29	20	21	0.221	0.179	0.263	26	19	20
Qantas	AP	0.068	0.004	0.132	8	2	8	0.100	0.041	0.158	7	7	6	0.112	0.054	0.170	12	9	13
Thai Airways International	AP	0.198	0.052	0.344	22	8	24	0.209	0.057	0.361	22	11	25	0.164	0.060	0.267	21	11	21
China Southern Airlines	CHNA	0.140	0.281	0.000	16	24	1	0.143	0.286	0.000	14	25	1	0.133	0.265	0.000	14	27	1
China Airlines	CHNA	0.065	0.033	0.097	7	5	5	0.136	0.045	0.226	11	8	14	0.107	0.143	0.071	11	16	4
China Eastern Airlines	CHNA	0.157	0.261	0.053	18	23	3	0.192	0.294	0.090	18	26	3	0.216	0.293	0.140	25	28	9
Japan Airlines International	CHNA	0.135	0.168	0.101	15	21	6	0.302	0.218	0.386	32	23	30	0.311	0.231	0.391	30	24	26
Iberia	EURU	0.199	0.105	0.294	23	14	20	0.091	0.081	0.101	6	16	4	0.159	0.118	0.201	20	15	15
Turkish Airlines (THY)	EURU	0.234	0.153	0.315	28	19	21	0.262	0.175	0.349	30	21	22	0.169	0.169	0.170	23	18	12
Eva Air	AP	0.004	0.000	0.009	2	1	2	0.028	0.000	0.056	3	1	2	0.000	0.000	0.000	1	1	1
Virgin Atlantic Airways	EURU	0.178	0.000	0.357	19	1	25	0.155	0.000	0.310	17	1	19	0.106	0.000	0.212	10	1	16
Asiana Airlines	CHNA	0.124	0.000	0.247	14	1	15	0.136	0.057	0.215	12	10	11	0.167	0.187	0.148	22	20	10
Etihad Airways	ME	0.000	0.000	0.000	1	1	1	0.198	0.035	0.361	21	4	24	0.158	0.099	0.217	19	14	17
All Nippon Airways	CHNA	0.286	0.305	0.267	31	25	16	0.290	0.317	0.263	31	27	17	0.228	0.210	0.246	28	23	19
Malaysia Airlines	CHNA	0.023	0.047	0.000	3	7	1	0.212	0.063	0.361	23	13	26	0.152	0.000	0.305	16	1	24
TAM Linhas Aereas	LA	0.221	0.241	0.201	26	22	13	0.196	0.224	0.168	19	24	8	0.153	0.191	0.116	17	21	8
Air India	CHNA	0.000	0.000	0.000	1	1	1	0.000	0.000	0.000	1	1	1	0.104	0.207	0.000	9	22	1
Saudi Arabian Airlines	ME	0.151	0.119	0.182	17	15	11	0.233	0.098	0.368	27	17	28	0.194	0.241	0.148	24	25	11
Qatar Airways	ME	0.188	0.054	0.322	20	9	22	0.213	0.059	0.367	24	12	27	0.064	0.023	0.105	7	3	6
Aeroflot-Russian Airlines	EURU	0.118	0.000	0.236	13	1	14	0.109	0.000	0.217	8	1	13	0.295	0.255	0.335	29	26	25
Alitalia	EURU	0.226	0.163	0.288	27	20	18	0.019	0.038	0.000	2	5	1	0.000	0.000	0.000	1	1	1

With regard to the Middle-Eastern airlines, Emirates was by far the most efficient airline. Qatar managed to improve its rank from 24st in 2010 to seventh in 2012–2013. Saudi Arabian Airlines and Etihad Airways were mostly ranked in the second third. TAM Linhas Aereas from Latin America was also in a position similar to Saudi Arabian Airlines and Etihad Airways. In the US and Canada region, United Airlines and Air Canada were found to be respectively the region's best and the worst performers. Another highlight from this region was Delta Air Lines, which showed a remarkable improvement in the years 2011 to 2013, compared to the previous period of study; its pollution-adjusted efficiency rank changed from 24th in 2007 to about fourth in the years 2011 to 2013.

