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Have Asian airlines caught up with European Airlines? A by-production efficiency analysis

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Have Asian Airlines caught up with European Airlines? A By-Production Efficiency Analysis

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Keywords: data envelopment analysis; aviation; meta-efficiency; emissions.

JEL Classification: D21, C14, Q53

1. Introduction

The aviation industry is a key enabler for the movement of passengers and freight around the world. It is a highly dynamic industry, and over the last 40 years has undergone a number of structural changes requiring significant adjustments to business models to ensure sustainability. The Asian region, led by China and India, has expanded rapidly and become the world's largest aviation market with regard to international departures and international freight in the last decade (IATA, 2014a). In 2012, China was the second-largest domestic passenger air transport market after the US, with a remarkable growth rate of 9.5 per cent (IATA, 2013). Asian airlines also boasted the world's highest margins and largest profits, despite a weakening of the freight segment since 2011 (ICAO, 2013).

While economic growth has been immense, the ecological side of the aviation industry has been mainly ignored. Asian airlines have not faced the threat of serious ETSs, such as the existing ETS in Europe, and some countries (such as China) have even prohibited their airlines from participating in the EU ETS. Regions such as the EU are classified as being in IATA's market evolution Phase 3: the market is large and demand is mature, with privatised companies operating in a deregulated market with minimal government intervention. Airlines in this classification are expected to be highly technically efficient, with competitive air ticket prices that are sensitive to changes in costs and low overall profit margins. In addition to high competitiveness and shrinking profit margins, EU airlines have also needed to adapt to increases in operating costs as they have improved their pollution efficiency to comply with ETSs from 2012 (IATA, 2011). IATA reports that the Asian region is in Phase 2 of its evolution, with rapidly increasing demand, a mixture of private and state-owned enterprises, and a highly regulated market with some degree of liberalisation. These factors should lead to decreasing prices and improvement in technical and profit-oriented efficiencies.

We argue that the regulatory differences between Asia and the EU should result in Asian airlines to be less environmentally efficient and more technically efficient (to gain a larger market share and profit) than their European counterparts. If this is true, then the new ETSs or emission reduction regulations in the Asian region could negatively affect the performance of region's carriers (see also Beltrán-Esteve and Picazo-Tadeo, 2015; Doganay et al., 2014). This is a crucial issue, because several Asian countries (such as Japan and Korea) have begun to include airlines in their current ETSs, or are designing new ETSs that include aviation emissions. For instance, Thailand's planned 2017 ETS will put further pressure on Asian airlines to consider their carbon footprints. This study, therefore, compares the technical and pollution-adjusted efficiencies of major Asian airlines on the cusp of ETS regulation with those of European airlines that have met EU ETS requirements since 2012 and are operating in a mature emissions trading market.

Besides the difference in maturity and environmental consciousness, the EU and the Asian market share many similarities (more than other IATA-defined regions, such as North or South America or Africa) which further justifies a meaningful direct comparison. For example, their shares of the international aviation market for both freight and passengers are very similar: in 2013, Asia accounted for 29.3 per cent of the passenger market and 38.8 per cent of the freight market; while Europe accounted for 33.8 per cent and 38.8 per cent respectively (IATA, 2014b). Airlines from both regions face similar costs of capital, at 7.5 to 8.3 per cent in Asia and 7.7 per cent in Europe (network/LCC in 2012).[1] The cost of aviation fuel is a major expense for both regions, approximately 33 per cent of the total operating costs in 2013. Further, both regions have similar international passenger load factors: in 2012, passengers represented 78.0 per cent of international loads in Asia and 77.8 per cent in Europe (ICAO, 2013). These similarities allow this study to make meaningful insights into the technical and environmental efficiencies of these airlines relating to the life of older aircraft, and replacement policies or fuel substitutes such as biofuels, which will assist management decisions. Policy makers may also benefit from information to assist them drive ecological and technical improvements in the aviation sector.

An important requirement in comparing heterogeneous decision-making units (here, Asian and European airlines) is the definition of an identical comparison basis. To this aim, Hayami and Ruttan proposed the concept of a meta-production technology to describe the 'full range of alternatives … only partially available to individual producers in a particular country [region, in this study]' (1970, p. 898). In other words, the meta-production function 'can be regarded as the envelope of commonly conceived neoclassical production functions' (Hayami and Ruttan, 1971, p. 82). It therefore provides tools for meaningful comparisons between different groups. The concept implies that all producers have potential access to the same technology. However, 'specific circumstances such as the qualities and quantities of the natural endowments, the structure of relative prices of the inputs, and the basic economic environment' may lead producers to operate on different local parts of the meta-technology (Lau and Yotopoulos, 1989, p. 242). Simply, producers do not operate on a universal (global)

[1] North America, in contrast, possesses 14.3 per cent of the passenger market and 21 per cent of the freight market. The cost of capital in this region is only 2−4 per cent which is significantly lower and different than those in Europe or Asia.

production function, but rather on restricted parts of the production function due to the adoption and diffusion of technology (Gunaratne and Leung, 1996). Recently, the concept of meta-production has been extended to stochastic frontier estimation (Battese and Rao, 2002; Battese et al., 2004). O'Donnell et al. (2008) also propose formulation in the case of a DEA framework. However, because meta-frontier estimation assumes that different existing technologies are combinable, some parts of the virtual global frontier can be infeasible, and not attainable by producers (Breustedt et al., 2007).[2] Therefore, Breustedt et al. (2007) proposes the estimation of a less restrictive and non-concave meta-frontier to overcome this potential drawback of the classic meta-technology estimation. The inclusion of undesirable outputs in production technology models has been the subject of consideration discussion in the DEA literature (Dakpo et al., 2016). Suggested approaches include, for example, treating undesirable outputs as free disposable inputs (Hailu and Veeman, 2001), and considering them as outputs under the weak disposability assumption—WDA (Färe and Grosskopf, 2009). These do, however, have many limitations (Coelli et al., 2007; Murty, 2010; 2012; 2015; Salim et al., 2016). Murty et al.'s (2012) innovative by-production model, on the other hand, is grounded in solid theoretical reasoning: unlike the earlier approaches (pollution as input or as output under WDA) that use a single (equation) representation of a pollution-generating technology, the by-production approach is based on a multi-equation representation. It assumes one intended technology for the production of the good outputs and one unintended technology for the generation of pollution or undesirable outputs, so that the global technology lies at the intersection of the previous two technologies. This study uses the non-parametric DEA method and proposes an extension of the by-production technology to the estimation of a non-concave meta-frontier in order to rank the airlines in both Asia and Europe.[3] This new extension includes carbon dioxide equivalent (CO_2-e) as an undesirable output in addition to a load measure.

The paper is structured as follows: Section 2 provides a brief review of literature, while Section 3 outlines existing policies and regulations relevant to the study. Subsequently, methodology and data are presented in Section 4. Section 5 discusses the findings of this study, and concluding remarks are presented in Section 6.

[2] This case will be discussed later in the paper.

[3] It is worth noting that the potential problem of DEA-based scores of efficiency to rank DMUs is that those scores are obtained with a different set of efficient units and different weights, which might render comparisons among inefficient units meaningless (Kao and Hung, 2005). However, our approach in this paper is not to establish a systematic ranking of airlines but to provide the magnitude of the inefficiencies in the best state of nature (even in the presence of ties). Besides, practically, it might be interesting to consider the projection that requires lesser effort for a firm to reach the production. We would like to thank the anonymous Reviewer for underlying this point.

