Lee, Boon L., Wilson, Clevo, & Pasurka, Jr., Carl A. (2013) *The Good, the Bad and the Efficient : Productivity, efficiency and technical change in the Airline Industry, 2004:2008.* QUT Business School, Brisbane, Australia. [Working Paper]

The Good, the Bad and the Efficient: Productivity, efficiency and technical change in the Airline Industry, 2004-2008

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Any errors, opinions, or conclusions are the authors' and should not be attributed to the U.S. Environmental Protection Agency. The authors would also like to thank the National Library Board of Singapore for their assistance in data retrieval.

Abstract

This study models the joint production of desirable and undesirable output production (that is, CO_2 emissions) of airlines. The Malmquist-Luenberger productivity index is employed to measure productivity growth when undesirable output production is regulated and unregulated. The results show that pollution abatement activities of airlines lowers productivity growth which suggests the traditional approach of measuring productivity growth, which ignores CO_2 emissions, overstate "true" productivity growth.

KEYWORDS: Malmquist-Luenberger; pollution abatement; undesirable output; CO_2; efficiency; technical change; efficiency change.

JEL CLASSIFICATION: C43; D24; L93; Q50

1.0 Introduction

The past decade has seen major steps taken by airlines to reduce carbon emissions by making fuel consumption more efficient. These attempts, largely driven by commercial interests, include collaboration between aircraft and engine manufacturers to develop and adopt innovative technologies and high performing products in order to make airlines more efficient, cost-effective and environmentally friendly. While aircraft have become more environmentally friendly, the question is have the efforts that have been spent on such improvements actually raised the efficiency and performance of airlines over time?

Airline efficiency studies in the past have employed widely accepted methods such as Data Envelopment Analysis (DEA) or Stochastic Frontier Analysis (SFA). Such studies include Adler and Golany (2001), Alam *et al.* (2001), Banker and Johnston (1994), Barbot *et al*. (2008), Barros and Peypoch (2009), Bhadra (2009), Semenick and Sickles (1998), Coelli *et al*. (1999), Distexhe and Perelman (1994), Färe *et al*. (2007), Gillen and Lall (1997), Good *et al*. (1993), Good *et al*. (1995), Greer (2006, 2008), Inglada *et al*. (2006), Ouellette *et al*. (2010), Scheraga (2004), Sickles *et al*. (2002) and Tofallis (1997). However, these studies do not take into account undesirable outputs such as carbon dioxide (CO_2) and nitrogen oxide (NOx) emissions that are inherent to airline operations. The production of desirable outputs, such as tonne kilometres performed, almost inevitably result in the generation of pollution (that is, an undesirable output). The fact that desirable and undesirable outputs are jointly produced implies that it is costly to reduce the undesirable outputs that are generated since reducing the undesirable outputs would require re-allocation of existing resources. This is not only costly, but it is likely to reduce the production of desirable outputs given a fixed level of inputs. Furthermore, traditional measures of productivity have thus far ignored the output of pollution abatement activities because typically no market prices are available for these undesirable outputs. As such, productivity indices that ignore reductions in undesirable outputs provide an incomplete and incorrect picture of a firm's true productivity growth. Therefore, in this paper we use airline data to model the joint production of desirable and undesirable output production and to calculate productivity growth when undesirable output production is regulated and when it is not regulated.

To measure the 'pollution internalised' performance of airlines, this study adopts the Malmquist-Luenberger (ML) productivity index developed by Chung *et al*. (1997). The ML productivity index is a nonparametric linear programming model that estimates the directional distance function and allows for the inclusion of undesirable outputs (pollution) without requiring information on shadow prices. Chung *et al*. (1997) who examined the case of Swedish paper and pulp mills credits a firm for simultaneously reducing production of the undesirable output and increasing production of the desirable output. This is an indication to firms as to whether their productivity has improved over time after internalising pollution. Since the Chung et al. (1997) study, the ML approach has gained popularity and been employed in numerous studies using country, regional, industry, and plant-level data. At the macro level, Jeon and Sickles (2004) investigated productivity change when CO_2 emissions were taken into account in selected OECD and Asian countries. Zofio and Prieto (2001) applied similar efficiency measures on OECD countries. Oh and Heshmati (2010) employed a sequential ML approach on 26 OECD countries for the period 1970-2003 while incorporating CO_2 as the undesirable output. At the regional level, Weber and Domazlicky (2001) and Färe *et al*. (2001) applied similar efficiency measures considering pollution for US state manufacturing. Zhang *et al*. (2011)