Based on these pollution-adjusted measures, the findings of Table 4 reveal that: 1) United Airlines was the most efficient airline; 2) All Nippon Airways and Air China[12] were across the years among the least efficient airlines; 3) no European airline (from the EU) was found to be among the 10 least efficient airlines[13] after 2009; 4) no Chinese airline was found to be among the world's most efficient airlines; 5) airlines from almost all regions were found to be among the top 10 best performers.

The results on the LHM TFP (pollution-adjusted productivity) change, considering both good and bad outputs, can now give us a more in-depth understanding of airline performance. Any airline with high values of LG and LB (see Tables 5 and 6) can be seen as a good performer in managing both good- and bad-output productivities. However, as can be seen in Tables 5 and 6, there are not many airlines with positive LGs and LBs (positive productivity change), and there are many airlines that performed well based on one productivity component (LG or LB), but not on the other. Let us consider the period 2007 to 2008 to describe this better. Based on Table 5, Air India, with the highest LB but a negative LG, had the highest LHM TFP (pollution-adjusted productivity) change, and hence is ranked first in the list. In the same way, but with highest levels of LG, Qatar and TAM Linhas Aereas managed to be the second and third, respectively, in terms of the LHM TFP change in 2007 to 2008. Of special note is Etihad Airways, which had the largest positive change of LG (0.279); but because its LB was by far the poorest in comparison with others (-0.322), its LHM TFP change is ranked 29th. Eva Air and Malaysia Airlines were found to show the least productive changes in the period 2007 to 2008 (based on their LHM TFP values), because both their LGs and LBs were highly negative and largely lower than their rivals'. On the other hand, the LG and LB values of Iberia and Delta Airlines in the period 2007–2008 were both positive, indicating they experienced progress in terms of maximising TKA (LG) and also in terms of solely environmental performance (LB). However, because these are not the largest values in comparison with those of other airlines, they are ranked, respectively, fourth and fifth among all airlines.

[12] Using a dynamic model and total revenue as desirable output, Cui et al. (2016b) also found similar results for Air China and stated that this airline should exert more effort in controlling its emission volume. They suggested the fleet upgrade as an important tool for this aim.

[13] This finding is also in line with those of network SBMs in Cui and Li (2016) and Li et al. (2016a) which also showed that the average efficiency of European airlines was higher that of non-European airlines.

Table 5. By-production LHM TFP change and its components, 2007–2008, 2008–2009, and 2009–2010