2. Literature review

Existing airline policy and operations literature does include comparisons between European and Asian airlines; however, analyses are limited, and are derived from studies that look at international carriers including carriers from these two regions. For example, Barbot et al. (2008) used DEA and the total factor productivity index for the year 2005 to analyse a sample of 49 airlines including eight Asian and 17 European full-service carriers (FSCs), finding that the north Asian and Chinese airlines were more technically efficient and effective than European airlines. Rey et al. (2009) decomposed the changes in productivity of 18 international airlines including four Asian and seven European airlines over the period 1996 to 2000. They found that Asian airlines were relatively more economically efficient than European and North American airlines, while the average productivity of the whole sample showed a general improvement over the study period. Michaelides et al. (2009) estimated the technical efficiency of 24 FSCs (including seven Asian, eight European and five US airlines) for the period 1991–2000. They conclude that Asian airlines are the most technically efficient and, together with US airlines, more efficient than European airlines. Merkert and Hensher (2011) applied a two-stage DEA approach, with partially bootstrapped random effects and Tobit regressions to determine the efficiency of 58 passenger airlines (19 Asian, 18 European) over the two fiscal years of 2007–2008 and 2008–2009. Their findings, counter to the earlier studies, suggest that American and European airlines were on average more efficient than Asian airlines. Arjomandi and Seufert (2014) use bootstrapped DEA to assess the technical and environmental efficiency for 48 of the world's major airlines (17 Asian, 16 European) for the period 2007–2010. They found that Chinese and north Asian airlines were among the technically most efficient airlines worldwide; while in regard to environmental efficiency (considering CO_2-e as bad output) European airlines ranked the highest. Chang et al. (2014) employ an extended environmental slacks-based measure DEA model with the weak disposability assumption for 27 international airlines (eight Asian, eight European) in the year 2010 to identify their economic and environmental efficiency. Their findings suggest that Asian airlines are in general efficient, followed by European and American airlines. In their analysis, Chang et al. (2014) use fuel as input and CO_2-e emissions as output.[4] Cui and Li (2015) estimate the efficiency of 11 airlines (six Asian, three European) for the period 2008 to 2011 using the virtual frontier benevolent DEA cross-efficiency model (VFB-DEA). Their findings suggest that capital efficiency had an impact on energy efficiency, and that Asian

[4] It is worth emphasizing that there is a direct correlation, by a factor around 3, between fuel and CO2-e emissions which may render difficult the environmental efficiency estimation under the assumption of fixed levels of inputs.

airlines were the most energy inefficient and the Global Financial Crisis impacted negatively on their environmental performance. Similar to Chang et al. (2014), the latter study uses fuel as an input and CO_2-e emissions as an output. Wanke et al. (2015) show stagnated efficiency of 35 Asian airlines during the period 2006–2012. These two studies highlight the structural differences and relative maturity of the European and Asian aviation market, which this study investigates further.

In recent years, a new strand of the literature on airline performance has focused on the network DEA efficiency of companies. For instance, Mallikarjun (2015) has examined the efficiency of US airlines considering three different stages of production (operations, services and sales). This network scheme was extended to a virtual frontier network slack-based measure by Li et al. (2015) to evaluate energy efficiency of 22 international airlines. In terms of environmental impacts, Li et al. (2016a) considered the greenhouse gas emissions to evaluate the network efficiency of the inclusion of aviation into the EU ETS. Li et al. (2015 and 2016a) assumed both weak and strong disposability for analysing undesirable outputs, revealed that European airlines have a higher average efficiency than non-European airlines. Cui et al. (2016a) also conducted a similar exercise using a network range-adjusted measure assuming both strong and weak disposability for detrimental outputs (see also Li and Cui, 2017a). In the same vein, Cui and Li (2016) considered two stages in their network framework (the operations and carbon abatement stages) to examine the energy efficiency of 22 international airlines. Consistent with the previous network studies, Cui and Li (2016) found higher average efficiency for European airlines compared with non-European airlines.[5] Also very recently, Cui and Li (2017b; 2017c) and Li and Cui (2017b) employed different network models to predict the impact of the Carbon Neutral Growth from 2020 (CNG2020) strategy on airline efficiency performance.

A number of recent studies have also employed dynamic models to investigate the performance of international airlines. Li et al. (2016b) explored the energy efficiency of international airlines using a virtual frontier dynamic range-adjusted measure over the period from 2008 to 2012. Their model was based on the classic DEA models that treat capital stock as the dynamic factor or carryover effect. Wanke and Barros (2016) adopted the model introduced by Li et al. (2016b) to investigate efficiency of Latin American airlines. Cui et al. (2016b) use a virtual frontier dynamic slacks-based measure to estimate airline energy efficiency and discuss the impacts of some external factors. Cui et al. (2016c) then introduced

[5] See also Xu and Cui (2017) for a four-stage network analysis of 19 international airlines.

two dynamic environmental DEA models to analyse the effect of the emission limits on airline efficiency. Cui et al. (2016c) showed that the emission limits play a certain positive role in the sustainable growth of the large network carriers. Cui and Li (2017a) proposed a dynamic epsilon-based measure to evaluate efficiencies of 19 international airlines during 2009–2014. They found Scandinavian, Emirates and Cathay Pacific as the most efficient airlines among others.

Overall, the studies outlined here assume that airlines from different regions of the world share the same production technology and face similar environmental conditions. However, as mentioned previously in this paper, this may not be the case, and heterogeneous production technologies need to be properly taken into account. Therefore, to avoid this issue in our comparison of Asian and European airlines, we consider local frontiers and meta-frontiers. Further, this paper extends the literature treating CO_2 as a negative output. In his recent survey of alternative methodologies and empirical analyses for airline performance, Yu stated 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' (Yu, 2016: p.11). This paper builds upon this body of literature by offering additional insights on the inclusion of undesirable output in the efficiency measurement of airlines. For this aim, we also provide an extension of the by-production technology to the estimation of a non-concave meta-frontier.

3. Methodology

Since the seminal work of Farrell (1957) and the development of the distance function approach (Shephard, 1970), nonparametric DEA efficiency evaluation has required homogeneity in the decision-making units (DMUs) under evaluation (Charnes et al., 1978). However, the production units involved in a particular economic activity usually face different constraints and opportunities (different environmental characteristics) and hence adopt specific technology sets (Arjomandi et al., 2015; Salim et al., 2016; Thilakaweera et al., 2016; Le, et al.,2017). In such cases, measuring efficiency using predominantly exogenous environmental factors may result in inaccurate and misleading results (Daraio and Simar, 2007). To overcome this situation and obtain comparable technical inefficiencies, the meta-frontier developed by Battese and Rao (2002), and extended to the DEA case by O'Donnell et al. (2008), is used in this study.[6] We have extended this meta-frontier by incorporating the by-

[6] Although the concept of meta-production can be dated to the end of the 1970s, its introduction in performance evaluation is recent.

production technology, thereby accounting for the presence of undesirable outputs. To do this, we estimate different production frontier technologies relative to the homogeneous groups and then estimate an appropriate meta-technology that will envelop all the group-specific frontiers. An interesting feature is that to compare DMUs, inefficiencies can be decomposed into two components: the technology gap ratio and the group-specific technical inefficiency. The former captures the role of the environment on the production technology and then refers to the inefficiency relative to the best available technology,[7] and the latter is the traditional technical inefficiency measured in a particular group of DMUs.

Let x represent a vector of inputs ($x \in \mathbb{R}_+^P$) used to produce y and b, which are respectively a vector of good outputs ($y \in \mathbb{R}_+^S$) and a vector of bad outputs ($b \in \mathbb{R}_+^R$). Q denotes the number of total DMUs. The DMUs can be split into N homogeneous groups, each with $Q_1, \dots, Q_N$ DMUs. The technology of group k of firms can be represented by:

$$T_k = [(x, y, b) |\ x \text{ can produce } y \text{ and } b \text{ in group } k] \qquad (1)$$

The meta-technology can be expressed as:

$$T = [(x, y, b) |\ x \text{ can produce } y \text{ and } b \text{ for all the sample}] \qquad (2)$$

and $T = T_1 \cup \dots \cup T_N$.

As pointed out in Tiedemann et al. (2011), the common meta-technology estimated as a pooled of all technologies may provide erroneous results because of the presence of infeasible inputs–outputs bundles. This situation is depicted in Figure 1, where the meta-technology is estimated as if the DMUs formed a single group.

[7] Note that it is assumed that all the production entities have potential access to all the available technologies.

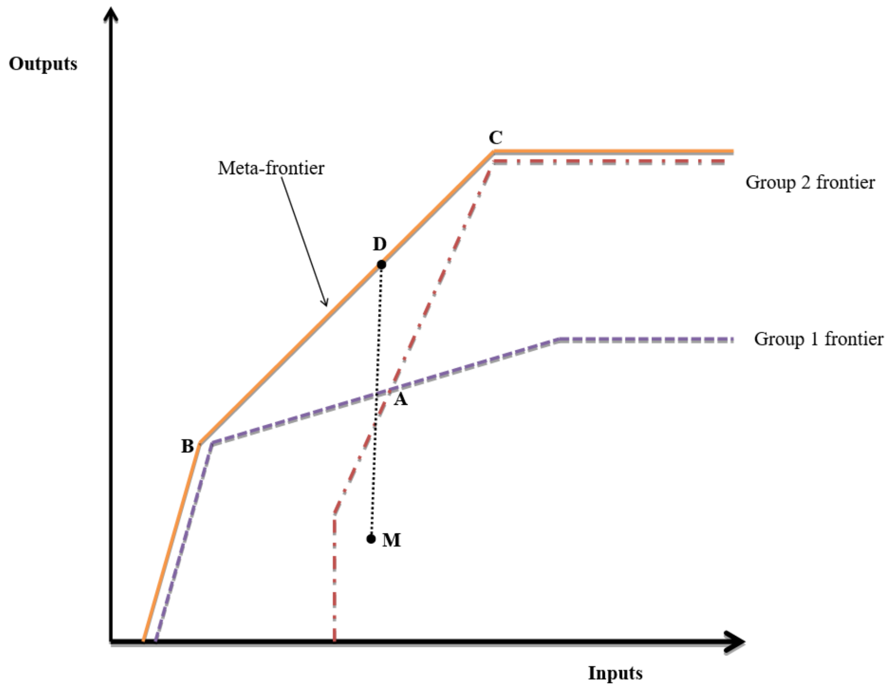

Figure 1: Concave meta-frontier adapted from Tiedemann et al. (2011, p. 578)

The infeasible sets of inputs–outputs combinations are represented by the triangle ABC, where no inputs or outputs are feasible by either the technology of the Group 1 or the technology of the Group 2. So, a chosen DMU_M is projected on the meta-frontier in point D, which is not accessible by any of the group specific technology. Tiedemann et al. (2011) refer to this situation as the concave meta-frontier; while Huang et al. (2010) propose the term 'pooling frontier'. Under this pooled technologies assumption, the production frontier is estimated for the specific group with respect to the regularity conditions. The proposed solution to overcome the weakness of the concave meta-frontier is to estimate a non-concave meta-technology, as sketched in Figure 2.