evaluated China's TFP growth using a sample size of thirty provincial regions and incorporating a weighted environmental factor as the undesirable output for the period 1989 to 2008. In similar fashion, Zhao (2012) compared TFP growth with CO_2 emissions as undesirable output across 28 districts of China between 1995 and 2007. Yu *et al*. (2008) employed micro data to study four airports of Taiwan for the period 1995 to 1999 with aircraft noise as the undesirable output. In Zhou *et al*. (2008), one-hundred studies on energy and environment based on DEA was also surveyed. However, as far as the authors can determine, no previous study of the airline industry has incorporated undesirable outputs into its measure of productivity change. We believe this is a more accurate measure of airline efficiency and productivity growth, and that our findings have important implications for airlines if CO_2 emissions are regulated in the future. In our paper, we construct production possibilities frontiers for twenty-two airlines for each year for the period, 2004-2008. Each airline is then compared to its best-practice frontier. Shifts in the frontier reflect technical change and movements toward the best-practice frontier reflect that an airline is catching-up to the frontier (that is, increased technical efficiency). The product of technical and efficiency change components yield the ML productivity change.

The objectives of the paper are two-fold. First, we compare and contrast the results of the productivity index under regulated and unregulated production technology.[1] The second objective is to compare the productivity levels of airlines over the study period 2004-2008, during which more airlines began focusing on reducing carbon emission either though the use of new technologies and/or adoption of new operational and management procedures that reduce carbon emissions.

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[1] The regulated production technology assumes that it is costly to dispose of the undesirable by-products, while the unregulated technology models the case when an airline is free to ignore its generation of undesirable by-products.

The structure of the paper is as follows. Section 2 describes the ML productivity index employed in this paper, while Section 3 contains a description of the data specifications. The results are discussed in Section 4 and Section 5 provides some conclusions and suggestions for further research.

2.0 Methodology: Malmquist–Luenberger Productivity Index

We model the joint production of desirable and undesirable outputs by specifying an environmental technology (see Färe et al. 2007a). This environmental technology is modelled by its output set, P(x). Three standard axioms are required to specify the technology: (1) inactivity is always possible, (2) finite inputs can only produce finite outputs, and (3) inputs are freely disposable. These standard axioms are supplemented by two environmental axioms: (1) weak disposability of outputs and (2) null-jointness. Our model assumes the desirable and undesirable outputs are jointly weakly disposable, while the desirable output is freely disposable. Weak disposability allow us reduce the desirable and undesirable outputs by identical proportions, while null-jointness assumes that production of the desirable output must be accompanied by the production of undesirable outputs. The environmental technology is depicted in Figure 1.