Airlines	Region	2007–2008						2008–2009						2009–2010					
		LHM	**LG**	**-LB**	**LHM rank**	**LG rank**	**LB rank**	**LHM**	**LG**	**-LB**	**LHM rank**	**LG rank**	**LB rank**	**LHM**	**LG**	**-LB**	**LHM rank**	**LG rank**	**LB rank**
Delta Air Lines	USC	0.112	0.043	0.069	5	10	4	-0.019	-0.102	0.083	21	26	9	-0.110	-0.056	-0.053	31	30	23
American Airlines	USC	-0.027	-0.086	0.059	27	30	7	-0.001	-0.110	0.110	18	29	5	0.020	0.019	0.001	8	17	9
United Airlines	USC	0.005	-0.055	0.060	23	28	5	0.002	-0.032	0.034	17	16	16	0.035	0.047	-0.011	7	12	14
Emirates	ME	0.009	0.099	-0.090	22	6	31	0.012	0.076	-0.064	16	6	29	-0.089	0.079	-0.168	29	8	32
Lufthansa	EURU	0.014	0.031	-0.018	19	16	21	0.090	-0.013	0.104	7	13	8	-0.002	0.020	-0.022	20	16	17
British Airways	EURU	0.047	-0.032	0.078	8	24	3	0.063	-0.045	0.108	10	17	6	0.003	-0.014	0.017	17	22	4
Cathay Pacific Airways	CHNA	0.060	0.108	-0.048	6	5	25	-0.053	-0.053	-0.001	27	19	20	0.011	0.032	-0.021	12	15	16
Air France	EURU	0.022	0.031	-0.009	15	17	17	0.070	-0.048	0.118	9	18	4	-0.015	-0.027	0.012	21	24	5
Singapore Airlines	CHNA	0.053	0.078	-0.025	7	7	23	0.046	-0.104	0.150	14	27	2	-0.042	-0.028	-0.014	25	25	15
Korean Air	CHNA	0.040	0.040	0.000	10	14	11	0.077	0.056	0.021	8	8	17	-0.051	-0.053	0.002	27	29	8
KLM Royal Dutch Airlines	EURU	0.029	0.042	-0.013	13	11	19	0.014	-0.063	0.077	15	21	10	0.039	0.051	-0.011	5	10	13
Air Canada	USC	0.039	0.042	-0.003	11	12	13	0.048	0.004	0.044	13	12	13	0.047	0.083	-0.036	4	7	21
Air China	CHNA	0.018	0.030	-0.012	18	19	18	-0.044	0.014	-0.058	24	10	28	0.037	0.098	-0.061	6	5	24
Qantas	AP	-0.019	-0.015	-0.004	25	22	14	-0.024	-0.068	0.044	22	23	14	0.009	-0.001	0.009	14	19	6
Thai Airways International	AP	-0.043	-0.037	-0.006	28	25	16	-0.047	-0.112	0.065	25	30	11	0.017	0.039	-0.022	10	14	18
China Southern Airlines	CHNA	0.020	0.005	0.015	16	21	10	0.102	0.168	-0.067	4	2	30	0.051	0.166	-0.116	3	2	31
China Airlines	CHNA	-0.063	-0.099	0.037	31	32	9	-0.087	0.010	-0.097	30	11	32	0.004	-0.033	0.037	16	26	3
China Eastern Airlines	CHNA	0.002	0.018	-0.016	24	20	20	-0.002	0.085	-0.087	19	5	31	-0.017	0.078	-0.095	22	9	28
Japan Airlines International	CHNA	-0.055	-0.053	-0.002	30	27	12	-0.141	-0.108	-0.033	31	28	24	-0.174	-0.297	0.123	32	33	1
Iberia	EURU	0.122	0.062	0.060	4	9	6	0.117	-0.031	0.148	3	15	3	-0.018	-0.012	-0.005	23	21	10
Turkish Airlines (THY)	EURU	0.032	0.109	-0.077	12	4	29	0.146	0.180	-0.033	1	1	25	0.010	0.098	-0.087	13	6	27
Eva Air	AP	-0.094	-0.061	-0.033	32	29	24	-0.055	-0.016	-0.040	28	14	26	0.002	-0.007	0.009	18	20	7
Virgin Atlantic Airways	EURU	0.011	0.030	-0.020	20	18	22	-0.017	-0.066	0.049	20	22	12	0.002	-0.045	0.047	19	28	2
Asiana Airlines	CHNA	0.009	0.066	-0.056	21	8	27	0.145	0.039	0.105	2	9	7	0.016	0.049	-0.033	11	11	20
Etihad Airways	ME	-0.043	0.280	-0.323	29	1	33	0.051	0.149	-0.098	12	3	33	0.052	0.150	-0.098	1	3	29
All Nippon Airways	CHNA	0.028	0.034	-0.005	14	15	15	-0.048	-0.058	0.010	26	20	18	-0.041	-0.035	-0.006	24	27	11
Malaysia Airlines	CHNA	-0.213	-0.052	-0.161	33	26	32	-0.177	-0.155	-0.022	33	33	23	-0.065	-0.059	-0.007	28	31	12
TAM Linhas Aereas	LA	0.137	0.190	-0.053	2	3	26	0.092	0.137	-0.045	5	4	27	0.017	0.133	-0.115	9	4	30
Air India	CHNA	0.146	-0.094	0.240	1	31	1	-0.148	-0.137	-0.011	32	31	21	0.008	0.040	-0.032	15	13	19
Saudi Arabian Airlines	ME	0.019	-0.031	0.050	17	23	8	-0.078	-0.081	0.003	29	24	19	-0.044	0.006	-0.051	26	18	22
Qatar Airways	ME	0.123	0.210	-0.087	3	2	30	0.058	0.075	-0.017	11	7	22	0.051	0.233	-0.182	2	1	33
Aeroflot-Russian Airlines	EURU	-0.025	0.040	-0.065	26	13	28	-0.043	-0.083	0.040	23	25	15	-0.215	-0.131	-0.083	33	32	26
Alitalia	EURU	0.043	-0.161	0.204	9	33	2	0.092	-0.150	0.242	6	32	1	-0.089	-0.018	-0.071	30	23	25