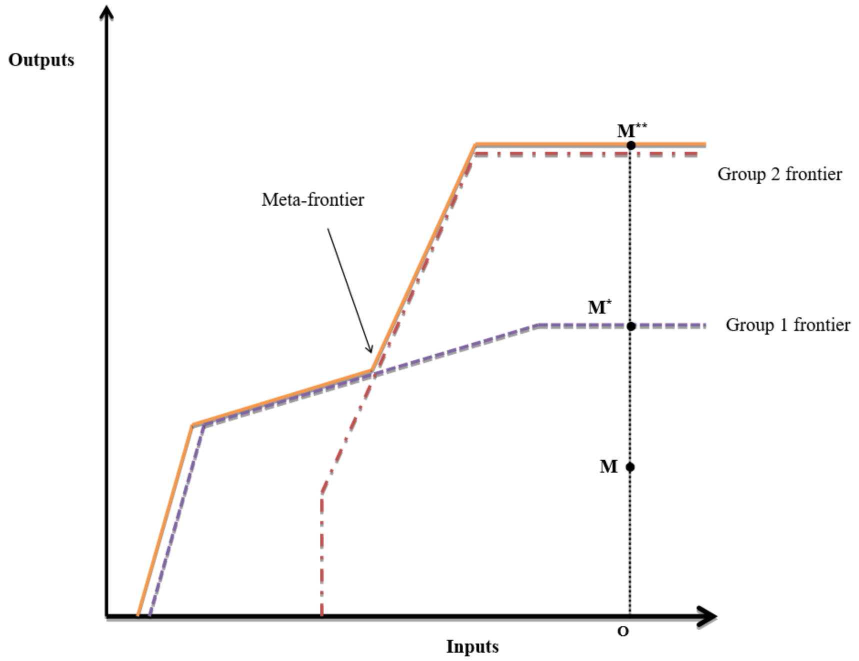

Figure 2: Non-concave meta-frontier, Tiedemann et al. (2011, p. 578)

Empirically, the solution resolves in a two-stage procedure: in a first step, the efficiency of the DMU M is estimated under its group frontier (let's assume this is Group 1). Its output technical efficiency equals $TE_1 = {}^{OM}/_{OM^*}$. Then, in a second stage, the efficiency is evaluated under an alternative technology (Group 2 frontier). The efficiency is computed as $TE_2 = {}^{OM}/_{OM^{**}}$. If $TE_2 < TE_1$, then the DMU M can still improve the optimal output level given the vector of inputs by the adoption of the best available technology in its production environment (the technology of Group 2). The meta-efficiency score is obtained by $TE_M = TE_2$. As previously mentioned, the meta-efficiency score can be decomposed into two parts: the technology gap ratio (TGR) and the group specific efficiency. Then, for the DMU M we have:

$$TE_M = TGR \times TE_1 \qquad (3)$$

The TGR therefore captures the potential efficiency improvement achievable by an airline evolving in a better environment. The group specific efficiency is related to the improvement within a homogeneous group of airlines. To go further, an extension which we term here as the 'mixed group efficiency' (MGE) has been proposed by De Witte and Marques (2009) to complete the TGR and give more insightful information. For the DMU M we have:

$$MGE = TE_M \times TE_1 \qquad (4)$$

This new ratio is a combination of a 'between' and a 'within' efficiency score (a mix of meta-frontier and group frontier efficiencies). MGE then measures an overall efficiency accounting for environmental or technology differences. As underlined in De Witte and Marques (2009), MGE will identify the degree of inefficiency if the group specific inefficiency is unchanged, and if airlines face a similar environment.

We have adapted all the above developments to the by-production approach of Murty et al. (2012).

The by-production meta-technology

Frisch (1965) provided some ideas on the representation of complex production system. According to Frisch, multi-output complex systems cannot be represented by a single functional form but by many relations linked together by what he called factor bands or product couplings. The factor bands sketch the relationships between inputs independently of outputs, while the product couplings describe relations between outputs independent from inputs. These ideas have recently been incorporated in new approaches to representing pollution-generating technologies in multi-equation modelling (Førsund, 2009; 2017). Here we combine the by-production approach developed by Murty et al. (2012) and the ideas discussed above to define a global technology that lies at the intersection of two sub-technologies: one for the production of good outputs and the other for the generation of bad outputs.

$$\mathrm{T} = T^g \cap T^b \qquad (5)$$

In the non-parametric framework of DEA the different sub-technologies can be represented under a variable returns-to-scale assumption as:[8]

[8] The returns-to-scale assumption is considered as many airlines do not operate at optimal scale and face regulations, imperfect competition and finance constraints. This assumption helps comparing operating firms of different sizes.

$$T^g = \left[(x,y,b) \in \mathbb{R}^{P+S+R} \mid \sum_{i=1}^{Q} \lambda_i x_i \leq x \, ; \, \sum_{i=1}^{Q} \lambda_i y_i \geq y \, ; \, \sum_{i=1}^{Q} \lambda_i = 1 \right] \qquad (6)$$

and

$$T^b = \left[(x,y,b) \in \mathbb{R}^{P+S+R} \mid \sum_{i=1}^{Q} \mu_i x_i \geq x \, ; \, \sum_{i=1}^{Q} \mu_i b_i \leq b \, ; \, \sum_{i=1}^{Q} \mu_i = 1 \right] \qquad (7)$$

The technologies in (6) and (7) describe the whole sample and they can be easily written for each specific group of DMUs.

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

$$\begin{aligned} \mathrm{T} = \Bigg[(x,y,b) \in \mathbb{R}^{P+S+R} \mid \sum_{i=1}^{Q} \lambda_i x_i \leq x \, ; \, \sum_{i=1}^{Q} \lambda_i y_i \geq y \, ; \, \sum_{i=1}^{Q} \lambda_i = 1 \, ; \sum_{i=1}^{Q} \mu_i x_i \\ \geq x \, ; \, \sum_{i=1}^{Q} \mu_i b_i \leq b \, ; \, \sum_{i=1}^{Q} \mu_i = 1 \Bigg] \end{aligned} \qquad (8)$$

In (8), the two sub-technologies are represented with two distinct intensity variables (λ, μ). In the good outputs sub-technology T^g, classic regularity conditions such as like the free disposability of inputs and outputs are imposed. However, under the bad outputs sub-technology T^b, the bad outputs satisfy the costly disposability assumption and the polluting inputs violate the free disposability assumption (Murty et al., 2012). Costly disposability implies that given a level of polluting inputs, there is a minimal level of pollution that can be generated, and the presence of technical inefficiencies can lead to the generation of higher levels of pollution.

Graphically, the good output frontier is concave while the bad output one is convex (see Figure 3). The form of this latter frontier systematically stems from the costly disposability assumption.[9] For an inefficient DMU_a, its corresponding dominating observations are

[9] On Figure 3, for simplicity, we have chosen to put the good output frontier above the bad output one.

obtained by a projection towards the north-west part of the frontier associated with the good outputs sub-technology (T^g). Under the bad outputs sub-technology (T^b), the projection is directed towards the south-east part of the frontier. Clearly under T^b the dominating observations of an inefficient observation use more inputs to generate less pollution, recalling Sueyoshi and Goto's (2012) 'managerial disposability', the ability of firms to increase inputs and simultaneously decrease their level of emissions. Such an outcome could only be feasible through managerial efforts or adaptive strategies to a political environment.[10] Intuitively, an increase in inputs may result in an increase of good outputs in line with the Porter hypothesis (Porter and van der Linde, 1995), however, this is beyond the scope of this paper.