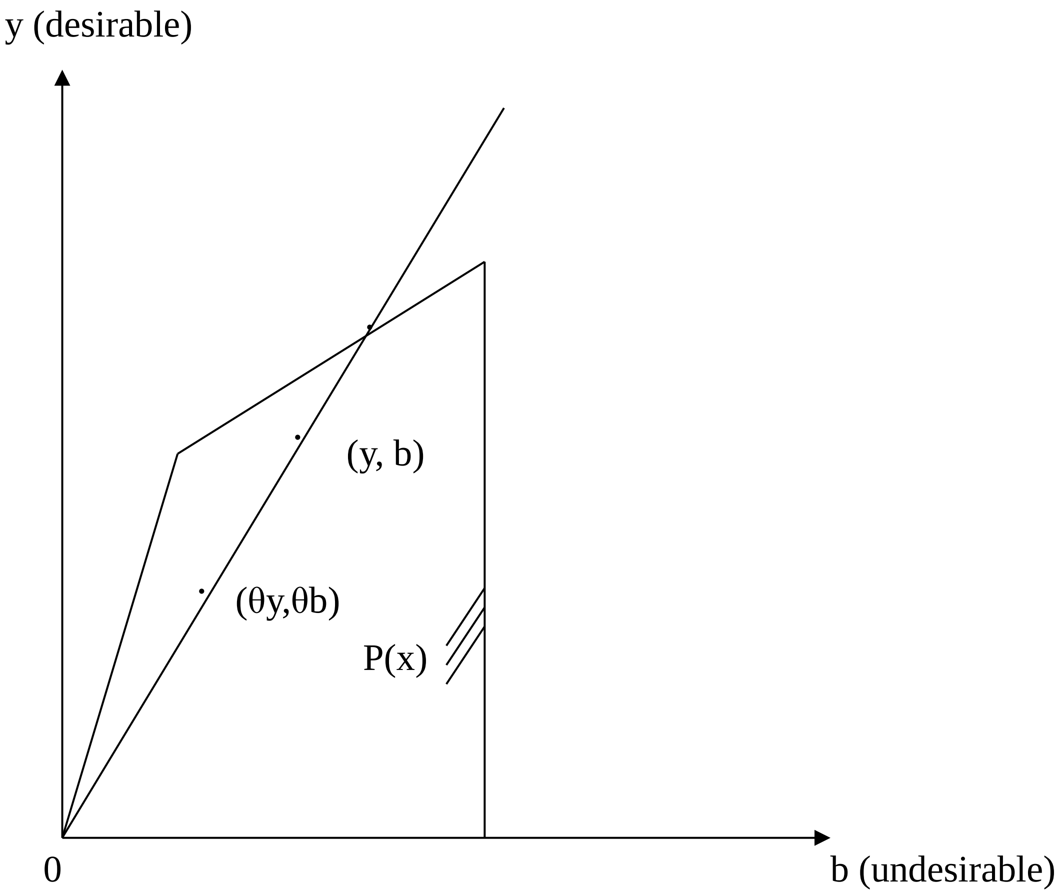

Figure 1. The Environmental Technology

In order to measure productivity change, technical change, and changes in technical efficiency, it is necessary to allow for shifts in the production frontier. To accomplish this task, our paper employs the output-oriented ML productivity index which is based on directional distance functions. The directional output distance function for time period t is defined as:

$$\vec{D}_o^t(x^t, y^t, b^t; g) = \sup[\beta(y^t, b^t) + \beta g \in P^t(x^t)] \tag{1}$$

where "g" is the direction vector in which outputs are scaled. In the case of airline services, g = (y^t, -b^t), the production of desirable outputs y (i.e., passenger and/or cargo carried) is increased, while undesirable output -b (i.e., CO_2) is decreased.[2] The directional distance function can thus be expressed as $\vec{D}_0^t(x^t, y^y, b^t; y^t, -b^t) \geq 0$ where a value of zero indicates the observation is technically efficient (i.e., is on the production frontier) and a value greater than zero indicates the observation is technically inefficient (i.e., it can simultaneously increase good output production and reduce bad output production). Furthermore, β is the maximum feasible expansion of desirable outputs and contraction of the undesirable outputs when the expansion and contraction are identical proportions for a given level of inputs. Since the theoretical framework behind the ML index is lengthy, for the sake of brevity we direct readers to studies such as Chung *et al*. (1997), Färe *et al*. (2001), Kumar (2006) and Färe *et al*. (2007).