*Note***:** LB values are multiplied by -1 for the sake of interpretation convenience. '–LB' instead of 'LB' is provided in the table.

Table 6. By-production LHM TFP change and its components, 2010–2011, 2011–2012, and 2012–2013

Airlines	Region	2010–2011						2011–2012						2012–2013					
		LHM	LG	-LB	LHM rank	LG rank	LB rank	LHM	LG	-LB	LHM rank	LG rank	LB rank	LHM	LG	-LB	LHM rank	LG rank	LB rank
Delta Air Lines	USC	0.245	0.625	-0.380	4	1	31	0.004	-0.038	0.042	18	25	5	-0.024	0.005	-0.029	27	24	18
American Airlines	USC	0.000	0.005	-0.005	23	31	2	-0.025	-0.039	0.014	26	26	13	0.134	0.563	-0.428	2	1	33
United Airlines	USC	-0.160	0.379	-0.539	32	4	33	-0.103	-0.129	0.026	32	31	10	-0.098	-0.115	0.017	32	32	9
Emirates	ME	0.090	0.216	-0.126	8	8	28	0.007	0.154	-0.147	16	4	32	0.069	0.138	-0.069	7	7	23
Lufthansa	EURU	0.014	0.096	-0.082	19	15	24	0.013	-0.021	0.034	14	22	8	0.001	-0.019	0.019	21	26	8
British Airways	EURU	-0.018	0.029	-0.047	28	29	15	-0.019	0.006	-0.026	25	19	19	-0.005	0.016	-0.022	23	19	17
Cathay Pacific Airways	CHNA	0.018	0.095	-0.077	18	16	21	0.029	0.088	-0.060	10	11	24	0.078	0.005	0.073	6	23	2
Air France	EURU	0.045	0.086	-0.041	12	17	11	0.017	0.001	0.016	13	21	12	0.044	0.009	0.036	9	22	6
Singapore Airlines	CHNA	0.070	0.139	-0.069	10	11	19	0.000	0.056	-0.055	20	12	22	-0.009	0.009	-0.018	25	21	15
Korean Air	CHNA	0.141	0.186	-0.045	7	9	12	0.023	0.053	-0.030	12	14	20	0.019	0.017	0.002	15	18	11
KLM Royal Dutch Airlines	EURU	-0.014	0.039	-0.053	27	25	17	-0.025	-0.024	-0.001	27	23	14	0.008	0.003	0.005	19	25	10
Air Canada	USC	0.012	0.035	-0.023	20	27	4	-0.001	0.003	-0.004	21	20	15	-0.035	-0.023	-0.012	29	27	14
Air China	CHNA	0.036	0.065	-0.029	13	20	6	0.062	0.045	0.018	3	16	11	-0.036	0.059	-0.095	30	15	26
Qantas	AP	0.036	0.061	-0.025	14	22	5	-0.047	-0.078	0.031	29	27	9	-0.050	-0.086	0.036	31	31	5
Thai Airways International	AP	0.033	0.051	-0.019	16	24	3	0.012	-0.027	0.039	15	24	6	0.025	0.088	-0.063	14	11	22