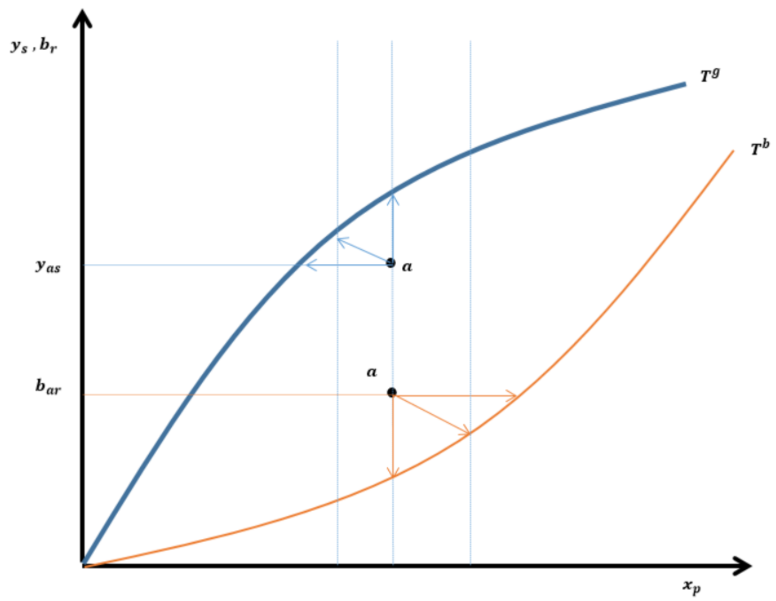

Figure 3: The by-production representation

Murty et al. (2012) suggest that an efficiency score (EFF_{by}) can be derived as an extension of the Russell index proposed by Färe and Lovell (1978):

$$EFF_{by}(x, y, b; \mathrm{T}) = \frac{1}{2}\min_{\theta,\omega}[\frac{\sum_s \theta_s}{S} + \frac{\sum_r \omega_r}{R} \mid (x, y \oslash \theta, \omega \otimes b) \in \mathrm{T}] \quad (9)$$

where $y \oslash \theta = (y_1/\theta_1, \dots, y_S/\theta_S)$ and $\omega \otimes b = (\omega_1 b_1, \dots, \omega_R b_R)$. θ_s is the efficiency score for good output s $(\theta \leq 1)$ i.e. the ratio of the observed good output to the maximum

10 Sueyoshi and Goto (2012) have also discussed the 'natural disposability' which corresponds to the situation where firms decrease their inputs in order to reduce pollution.

attainable good output, ω_r is the efficiency score for bad output r ($\omega \leq 1$) i.e. the ratio of the minimum attainable bad output to the observed bad output level, and T is the technology described in (8). Basically, if for instance $\theta_1 = 0.9$ this means that the evaluated observation is at 90% of the potential production of output 1, besides if $\omega_1 = 1.15$ then the evaluated firm generates 15% more bad output 1 yet it can offset this extra production without deteriorating the level of good outputs. The interpretation of θ_s and ω_r is similar for all the outputs. More simply equation (9) can be rewritten as follows:

$$EFF_{by}(x,y,b;\mathrm{T}) = \frac{1}{2}\min_{\theta}[\frac{\sum_s \theta_s}{S} \mid (x, y \oslash \theta, b) \in T^g] + \frac{1}{2}\min_{\omega}[\frac{\sum_r \omega_r}{R} \mid (x, y, \omega \otimes b) \in T^b] \tag{10}$$

$$EFF_{by}(x,y,b;\mathrm{T}) = \frac{1}{2}\left[EFF_{by}^{1}(x,y,b,T^g) + EFF_{by}^{2}(x,y,b,T^b)\right] = \frac{1}{2}\left[\beta_g + \beta_b\right] = \beta \tag{11}$$

β_g is the average good output efficiency score while β_b is the one corresponding to the generation of bad outputs $\left(\beta_g = \frac{\sum_s \theta_s}{S} \wedge \beta_b = \frac{\sum_r \omega_r}{R}\right)$. T^g and T^b represent the technologies described in (6) and (7), respectively.

Given the simplification of the efficiency computation as displayed in (11), where operational and environmental efficiencies are computed relative to their respective independent sub-technology, our meta-frontier expansion (contribution) can be easily implemented. For each sub-technology, we build a non-concave ‘meta-sub-frontier’ and for the global technology, we evaluate the performance as the arithmetic mean of two efficiency scores (as in (11)).

4. The data

To analyse airline efficiency it is essential to choose the most suitable combinations of both inputs and outputs. Differences such as Asian airlines’ comparatively lower labour expenses and lower tax and fuel expenses in the Middle East can result in different input units (Greer, 2009). Therefore, this study chose only physical measures as inputs and outputs. To ensure accuracy, we triangulated the input and output data provided by RDC Aviation (www.rdcaviation.com) and triangulated for accuracy with annual reports and other publicly-available resources. To further ensure homogeneity, we focus only on FSCs. Therefore, this sample comprises seven European FSCs (Lufthansa, British Airways, Air France, KLM Royal Dutch Airlines, Iberia, Virgin Atlantic Airways and Alitalia)[11] and fourteen Asian FSCs (Cathay Pacific Airways, Singapore Airlines, Korean Air, Air China, Thai Airways International, China Southern Airlines, China Airlines, China Eastern Airlines, Japan Airlines International, Eva Air, Asiana Airlines, All Nippon Airways, Malaysia Airlines and Air India) over the period 2007–2013. Here we include the largest full service airlines of each region; the meta-frontier analysis enables us to compare these companies irrespective of group size. With regard to the study period we choose to focus on the period 2007 to 2013 as year 2007 is before the mandatory inclusion of Airlines into the EU ETS in 2012 and even before the initial EU parliament conversation for including airlines in the ETS, in 2009. 2013 is the last year of the analysis, as 2014 saw the first commercial biofuel-powered flights (50 per cent biofuel and A1 jet fuel). This would need additional requirements on the model, while we were not able to access information on biofuel use of individual airlines.[12]

Our selected inputs and outputs have a strong foundation in the existing DEA airline efficiency and productivity literature (Arjomandi and Seufert, 2014; Barla and Perelman, 1989; Charnes et al., 1996; Greer, 2006; Inglada et al., 2006). This study employs labour and capital as major inputs and tonne kilometres available (TKA) and CO_2-e emissions as outputs (Table 1). Labour is measured as the number of full-time equivalent flight staff, such as pilots and flight attendants, who represent the major business function of an airline.[13] To measure capital we use Coelli et al's, (1999, p. 262) widely-applied definition: 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)'. This definition of capital prevents the inclusion of performance biases, which could arise from aircraft maintenance and other external factors. It has been used in several studies (e.g. Barla and Perelman, 1989; Coelli et al., 2002; Coelli et al., 1999; Ray, 2008) mainly because of the high degree of complementarity between fuel consumption and the capital (that is more than 0.95 in our case) and also when the consistency of fuel

[11] Turkish Airlines, even though geographically located in Europe, is not included in this study, as it is not a member of the EU and therefore not subject to the EU ETS.

[12] Also see recent study of Seufert et al. (2017) which highlights that it is meaningful to study the efficiencies of major international airlines during this period.

[13] See Coelli et al. (1999) and Greer (2008) for an in-depth explanation of this input.

consumption data is a concern (Coelli et al., 1999). 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, is used as the good output in this study. According to Barla and Perelman (1989), Coelli et al. (1999) and Inglada et al. (2006), TKA is not influenced by the efficiency of airline marketing and is a capacity indicator; therefore, TKA can be seen as a reliable output measure (Greer, 2009; Seufert et al., 2017).

Table 1. Descriptive statistics of the inputs and outputs over the period of study (2007-2013)

Variable	**Minimum**	**Maximum**	**Mean**	**Stand. Dev.**	**Relative Stand. Dev.**
ALL AIRLINES-147 observations					
The inputs					
Number of Employees	1.66	25.51	8.67	5.29	0.61
Capital	1.95	15.40	6.99	3.50	0.50
The outputs					
TKA	23.33	191.12	87.21	45.52	0.52
CO_2-e (undesirable output)	2.76	22.09	8.80	4.69	0.53
ASIAN AIRLINES-98 observations					
The inputs					
Number of Employees	1.66	19.02	7.37	3.85	0.52
Capital	2.17	13.69	6.10	2.65	0.43
The outputs					
TKA	26.37	175.89	74.52	33.88	0.45
CO_2-e (undesirable output)	2.76	13.10	7.40	3.01	0.41
EUROPEAN AIRLINES-49 observations					
The inputs					
Number of Employees	1.75	25.51	11.27	6.69	0.59
Capital	1.95	15.40	8.77	4.28	0.49
The outputs					
TKA	23.33	191.12	112.59	54.73	0.49
CO_2-e (undesirable output)	3.69	22.09	11.58	6.06	0.52

Notes: Number of employees is measured as full-time equivalent staff expressed in thousands. The presented values of number of employees are divided by 1000. 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}. CO_2-e represents the tonnes of Carbon Dioxide equivalent emitted by each airline for their flight business and is divided by 10^6.