The directional distance function expressed in (1) measures the efficiency of observations at time t based on the technology at time t. We operationalise our ML productivity index by defining two additional directional distance functions. The second directional distance function is a variation of equation (1) in which the technology and observation being evaluated are both from period t+1. The third directional distance function is a mixed period problem in which the technology is from period t+1 and the observation being evaluated is from period t. The mixed period problem allows us to measure shifts in the production frontier. Having defined the directional distance functions, the ML index of productivity between period t and t+1 is:

$$ML_t^{t+1} = \left[1 + \vec{D}_0^{t+1}\,(x^t, y^t, b^t; y^t, -b^t)\right] \Big/ \left[1 + \vec{D}_0^{t+1}\,(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1})\right] \qquad (2)$$

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[2] Detailed comparison of Shepherd's output distance function and Chung, Färe, Grosskopf directional distance function can be found in Chung *et al*. (1997).

Like the Malmquist index, the ML index can also be decomposed into changes in efficiency change (MLEFFCH) and technical change (MLTECH). This can be written as follows:

$$\mathrm{MLEFFCH}_{\mathrm{t}}^{\mathrm{t+1}} = \left[1 + \vec{\mathrm{D}}_0^{\mathrm{t}}\ (\mathrm{x}^{\mathrm{t}}, \mathrm{y}^{\mathrm{t}}, \mathrm{b}^{\mathrm{t}}; \mathrm{y}^{\mathrm{t}}, -\mathrm{b}^{\mathrm{t}})\right] / \left[1 + \vec{\mathrm{D}}_0^{\mathrm{t+1}}\ (\mathrm{x}^{\mathrm{t+1}}, \mathrm{y}^{\mathrm{t+1}}, \mathrm{b}^{\mathrm{t+1}}; \mathrm{y}^{\mathrm{t+1}}, -\mathrm{b}^{\mathrm{t+1}})\right] \quad (3)$$

$$\mathrm{MLTECH}_{\mathrm{t}}^{\mathrm{t+1}} = \left[1 + \vec{\mathrm{D}}_0^{\mathrm{t+1}}\ \left(\mathrm{x}^{\mathrm{t}}, \mathrm{y}^{\mathrm{t}}, \mathrm{b}^{\mathrm{t}}; \mathrm{y}^{\mathrm{t}}, \text{-}\mathrm{b}^{\mathrm{t}}\right)\right] / \left[1 + \vec{\mathrm{D}}_0^{\mathrm{t}}\ \left(\mathrm{x}^{\mathrm{t}}, \mathrm{y}^{\mathrm{t}}, \mathrm{b}^{\mathrm{t}}; \mathrm{y}^{\mathrm{t}}, \text{-}\mathrm{b}^{\mathrm{t}}\right)\right] \quad (4)$$

Like the Malmquist productivity index, the ML productivity index indicates productivity improvements if its values are greater than one and decreases in productivity if the values are less than one.

Equation (3) measures the change in output efficiency between two periods. If $MLEFFCH_t^{t+1}$ exceeds 1.00, it indicates that an airline is closer to the frontier in period *t* + 1 than it was in period *t*. If the value is less than one, then the airline is "falling behind" the frontier. Equation (4) measures technical change which illustrates shifts in the production possibilities frontier. If this shift is in the direction of more desirable outputs with fewer undesirables, then the value of $MLTECH_t^{t+1}$ exceeds 1.00. If the value is less than one, then technical regression has occurred. In order to calculate the ML index and its decompositions, three directional distance functions, which are specified as LP problems, must be solved. Let us assume that if at a given time t=1,….T, there are k=1,…K airlines of inputs and outputs, the model can be expressed as:

$$P(x) = (y, b)\colon \sum_{k=1}^{K} z_k\, y_{km}^t \geq y_m^t\ , m = 1, \ldots M. \quad (5)$$

$$\sum_{k=1}^{K} z_k\, b_{kj}^{t} = b_j^t, j = 1, \ldots J.$$

$$\sum_{k=1}^{K} z_k\, x_{kn}^{t} \leq x_n^t\, , n = 1, \ldots N.$$

$$z_k \geq 0\ , k = 1, \ldots K.$$

which exhibits constant returns to scale so that:

$$P(\lambda x) = \lambda P(x)\ , \lambda > 0 \tag{6}$$

and strong disposability of inputs:

$$x' \geq x \Rightarrow P(x') \supseteq P(x) \tag{7}$$

The inequalities for inputs and desirable outputs in (5) reflect the assumption that they are freely disposable. The undesirable outputs are assumed to be costly to dispose of (i.e., weakly disposable) and, therefore, are modelled as equalities. Hence, the weak disposability technology is the regulated technology. When the bad output constraint is excluded from the LP problem, this allows us to model the case when the bad is freely disposable (i.e., the unregulated technology). The non-negativity constraints on the intensity variables, z_k, allow the model to exhibit constant returns to scale.[3] The directional distance functions for the ML productivity index can be calculated as solutions to the linear programming (LP) problem as follows:

$$\vec{D}_0^t\left(x^{t,k'}, y^{t,k'}, b^{t,k'}; y^{t,k'}, -b^{t,k'}\right) = \max\beta \tag{8}$$

$$s.t. \sum_{k=1}^{K} z_k\, y_{km}^{t} \geq (1+\beta) y_{k'm}^{t}\, , m = 1, \ldots M.$$

$$\sum_{k=1}^{K} z_k\, b_{kj}^{t} = (1-\beta) b_{k'j}^{t}\, , j = 1, \ldots J.$$

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[3] This is a necessary condition for the resulting productivity indices to be a true total factor productivity index (Färe and Grosskopf, 1996).

$$\sum_{k=1}^{K} z_k\, x_{kn}^{t} \le x_{k'n}^{t}\; n = 1, \dots N.$$

$$z_k \ge 0\ ,\ k = 1,\dots K.$$

In order to eliminate the incidence of infeasible LP problems, we follow the strategy adopted by Färe et al. (2007a). First, we use only the mixed-period LP problem with t+1 as the reference technology evaluating observations form period t. This resembles Equation (8) except that the time superscripts (t) on the right-hand side of the constraints differ from the time superscripts (t+1) on the left-hand side of the constraints. While only one mixed-period LP problem has the drawback of not using the case with period t as the reference technology to evaluate observations from period t+1, combining it with 2-year windows for the reference technology allows us to eliminate the possibility of infeasible LP problems. Under a 2-year window reference technology, the frontier (i.e., reference technology) for 2005 would be constructed from data in 2004 and 2005.

3.0 Data

The data are mainly drawn from the World Air Transport Statistics (WATS) of the International Air Transport Association (IATA). It provides operational statistics for over three hundred airlines, of which twenty-two airlines comprise the dataset of this study. Secondary sources were also relied upon to supplement our data; namely fuel burn and CO_2 data which were purchased from RDC Aviations Limited (via http://www.rdcaviation.com/). The methodology to derive CO_2 estimates are described in RDC Aviation 2011, *RDC Emissions Calculator: Methodology Document* (v.1.4) and available upon request from RDC Aviation.

The directional distance functions employed in the study require quantities of inputs and quantities of outputs (both desirables and undesirables). Data specification of inputs and outputs follow a production approach to modelling airline behaviour, that is, aircraft are flown over a distance which consumes fuel (an input) to transport passengers and freight (i.e., the desirable output) over a certain distance. The production of desirable outputs, however inevitably generates pollution (that is, an undesirable output).

However, identifying inputs and outputs to satisfy the production of airline behaviour is problematic. In terms of outputs, most studies used revenue passenger kilometre (RPK) or tonne kilometres performed (TKP). As defined by International Civil Aviation Organization (ICAO), a passenger-kilometre is performed when a passenger is carried one kilometre. Calculation of passenger-kilometres equals the sum of the products obtained by multiplying the number of revenue passengers carried on each flight stage by the stage distance. Hence RPK is the number of revenue passengers carried per kilometre. Tonne kilometres performed is the sum of the product obtained by multiplying the number of total tonnes of revenue load (passengers, freight and mail) carried on each flight stage by the stage distance. These outputs are frequently used in studies such as Assaf and Josiassen (2012), Baltagi *et al*. (1995), Barbot *et al*. (2008), Barla and Perelman (1989), Bhadra (2009), Coelli *et al*. (1999), Cornwall, *et al*. (1990), Greer (2008), Oum *et al*. (2005), Oum and Yu (1995), Schmidt and Sickles (1984), and Vasigh and Fleming (2005). In turn, most of these studies used physical inputs such as the number of employees, materials, aircraft capacity, fuel and number of aircraft. Some studies also include financial indicators as either outputs and/or inputs when attempting cost efficiency analysis. Financial outputs are measured in terms of earnings before interest and taxes (EBIT) or revenue, while the financial inputs include operating costs (see Barros and Peypoch 2009 and Assaf and Josiassen 2011).