China Southern Airlines	CHNA	-0.013	0.069	-0.082	26	18	23	0.056	0.140	-0.084	4	5	26	0.014	0.123	-0.110	17	9	27
China Airlines	CHNA	0.004	0.037	-0.034	22	26	9	0.003	0.049	-0.046	19	15	21	0.034	0.043	-0.009	12	17	13
China Eastern Airlines	CHNA	0.035	0.113	-0.079	15	14	22	0.045	0.139	-0.093	6	6	28	0.083	0.196	-0.113	5	4	28
Japan Airlines International	CHNA	-0.063	-0.076	0.014	31	33	1	0.045	0.053	-0.008	7	13	17	0.044	0.084	-0.040	10	13	21
Iberia	EURU	0.075	0.120	-0.046	9	13	13	-0.013	-0.093	0.080	23	28	2	-0.246	-0.382	0.136	33	33	1
Turkish Airlines (THY)	EURU	0.397	0.563	-0.166	2	3	30	0.034	0.168	-0.134	9	2	31	0.095	0.245	-0.150	3	2	31
Eva Air	AP	-0.002	0.033	-0.035	24	28	10	-0.037	0.024	-0.061	28	17	25	0.016	0.045	-0.029	16	16	19
Virgin Atlantic Airways	EURU	-0.009	0.024	-0.033	25	30	8	-0.002	0.009	-0.010	22	18	18	-0.010	-0.043	0.033	26	28	7
Asiana Airlines	CHNA	0.007	0.059	-0.051	21	23	16	0.040	0.099	-0.059	8	10	23	0.134	0.171	-0.036	1	6	20
Etihad Airways	ME	0.060	0.131	-0.070	11	12	20	0.006	0.114	-0.107	17	9	29	0.052	0.172	-0.121	8	5	29
All Nippon Airways	CHNA	0.169	0.237	-0.068	6	7	18	0.110	0.117	-0.007	2	7	16	0.034	0.111	-0.077	13	10	24
Malaysia Airlines	CHNA	-0.035	-0.004	-0.030	29	32	7	-0.015	-0.120	0.105	24	30	1	0.002	0.127	-0.124	20	8	30
TAM Linhas Aereas	LA	-0.040	0.061	-0.101	30	21	27	0.117	0.529	-0.412	1	1	33	-0.006	-0.078	0.071	24	30	3
Air India	CHNA	-0.249	0.145	-0.394	33	10	32	-0.048	-0.096	0.049	30	29	4	0.040	0.059	-0.020	11	14	16
Saudi Arabian Airlines	ME	0.241	0.328	-0.088	5	6	25	-0.070	-0.136	0.066	31	32	3	0.009	0.015	-0.005	18	20	12
Qatar Airways	ME	0.269	0.358	-0.089	3	5	26	0.028	0.117	-0.088	11	8	27	-0.004	0.088	-0.092	22	12	25
Aeroflot-Russian Airlines	EURU	0.425	0.569	-0.144	1	2	29	0.050	0.162	-0.112	5	3	30	0.087	0.241	-0.154	4	3	32
Alitalia	EURU	0.022	0.069	-0.047	17	19	14	-0.143	-0.180	0.037	33	33	7	-0.030	-0.074	0.043	28	29	4

*Note***:** LB values are multiplied by -1 for the sake of interpretation convenience. '–LB' instead of 'LB' is provided in the table.