With regard to CO_2-e, there are currently no economic viable alternatives to the combustion of aviation fuels. As CO_2-e emissions are a direct result of flight activities, CO_2-e is used here as a bad output in airline performance. The CO_2-e data from RDC is calculated based on airplanes' fuel consumption, the sectors served and the schedule of all flights from each airline. The modelled CO_2-e figures provide significant benefits over those figures from annual reports or other company-originated information: modelled data excludes exogenous factors such as pilots' choices in routes, weather impacts, taxing on crowded airports and so on, which could affect the CO_2-e emissions of a particular airline, but is out of its control. Also, a single data source is superior to separate data from each airline, as assumptions and measurements are unified and consistent. Descriptive statistics for all the inputs and outputs are given in Table 1. The figures in this table reveal that, based on the inputs and outputs, European airlines are larger businesses than Asian airlines.

5. Empirical results

Although the data covers a seven-year period from 2007 to 2013, the analyses have been conducted using a pooled frontier (that is, one frontier for the whole period). This means that we do not consider technological progress and all the changes that occur are attributed to technical efficiency alone. This stringent assumption was governed by the data size (seven European and 22 Asian airlines). Since DEA is a nonparametric approach, it has a very slow convergence rate and therefore is sensitive to the sample size and the dimension of the analysis (Daraio and Simar, 2007). We therefore choose to pool all the data to increase the discrimination power in our analysis. Our choice is also strengthen with the recent study of Lee et al. (2016) that also considered CO_2 emissions in a productivity decomposition of many international airlines.[14] They found technical change was statistically insignificant, and suggested that 'because airlines face high operational costs, there is very little incentive to upgrade technologies' (Lee et al., 2016, p. 14).

While it is of common practice to compare groups of different sizes in the meta-frontier framework (Du et al. 2014; Oh, 2010; Oh and Lee, 2010; Mulwa and Emrouznejad, 2013), Zhang et al. (1998) have argued that efficiency scores tend to be higher when the number of units is lower (see also Staat, 2001). Accordingly, one has to be careful when comparing average efficiencies of samples with different sizes. We have therefore estimated bias-corrected efficiency scores in this study which account for sampling variations (Simar and Wilson, 1998). For this purpose, we have adopted the sub-sampling technique discussed in Simar and Wilson (2011) which consists of drawing (with replacement) a sample of size $\mathrm{m} < \mathrm{Q}$ (where Q is the total sample size) and computing the whole sample's the efficiency score using the new benchmark (sample of size m). This process is conducted $\mathrm{B} = 2000$ times. Besides, several values of m are considered (from 5% to 95% of the total sample size

[14] Lee et al. (2016) have used the weak disposability assumption to treat undesirable outputs.

with a 5% step). To retain a specific value for each observation we minimized the volatility criteria (standard deviation) following Politis et al. (2001) and Bickel and Sakov (2008). Using sub-sampling may in some cases result in infeasibility in the efficiency score estimation as the evaluated observation may not be in the benchmark of size $m < Q$. Lee and Zhu (2012) and Lee et al. (2011) are followed in this study for correcting such infeasibilities.

Tables 2 to 5 report the bias-corrected good-output, bad-output, and by-production efficiencies for major Asian and European airlines. For the sake of saving space, bias-corrected efficiency estimates of only three individual years (2007, 2010 and 2013) for all airlines and mean efficiencies are presented in Tables 2 to 4 and in Table 5, respectively.[15] For each of the three measures, the following scores are also provided: meta-efficiencies (TE_M), group-specific efficiencies (TE1), efficiencies with reference to the other group (TE2), the technology gap ratios (TGR) and the mixed group efficiencies (MGE). In Tables 2 to 4, airlines in each group are ordered based on their capital size.

As mentioned earlier, the TE1 values show the relative efficiencies of individual airlines in comparison with their own group members. Thus, the results listed in TE1 columns of Tables 2 to 4 give us a general idea about the best and worst performers of each specific market based on by-production, good-output and bad-output technologies. In Europe, Air France and British Airways fall into the top three-most-efficient airlines class in most of the years in terms of their by-production efficiencies. Lufthansa and Alitalia were found to be in the class of the three least (by-production) efficient European airlines in at least six years between 2007 and 2013. In Asia, based on the similar criteria (number of years being among the top-three or the worst-three performers based on by-production efficiencies), Cathay Pacific Airways, Singapore Airlines and Air India can be seen as the most efficient airlines, and All Nippon Airways, Asiana Airlines and Japan Airlines International as the least efficient.

Columns named TE2 and TGR in Tables 2 to 4 show the efficiencies of individual airlines with reference to the other groups' technology and the technology gap ratios, respectively, as detailed in the methodology section. In the case of Asian airlines, almost all the TGRs equal unity (in all the years) indicating that some of the Asian airlines have technologically dominated the European airlines, and hence made the Asian group's technology a major part of the meta-frontier technology. Such airlines have TE2 values greater than unity: their efficiency values show that these airlines can decrease their output but still be efficient in comparison with the airlines in the technology reference group (namely European airlines).

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

For by-production technology, among the Asian airlines, Singapore Airlines, Eva Air, Air India and Asiana Airlines have TE2 efficiency scores greater than unity in most of the years when compared with the European airlines group's technology. In the European region, Air France and Lufthansa constantly demonstrate TE2 efficiencies greater than one. The remaining airlines (in both regions) with unity TGR but TE2 lower than one still have the potential to improve their outputs based on the inputs that they are using.

Table 5 reveals that Asian airlines outperformed European airlines on average, for good-output TE_M in all years except 2007. However, European airlines show higher means of bad-output TE_M and by-production TE_M between 2011 and 2013 in comparison with those of the Asian airlines.

Before reaching a conclusion about the differences in the results for Asian and European airlines, there are two points worth noting about the reasons why the European airlines are technologically dominated by some of Asian airlines. First, the heterogeneity in the business environments and regulatory policies for these two regions, may favour Asian airlines and not reflect airline management. As a result of the EU ETS, European airlines are economically more limited to an increase in their TKA while keeping their profitability. Second, unlike Asian airlines, European airlines face constraints on growth and efficiency gains due to limited airport capacities and congested airspace in Europe. Therefore, in order to avoid such heterogeneity issues, we estimate MGE to measure the overall efficiency of each individual airline, incorporating the explicit and implicit environmental characteristics.

The mean of the MGE results in Table 5 shows that European airlines were closer to the frontiers for good-output, bad-output and by-production efficiencies in all years (except 2007 for bad-output efficiency and 2013 for good-output efficiency). Table 5 also show that the gap between European and Asian mean group efficiencies (mean MGEs) becomes wider over time for bad-output and by-production efficiencies in favour of European airlines.

In the case of bad-output MGEs, the gaps are relatively larger than those of good-output and by-production MGEs, particularly in the period after 2009, indicating that European airlines have generally performed better than their Asian rivals in terms of minimising their CO_2-e/fuel consumption.

Table 2. Bias-corrected estimated by-production, good-output and bad-output efficiencies for the year 2007