From the literature and framework of our study, we identify two outputs: tonne kilometres performed and CO_2 emissions (in tonnes).[4] Alternative output indicators such as RPK and revenue tonne kilometres (RTK) were not considered since TKP already includes all passengers, freight and mail. To include RPK and RTK would be double-counting. We also identify six inputs: (i) fuel burn, (ii) kilometres flown, (iii) number of employees, (iv) average aircraft capacity, (v) hours flown and (vi) total assets. Fuel burn is the total amount of fuel consumed for all flights. Kilometres flown is the total distance travelled by all flights for an airline. For the number of employees, we only considered labour that directly or indirectly contribute towards our defined outputs. Hence, only pilots, co-pilots and other cockpit personnel, cabin crew, maintenance and overhaul, and airport handling personnel are considered in our labour input. Labour employed for ticketing, sales, and promotions were not included in our estimates. Average aircraft capacity is the number of seats per aircraft measured by taking the ratio of available seat kilometres divided by kilometres flown. This input is a proxy for the average size of aircraft used by each airline. We do not use number of aircraft because aircraft sizes vary across airlines. Hours flown is the total number of hours of flight time. We include total assets to represent capital. This input is a proxy for the quality of equipment used, which suggests that a higher value indicates higher quality equipment that directly or indirectly have an impact on CO_2 emissions. Data on total assets were originally in US dollars based on official exchange rates and thus are not feasible for international

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[4] According to the U.S. Department of Transportation, Center for Climate Change and Environmental Forecasting, CO_2 constitutes roughly 70 percent of aircraft engine emissions. While other pollutants such as NO_x are produced, we only use CO_2 as this is the main pollutant emitted by airlines (Mendes and Santos, 2008).

comparisons since they are heavily influenced by capital flows and do not reflect real price differences between countries (Lee *et al*, 2007). As such total assets were first converted back into national currencies before converting into a numéraire currency (US dollar) using the transport purchasing power parity (PPP) drawn from the World Bank 2008, *Global Purchasing Power Parities and Real Expenditures: 2005 International Comparison Program*. As the dataset was for the period 2004-2008, PPPs for these years are needed but only 2005 PPPs were available from the above source. To derive a set of PPPs for the period 2004-2008, the 2005 PPP was extrapolated to all other years using the following expression:

$$PPP_{j,t+1} = PPP_{j,t} \times \left(CPI_{j,(t,t+1)}/CPI_{US,(t,t+1)}\right) \tag{9}$$

where $\mathrm{PPP}_{j,t}$ is the PPP for country *j* in period *t* relative to the United States. In the current study, $\mathrm{PPP}_{j,t}$ is the 2005 PPP. The national price movements are measured through the transport and communications consumer price index (CPI) for country j for the period *t+1* relative to period *t* under the assumption that the CPIs are representative of the changes in prices of airlines. This approach is also employed by OECD in the *National Accounts of OECD countries Volume 1: Main Aggregates*.

4.0 Results

Descriptive statistics for the data are presented in Table 1. The data shows that the mean values for outputs and inputs increased between 2004 and 2007 with a slight decline in 2008 for both Y1(CO2 emissions) and Y2 (TKP). The minimum and maximum values for CO_2 emissions decline after 2006. This suggests that reductions in CO_2 levels may be due to airlines utilising improved technology in reducing fuel-burn. This is further evident in the ratio of fuel burn per TKP which shows a decline since 2004 suggesting that airlines have become more fuel efficient. Such implications need to be supported by further analysis with the use of the ML productivity index.