Focusing on the regions, in the Middle East, one may not see any obvious highlights by looking at the LHM TFP results; however, when the LG and LB changes are compared, the findings are very interesting (Tables 5 and 6). Emirates, Etihad Airways and Qatar Airways have constantly shown very high and positive LG changes in any of the periods, but when it comes to the LB changes, we see the opposite: all the values are highly negative with no exceptions in all periods. Therefore, they are ranked among the most productive airlines in terms of good-output productivity change, but positioned as the worst performers when it comes to changes in environmental productivity. This may indicate that the Middle Eastern airlines are focusing on marketing strategies more than fuel/CO_2 reduction. Chinese airlines were found to be somewhat similar to their Middle Eastern rivals. Air China and China Southern Airlines show high and positive LGs, but negative LBs. China Eastern improved its LHM TFP substantially over time. But this was again due to its LG improvements over time only. Its LB values were always negative and even worsened over time. Hence, a similar conclusion as for the Middle Eastern airlines may also be drawn for Chinese airlines as well as airlines such as Aeroflot-Russian Airlines (from the Russian region), All Nippon Airways, Asiana, China Airlines, Cathay Pacific Airways and Japan Airlines (from the north Asia region), TAM Linhas Aereas (from the Latin America region) and Turkish Airlines (from the European region), which also show very similar LG and LB changes in most of the periods. On the other hand, European airlines show significant improvements in their LB values, and thus in 2012–2013, all the EU airlines, except British Airways, showed positive LBs.

With regard to LG changes, European airlines are ranked in the middle third among all airlines, but when it comes to exclusive environmental productivity change, they performed relatively better. See, for example, the performance of Iberia, Air France, Alitalia and Lufthansa in different years. With regard to the North American airlines, the good- and bad-output TFP changes vary over time.

6. Conclusions

This paper analyses the pollution-adjusted efficiency and productivity of the world's major airlines using innovative and recent DEA by-production models covering the period 2007 to 2013. Unlike the traditional Hicks-Moorsteen total factor productivity index, our indicator includes undesirable outputs using a representation of polluting technologies (by-production). The flexibility offered by this multi-technology approach allows us to decompose the global TFP into good- and bad-output components, thus providing insights into pollution-adjusted productivity change sources. As recently identified in some of the aforementioned literature (Dakpo et al., 2016; Førsund, 2017), other models considering pollution as an input under the strong disposability assumption or as an undesirable output under the WDA fail both to represent the production process that generates pollution in terms of trade-offs and to satisfy thermodynamic laws.

Based on the findings of this study, one may argue that ETSs can trigger an environmental awareness or (cost) pressure for airlines to take their carbon footprint more seriously into account in their business strategy. That is, airlines facing either inclusion or the direct cost of an ETS are more likely to consider their environmental efficiency. Also, our findings suggest that, for our period of research, Middle Eastern airlines were less concerned about their environmental performance, most likely because fuel was cheaper and they were less concerned about the cost impact of higher fuel consumption. In contrast, European Airlines (those which are part of the EU ETS) show high pollution-adjusted efficiency and improvements in LHM productivity, which can be due to cost pressures and a potential higher environmental awareness of their passengers. Turkish Airlines, which has not been part of the EU ETS, might be a good counter example to show that a lack of incentive directly leads to a lack of LB improvements. Similarly, it can be argued that since Japan's regional and national ETSs did not include aviation emissions and they did not pose a threat to their financial bottom line, resulting in the airlines behaving as though they do not need to comply with an ETS at all.

Future research could take other aspects, such as marketing, costs and profit, into account to provide a more detailed picture of airline business operations. For this aim, the network and dynamic by-production approaches can provide interesting insights into the performance of the airlines. While we considered the uniformity of CO_2-e data by RDC compelling, more comprehensive actual data could provide additional insights into the eco-efficiency and eco-effectiveness changes of airlines' ground and other operational activities.

As fuel costs are not directly included in our model, regional differences in fuel costs for airlines do not have a direct bearing on our results. Future studies could also investigate the relative significance of regional differences in fuel costs compared with the impact of the EU ETS by considering altered sets of inputs and outputs or utilising a different type of undesirable output. This could be a valuable investigation of airlines' performance, as an ETS or any other factor that results in higher fuel prices (or even higher price volatility) may trigger airlines to improve fuel efficiency in order to minimise operating costs, thereby reducing exhaust emissions. Future studies could also extend the study period beyond 2013 and include the effect of biofuels on airline technical and environmental efficiency and productivity.

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