	Good-output efficiency					Bad-output efficiency					By-production efficiency				
European Airlines	**TE_M**	**TE1**	**TE2**	**TGR**	**MGE**	**TE_M**	**TE1**	**TE2**	**TGR**	**MGE**	**TE_M**	**TE1**	**TE2**	**TGR**	**MGE**
Lufthansa	0.942	0.942	0.955	1.000	0.888	0.823	0.823	2.115	1.000	0.677	0.883	0.883	1.535	1.000	0.783
British Airways	0.967	0.967	1.018	1.000	0.934	0.780	0.780	1.969	1.000	0.608	0.873	0.873	1.494	1.000	0.771
Air France	0.919	0.954	0.919	0.963	0.877	0.822	0.822	1.977	1.000	0.676	0.871	0.888	1.448	0.981	0.777
KLM Royal Dutch Airlines	0.939	0.985	0.939	0.953	0.925	0.744	0.828	0.744	0.899	0.616	0.841	0.906	0.841	0.926	0.770
Iberia	0.881	0.915	0.881	0.963	0.806	0.662	0.740	0.662	0.896	0.490	0.772	0.827	0.772	0.929	0.648
Virgin Atlantic Airways	0.245	0.796	0.245	0.307	0.195	0.570	0.876	0.570	0.651	0.499	0.408	0.836	0.408	0.479	0.347
Alitalia	0.751	0.872	0.751	0.862	0.655	0.522	0.682	0.522	0.765	0.356	0.637	0.777	0.637	0.814	0.505
MEAN	0.806	0.919	0.815	0.864	0.754	0.703	0.793	1.223	0.887	0.560	0.755	0.856	1.019	0.876	0.657
Asian Airlines															
Cathay Pacific Airways	0.933	0.933	0.979	1.000	0.870	0.779	0.779	0.855	1.000	0.606	0.856	0.856	0.917	1.000	0.738
Singapore Airlines	0.986	0.986	1.014	1.000	0.972	0.816	0.816	0.969	1.000	0.666	0.901	0.901	0.992	1.000	0.819
Korean Air	0.915	0.915	0.949	1.000	0.837	0.514	0.514	0.638	1.000	0.265	0.715	0.715	0.793	1.000	0.551
Air China	0.854	0.854	0.880	1.000	0.729	0.625	0.625	0.740	1.000	0.391	0.740	0.740	0.810	1.000	0.560
Thai Airways International	0.907	0.907	0.959	1.000	0.822	0.614	0.614	0.714	1.000	0.377	0.760	0.760	0.837	1.000	0.600
China Southern Airlines	0.738	0.738	0.786	1.000	0.545	0.882	0.882	0.977	1.000	0.778	0.810	0.810	0.882	1.000	0.662
China Airlines	0.281	0.921	0.281	0.305	0.259	0.742	0.742	1.221	1.000	0.551	0.512	0.832	0.751	0.653	0.405
China Eastern Airlines	0.731	0.731	0.795	1.000	0.535	0.801	0.801	0.966	1.000	0.641	0.766	0.766	0.880	1.000	0.588
Japan Airlines International	0.818	0.818	0.864	1.000	0.669	0.828	0.828	0.928	1.000	0.686	0.823	0.823	0.896	1.000	0.677
Eva Air	0.995	0.995	2.339	1.000	0.990	0.959	0.959	1.388	1.000	0.919	0.977	0.977	1.863	1.000	0.954
Asiana Airlines	0.513	0.513	2.509	1.000	0.263	0.722	0.722	0.957	1.000	0.522	0.618	0.618	1.733	1.000	0.392
All Nippon Airways	0.703	0.703	0.768	1.000	0.494	0.600	0.600	0.736	1.000	0.360	0.651	0.651	0.752	1.000	0.427
Malaysia Airlines	0.923	0.923	0.957	1.000	0.852	0.926	0.926	1.281	1.000	0.857	0.925	0.925	1.119	1.000	0.855
Air India	0.221	0.221	2.056	1.000	0.049	0.882	0.882	1.387	1.000	0.778	0.551	0.551	1.721	1.000	0.413
MEAN	0.751	0.797	1.152	0.950	0.635	0.764	0.764	0.983	1.000	0.600	0.757	0.780	1.068	0.975	0.617

Table 3. Bias-corrected estimated by-production, good-output and bad-output efficiencies for the year 2010

	Good-output efficiency					Bad-output efficiency					By-production efficiency				
European Airlines	**TE_M**	**TE1**	**TE2**	**TGR**	**MGE**	**TE_M**	**TE1**	**TE2**	**TGR**	**MGE**	**TE_M**	**TE1**	**TE2**	**TGR**	**MGE**
Lufthansa	0.945	0.945	0.971	1.000	0.893	0.879	0.879	2.104	1.000	0.773	0.912	0.912	1.537	1.000	0.833
British Airways	0.981	0.999	0.981	0.981	0.980	0.224	0.902	0.224	0.248	0.202	0.602	0.950	0.602	0.615	0.591
Air France	0.925	0.955	0.925	0.968	0.883	0.905	0.905	1.874	1.000	0.820	0.915	0.930	1.399	0.984	0.852
KLM Royal Dutch Airlines	0.943	0.988	0.943	0.955	0.931	0.813	0.900	0.813	0.903	0.732	0.878	0.944	0.878	0.929	0.832
Iberia	0.909	0.939	0.909	0.968	0.853	0.818	0.920	0.818	0.889	0.752	0.863	0.929	0.863	0.929	0.803
Virgin Atlantic Airways	0.316	0.522	0.316	0.604	0.165	0.560	0.935	0.560	0.599	0.524	0.438	0.729	0.438	0.602	0.344
Alitalia	0.522	0.889	0.522	0.588	0.464	0.915	0.915	1.112	1.000	0.838	0.719	0.902	0.817	0.794	0.651
MEAN	0.791	0.891	0.795	0.866	0.739	0.731	0.908	1.072	0.806	0.663	0.761	0.900	0.934	0.836	0.701
Asian Airlines															
Cathay Pacific Airways	0.943	0.943	0.984	1.000	0.889	0.809	0.809	0.882	1.000	0.655	0.876	0.876	0.933	1.000	0.772
Singapore Airlines	0.995	0.995	1.023	1.000	0.991	0.861	0.861	0.989	1.000	0.741	0.928	0.928	1.006	1.000	0.866
Korean Air	0.916	0.916	0.959	1.000	0.838	0.582	0.582	0.674	1.000	0.339	0.749	0.749	0.817	1.000	0.589
Air China	0.841	0.841	0.871	1.000	0.708	0.616	0.616	0.662	1.000	0.380	0.729	0.729	0.766	1.000	0.544
Thai Airways International	0.926	0.926	0.955	1.000	0.858	0.567	0.567	0.711	1.000	0.321	0.746	0.746	0.833	1.000	0.590
China Southern Airlines	0.756	0.756	0.793	1.000	0.572	0.916	0.916	1.045	1.000	0.838	0.836	0.836	0.919	1.000	0.705
China Airlines	0.904	0.904	2.043	1.000	0.818	0.729	0.729	1.117	1.000	0.532	0.817	0.817	1.580	1.000	0.675
China Eastern Airlines	0.734	0.734	0.782	1.000	0.539	0.864	0.864	0.995	1.000	0.747	0.799	0.799	0.888	1.000	0.643
Japan Airlines International	0.756	0.756	0.825	1.000	0.572	0.630	0.630	0.764	1.000	0.397	0.693	0.693	0.794	1.000	0.484
Eva Air	0.804	0.804	2.445	1.000	0.646	0.897	0.897	1.255	1.000	0.805	0.850	0.850	1.850	1.000	0.726
Asiana Airlines	0.882	0.882	2.299	1.000	0.778	0.736	0.736	0.995	1.000	0.541	0.809	0.809	1.647	1.000	0.660
All Nippon Airways	0.692	0.692	0.759	1.000	0.479	0.677	0.677	0.791	1.000	0.459	0.685	0.685	0.775	1.000	0.469
Malaysia Airlines	0.862	0.862	0.941	1.000	0.744	0.555	0.555	0.899	1.000	0.308	0.709	0.709	0.920	1.000	0.526
Air India	0.870	0.870	1.009	1.000	0.757	0.929	0.929	1.516	1.000	0.863	0.899	0.899	1.262	1.000	0.810
MEAN	0.849	0.849	1.192	1.000	0.728	0.741	0.741	0.950	1.000	0.566	0.795	0.795	1.071	1.000	0.647

Table 4. Bias-corrected estimated by-production, good-output and bad-output efficiencies for the year 2013