Table 1: Descriptive Statistics (2004-2008), (in thousands)

Year	Variable	Mean	Standard deviation	Minimum	Maximum
2004	X1- Fuel burn (tonnes)	3,938.25	3,266.20	232.46	12,569.70
	X2- Kilometres flown	524,312.95	435,499.55	41,712.00	1,686,127.00
	X3- Average aircraft capacity	0.20	0.05	0.12	0.34
	X4- Number of employees	21.97	15.58	2.76	51.87
	X5- Hours flown	803.32	634.85	61.74	2,252.40
	X6- Total assets	8,157,506.39	8,800,100.88	5,096.43	25,462,208.00
	Y1- CO_2 (tonnes)	12,433.06	10,311.38	733.88	39,682.56
	Y2- Tonne kms performed	9,961,502.19	6,794,955.82	558,760.05	22,209,640.54
2005	X1- Fuel burn (tonnes)	4,017.31	3,233.74	292.93	12,157.75
	X2- Kilometres flown	531,562.55	425,159.85	43,143.00	1,647,993.00
	X3- Average aircraft capacity	0.20	0.05	0.13	0.33
	X4- Number of employees	20.70	14.59	2.97	48.13
	X5- Hours flown	811.73	620.63	63.70	2,207.41
	X6- Total assets	8,283,237.76	8,876,581.79	5,059.14	26,040,745.00
	Y1- CO_2 (tonnes)	12,682.64	10,208.92	924.78	38,382.01
	Y2- Tonne kms performed	10,328,077.54	6,870,530.75	619,674.71	23,405,877.88
2006	X1- Fuel burn (tonnes)	4,057.21	3,206.99	296.46	12,416.31
	X2- Kilometres flown	529,316.05	415,202.05	45,380.00	1,602,735.00
	X3- Average aircraft capacity	0.20	0.05	0.13	0.32
	X4- Number of employees	20.52	14.57	2.76	46.56
	X5- Hours flown	801.74	601.37	67.26	2,149.51
	X6- Total assets	8,798,681.08	9,247,068.75	4,463.16	25,849,615.00
	Y1- CO_2 (tonnes)	12,808.61	10,124.45	935.93	39,198.29
	Y2- Tonne kms performed	10,710,671.53	7,004,044.20	620,015.72	23,902,163.92
2007	X1- Fuel burn (tonnes)	4,166.24	3,181.69	284.28	11,951.28
	X2- Kilometres flown	540,040.18	409,616.64	47,834.00	1,546,819.00
	X3- Average aircraft capacity	0.20	0.04	0.13	0.31
	X4- Number of employees	19.86	14.04	2.47	47.31
	X5- Hours flown	817.26	596.31	69.58	2,078.85
	X6- Total assets	10,365,367.47	10,850,384.72	4,495.98	32,284,763.00
	Y1- CO_2 (tonnes)	13,152.80	10,044.61	897.48	37,730.19
	Y2- Tonne kms performed	11,212,439.27	7,237,795.20	583,265.97	23,307,339.16
2008	X1- Fuel burn (tonnes)	4,141.19	3,001.53	277.84	11,321.03
	X2- Kilometres flown	553,749.50	393,874.14	47,028.00	1,484,097.00
	X3- Average aircraft capacity	0.20	0.04	0.13	0.31
	X4- Number of employees	20.52	13.97	2.54	47.18
	X5- Hours flown	840.39	579.81	67.95	2,006.00
	X6- Total assets	9,308,263.32	9,381,048.63	2,673.84	28,021,154.00
	Y1- CO_2 (tonnes)	13,073.73	9,475.82	877.14	35,740.51
	Y2- Tonne kms performed	11,118,963.20	6,824,994.89	569,595.03	22,159,937.60

In this section, the results of efficiency performance based on ML and Malmquist productivity index are presented. As mentioned earlier where the index is greater (less) than 1.00 denotes improvement (deterioration) in the relevant performance.