	Good-output efficiency					Bad-output efficiency					By-production efficiency				
European Airlines	**TE_M**	**TE1**	**TE2**	**TGR**	**MGE**	**TE_M**	**TE1**	**TE2**	**TGR**	**MGE**	**TE_M**	**TE1**	**TE2**	**TGR**	**MGE**
Lufthansa	0.969	0.969	1.024	1.000	0.939	0.506	0.506	2.231	1.000	0.256	0.738	0.738	1.628	1.000	0.598
British Airways	0.944	0.944	0.978	1.000	0.891	0.940	0.940	2.026	1.000	0.884	0.942	0.942	1.502	1.000	0.888
Air France	0.935	0.939	0.935	0.995	0.878	0.990	0.990	2.037	1.000	0.979	0.962	0.965	1.486	0.998	0.929
KLM Royal Dutch Airlines	0.904	0.943	0.904	0.959	0.852	0.827	0.907	0.827	0.912	0.751	0.865	0.925	0.865	0.935	0.801
Iberia	0.845	0.897	0.845	0.942	0.759	0.695	0.922	0.695	0.753	0.641	0.770	0.910	0.770	0.848	0.700
Virgin Atlantic Airways	0.219	0.821	0.219	0.267	0.180	0.608	0.950	0.608	0.641	0.578	0.414	0.885	0.414	0.454	0.379
Alitalia	0.478	0.478	2.063	1.000	0.228	0.907	0.932	0.907	0.973	0.845	0.692	0.705	1.485	0.987	0.536
MEAN	0.756	0.856	0.995	0.880	0.675	0.782	0.878	1.333	0.897	0.705	0.769	0.867	1.164	0.889	0.690
Asian Airlines															
Cathay Pacific Airways	0.896	0.896	0.922	1.000	0.804	0.939	0.939	1.059	1.000	0.882	0.918	0.918	0.990	1.000	0.843
Singapore Airlines	0.981	0.981	0.990	1.000	0.962	0.548	0.548	1.313	1.000	0.300	0.764	0.764	1.152	1.000	0.631
Korean Air	0.893	0.893	0.932	1.000	0.797	0.761	0.761	0.819	1.000	0.579	0.827	0.827	0.876	1.000	0.688
Air China	0.772	0.772	0.805	1.000	0.596	0.699	0.699	0.782	1.000	0.489	0.736	0.736	0.793	1.000	0.542
Thai Airways International	0.886	0.886	0.913	1.000	0.785	0.658	0.658	0.738	1.000	0.433	0.772	0.772	0.826	1.000	0.609
China Southern Airlines	0.756	0.756	0.779	1.000	0.572	0.464	0.464	1.022	1.000	0.216	0.610	0.610	0.900	1.000	0.394
China Airlines	0.827	0.827	0.884	1.000	0.684	0.629	0.629	1.113	1.000	0.395	0.728	0.728	0.999	1.000	0.540
China Eastern Airlines	0.739	0.739	0.769	1.000	0.546	0.875	0.875	0.939	1.000	0.765	0.807	0.807	0.854	1.000	0.656
Japan Airlines International	0.774	0.774	0.842	1.000	0.599	0.607	0.607	0.727	1.000	0.368	0.690	0.690	0.784	1.000	0.484
Eva Air	0.872	0.872	2.081	1.000	0.761	0.784	0.784	1.194	1.000	0.615	0.828	0.828	1.638	1.000	0.688
Asiana Airlines	0.780	0.780	0.798	1.000	0.608	0.605	0.605	0.973	1.000	0.367	0.693	0.693	0.886	1.000	0.487
All Nippon Airways	0.793	0.793	0.841	1.000	0.628	0.701	0.701	0.806	1.000	0.491	0.747	0.747	0.824	1.000	0.560
Malaysia Airlines	0.951	0.951	1.128	1.000	0.905	0.494	0.494	0.772	1.000	0.244	0.723	0.723	0.950	1.000	0.574
Air India	0.789	0.789	0.868	1.000	0.623	0.989	0.989	1.218	1.000	0.977	0.889	0.889	1.043	1.000	0.800
MEAN	0.836	0.836	0.968	1.000	0.705	0.697	0.697	0.963	1.000	0.509	0.767	0.767	0.965	1.000	0.607

Another finding based on the (by-production) MGE results is that the proportion of the European airlines among the five best performers generally increases over time (Tables 2 and 4). In 2007, two European airlines can be found among the top five most efficient airlines, but this number rises to three in 2008 to 2010 and to four in the years 2011 to 2013. That is, in the period 2011–2013, based on the by-production MGE estimates 80 per cent of the top five performers were European airlines.

With regard to the most efficient and inefficient individual airlines, by-production mixed group efficiencies show that the following airlines were among the five most efficient airlines in at least four of the studied years (out of seven years): British Airways, Air France, Air India, KLM Royal Dutch Airlines, Lufthansa and Singapore Airlines. On the other hand, the following airlines were found to be among the five least efficient airlines in at least four years: All Nippon Airways, Asiana Airlines, Japan Airlines International and Virgin Atlantic Airways. Between 2007 and 2013, the good-output and bad-output MGE values of individual airlines also show European airlines outperformed Asian airlines. For instance, the bad-output mixed group values presented in Tables 2 to 4 show that at most one European airline can be seen among the five least inefficient airlines in years 2007 and 2013. This airline was in fact Virgin Atlantic Airways that showed the lowest efficiencies in all three measures and also the least MGE scores in all years.

To provide more insights into the differences between groups' efficiencies, we have also displayed density distributions (Figures 4 to 6) and presented Kolmogorov Smirnov and Mann-Whitney test results (Table 6). The bias-corrected efficiency scores are used in these tests. Table 6 shows that there is a significant difference between Asian and European airline efficiency distributions, and, Figures 4 to 6 reveal that European airlines have considerably better access to the frontiers in all the efficiency types as they show higher concentrations close to unity. The high-density tail of European density distributions is mainly due to the poor performance of Virgin Atlantic Airways. As a robustness check, we have performed the Li (1996) test which is adapted for DEA by Simar and Zelenyuk (2006), to test whether the density distributions of the two airline groups are different. For the bootstrap procedure we considered $B = 2000$ iterations. Since the by-production is a multi-technology framework and following Dakpo et al. (2017), the convergence rate retained for the test is the smallest of all the technologies. The results of the test for the meta-technologies (Table 6) also reveal significant differences between Asian and European airlines.

Table 5. Means of bias-corrected by-production, good-output and bad-output efficiencies for Asian and European airlines, 2007–2013

	Good-output efficiency					Bad-output efficiency					By-production efficiency				
	TE_M	**TE1**	**TE2**	**TGR**	**MGE**	**TE_M**	**TE1**	**TE2**	**TGR**	**MGE**	**TE_M**	**TE1**	**TE2**	**TGR**	**MGE**
European Airlines															
2007	0.806	0.919	0.815	0.864	0.754	0.703	0.793	1.223	0.887	0.560	0.755	0.856	1.019	0.876	0.657
2008	0.827	0.959	0.832	0.866	0.790	0.771	0.835	1.259	0.926	0.643	0.799	0.897	1.045	0.896	0.717
2009	0.792	0.892	0.795	0.860	0.739	0.741	0.903	1.063	0.820	0.670	0.766	0.897	0.929	0.840	0.705
2010	0.791	0.891	0.795	0.866	0.739	0.731	0.908	1.072	0.806	0.663	0.761	0.900	0.934	0.836	0.701
2011	0.782	0.929	0.796	0.832	0.736	0.813	0.870	1.350	0.939	0.722	0.798	0.900	1.073	0.886	0.729
2012	0.780	0.875	1.009	0.899	0.703	0.823	0.889	1.361	0.929	0.740	0.802	0.882	1.185	0.914	0.722
2013	0.756	0.856	0.995	0.880	0.675	0.782	0.878	1.333	0.897	0.705	0.769	0.867	1.164	0.889	0.690
Asian Airlines															
2007	0.751	0.797	1.152	0.950	0.635	0.764	0.764	0.983	1.000	0.600	0.757	0.780	1.068	0.975	0.617
2008	0.839	0.839	1.197	1.000	0.716	0.769	0.769	1.000	1.000	0.608	0.804	0.804	1.099	1.000	0.662
2009	0.815	0.815	1.198	1.000	0.682	0.744	0.744	0.961	1.000	0.573	0.779	0.779	1.080	1.000	0.627
2010	0.849	0.849	1.192	1.000	0.728	0.741	0.741	0.950	1.000	0.566	0.795	0.795	1.071	1.000	0.647
2011	0.791	0.827	1.015	0.957	0.659	0.751	0.751	0.962	1.000	0.576	0.771	0.789	0.989	0.978	0.618
2012	0.828	0.828	1.045	1.000	0.690	0.715	0.715	0.976	1.000	0.524	0.771	0.771	1.010	1.000	0.607
2013	0.836	0.836	0.968	1.000	0.705	0.697	0.697	0.963	1.000	0.509	0.767	0.767	0.965	1.000	0.607

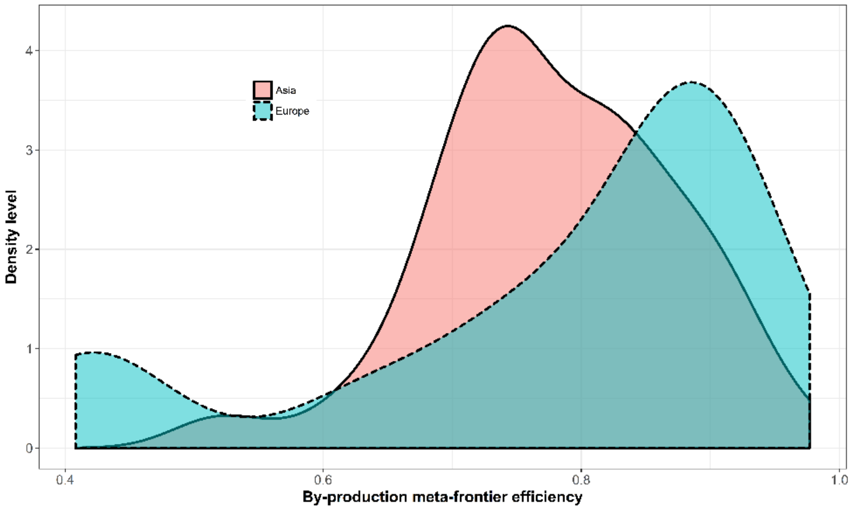

Figure 4: By-production meta-frontier efficiency distributions comparison between Asian and European airlines

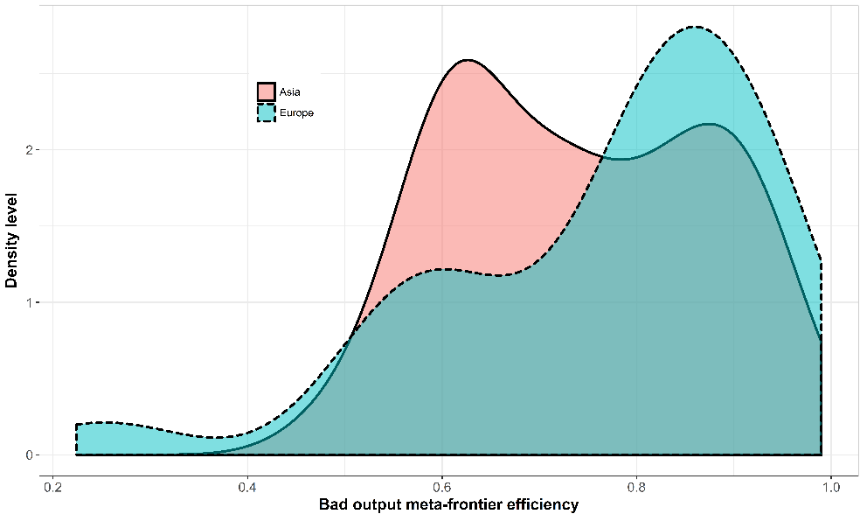

Figure 5: Bad-output meta-frontier efficiency distributions comparison between Asian and European airlines

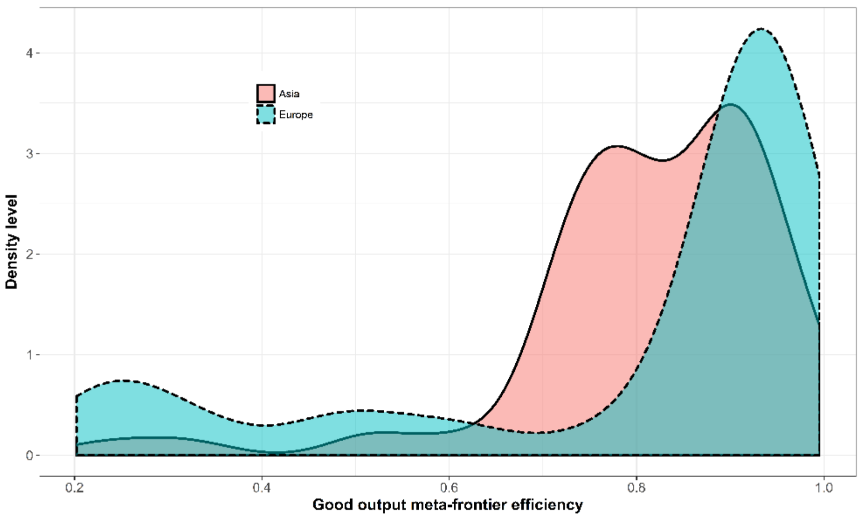

Figure 6: good-output meta-frontier efficiency distributions comparison between Asian and European airlines

Table 6. Kolmogorov Smirnov, Mann-Whitney, and Li test estimates on differences between regions' efficiencies

	Good-output meta-frontier efficiency (H0: Asia's meta-frontier efficiency is stochastically larger than that of Europe)		**Bad-output meta-frontier efficiency (H0: Asia's meta-frontier efficiency is stochastically larger than that of Europe)**		**By-production meta-frontier efficiency (H0: Asia's meta-frontier efficiency is stochastically larger than that of Europe)**	
	Test stat.	*p*-value	Test stat.	*p*-value	Test stat.	*p*-value
Kolmogorov Smirnov	D = 0.34694	0.0003844	D = 0.23469	0.02736	D = 0.31633	0.001448
Mann-Whitney	W = 1858	0.0129	W = 2021.5	0.05969	W = 1947	0.03119
Li test	Tn = 7.949	<2.22 e-16	Tn = 1.921	0.0255	Tn = 6.350	<2.22 e-16
Conclusion	*European airlines have better access to the frontiers*		*European airlines have better access to the frontiers*		*European airlines have better access to the frontiers*	
	Good-output technology gap (H0: Asia's technology gap is stochastically larger than that of Europe)		**Bad-output technology gap (H0: Asia's technology gap is stochastically larger than that of Europe)**		**By-production technology gap (H0: Asia's technology gap is stochastically larger than that of Europe)**	
	Test stat.	*p*-value	Test stat.	*p*-value	Test stat.	*p*-value
Kolmogorov Smirnov	D = 0	1	D = 0	1	D = 0	1
Mann-Whitney	W = 3992	1	W = 3577	1	W = 4097	<1
Conclusion	*Asian airlines have access to better technology*		*Asian airlines have access to better technology*		*Asian airlines have access to better technology*	
	Good-output mixed group efficiency (H0: Asia's MGE is stochastically larger than that of Europe)		**Bad-output mixed group efficiency (H0: Asia's MGE is stochastically larger than that of Europe)**		**By-production mixed group efficiency (H0: Asia's MGE is stochastically larger than that of Europe)**	
	Test stat.	*p*-value	Test stat.	*p*-value	Test stat.	*p*-value
Kolmogorov Smirnov	D = 0.41837	1.081e-5	D = 0.32653	0.0009434	D = 0.38776	5.418e-5
Mann-Whitney	W = 1675	0.001436	W = 1651.5	0.001043	W = 1604.5	0.00536
Li test	Tn = 10.56088	<2.22 e-16	Tn = 4.556393	<2.22 e-16	Tn = 7.877276	2.22 e-16
Conclusion	*European airlines are more efficient*		*European airlines are more efficient*		*European airlines are more efficient*	

6. Conclusion

This study provides an extension of the by-production approach developed in Murty et al. (2012) to account for group heterogeneity. To this aim, our extension deals with the estimation of a non-concave meta-frontier to overcome a weakness of the classic meta-frontier, where some parts of the global technology are not reachable by either of the group technologies involved (Tiedemann et al., 2011). The method has allowed us to obtain more detailed and sophisticated insights into the efficiency of European and Asian airlines compared with those of previous studies. The findings suggest that European airlines have put an increasing focus on environmental efficiency (and perhaps the greening) of their flight activities following the threat to include airlines in the EU ETS in 2009. The decomposition of efficiency factors provides a clear picture of EU airlines steadily improving their environmental efficiency, with some EU airlines leading within their own group and also in comparison to the group of Asian airlines. Such airlines can be seen as setting a performance benchmark for those that need to improve their performance by emulating peer airlines, though, they may be lacking a learning curve to emulate (Wanke and Barros, 2016). However, some Asian airlines also constituted a major part of the meta-frontier due to possible advantages in their aviation business environments. For instance, a number of major airports in Europe are already highly congested with scarcity of further time slots to land, and some were forced to implement night flight bans (for example, in Frankfurt Airport no flight is allowed to land between 11.00 pm and 5.00 am), and geographically, Europe's airspace is smaller than that in Asia. Additionally, landing fees in Europe are comparatively high, which adds a very economic dimension to the decision to increase TKA; while in Asia (and especially in China) these fees are relatively lower, allowing airlines to fly more frequently with a lower load factor, but still allowing them to be economically viable. Our results also reveal that European airlines have improved not only their environmental efficiency but also their good output efficiency compared with Asian airlines. These results may fit a version of Porter's hypothesis that environmental regulation may have a positive effect on the international competitiveness of European airlines.

Although most recent airline performance benchmarking literature adopts the network approach, our paper focusses on a single stage of production (i.e. operations) which captures the technological capabilities of companies (supply capacity) without assuming any behavioural assumptions such as cost minimization or profit maximization. This stage is a crucial part of the production network system and can directly be affected by the inclusion of

CO_2 emissions. As underlined in Mallikarjun (2015), all other stages of the airline network system involve some revenue generation or profit maximization activities. Nevertheless, the model developed here can be extended to the network framework of airline companies. Another extension could be the inclusion of the dynamic aspect which we have not accounted for in this paper due to lack of access to data on investment and capital depreciation variables. Depending on data availability, both network and dynamic approaches are interesting leads for future research. In addition, while this study provides novel insights into the efficiency of European and Asian airlines, a cost-efficiency analysis could also add another layer to our understanding of environmental efficiency and its determinants. However, such a study would have to deal with significant challenges of differing price levels on inputs and measurement issues on outputs.

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