Table 2 presents the decomposition results of the ML productivity index into its efficiency change and technical change components on an average annual basis for each airline when CO_2 emissions are included as an undesirable output. These are calculated using Equations (3) and (4), respectively. The average annual growth rates are based on geometric means which is the square root of the product of the 2-year window index.

Table 2: Decomposition of Average Annual Changes, 2004-2008 (Two-year window)

Airline	Accounting for undesirable output: CO_2			Ignoring undesirable output		
	ML	MLEFFCH	MLTECH	M	MEFFCH	MTECH
Air Canada	1.0133	1.0206	0.9929	1.0114	0.9823	1.0296
Air France	1.0239	1.0172	1.0066	1.0385	1.0306	1.0077
American Airlines	0.9943	1.0000	0.9943	0.9954	1.0000	0.9954
British Airways	1.0061	0.9945	1.0118	1.0085	0.9947	1.0138
Cathay Pacific	1.0005	1.0000	1.0005	1.0126	1.0038	1.0088
Continental Airlines	1.0592	1.0519	1.0069	1.0784	1.0671	1.0106
Czech Airlines	0.9973	1.0032	0.9941	0.9896	1.0128	0.9771
Delta Airlines	0.9855	0.9816	1.0039	0.9874	0.9808	1.0067
Ethiopian Airlines	1.0138	1.0197	0.9943	1.0672	1.0946	0.9750
Iberia	1.0030	1.0092	0.9939	1.0263	1.0356	0.9911
Jet Airways	0.9939	1.0000	0.9939	1.0079	1.0315	0.9771
Korean Airlines	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Lufthansa	1.0047	1.0016	1.0031	1.0049	1.0019	1.0030
Malaysian Airlines	0.9970	1.0043	0.9927	1.0155	1.0278	0.9880
NorthWest Airlines	0.9798	0.9808	0.9989	0.9686	0.9698	0.9987
Qantas	1.0133	1.0210	0.9925	1.0065	1.0110	0.9956
Singapore Airlines	0.9895	0.9895	1.0000	0.9885	0.9865	1.0021
SriLankan Airlines	0.9275	1.0207	0.9087	0.9923	1.0284	0.9649
Swiss International	0.9937	1.0017	0.9920	1.0178	1.0417	0.9770
Thai Airways	0.9173	1.0245	0.8954	0.9988	1.0276	0.9720
United Airlines	1.0402	1.0000	1.0402	1.0004	0.9845	1.0161
US Airways	1.0236	1.0288	0.9950	1.0980	1.0764	1.0201
Mean	0.9985	1.0076	0.9910	1.0138	1.0172	0.9967

Notes: ML: Malmquist-Luenberger Index; M: Malmquist Index

The ML productivity index reveals subtle variations in results, ranging from 8.27 percent annual productivity decline for Thai Airways to a 5.92 percent annual productivity increase for Continental Airlines. On average, productivity fell by 0.15 percent per year, largely from technical regress (-0.90 percent per year) with an annual improvement in technical efficiency of 0.76 percent. The results also show that when no credit is given for reducing the production of undesirable outputs, which is shown under the heading ‘Ignoring undesirable output’, annual productivity growth was 1.38 percent, whereas for the regulated production technology, it was -0.15 percent. From the sample of twenty-two airlines, twelve airlines showed productivity growth when credit was given to reducing CO_2 emissions while fifteen airlines showed productivity growth when CO_2 is freely disposable. The results confirm our hypothesis which shows more airlines recording ‘lower productivity’ under regulated production technology for CO_2 emissions. In other words, pollution abatement activities lower productivity as some of these resources are allocated to the improvement of technology in reducing CO_2 emissions instead of increasing the output of desirable output (that is, tonne kilometres performed). The results also suggest that the “traditional” productivity change, which focuses solely on the desirable output production, overstates the “true” productivity change of the airline industry.

The mean estimates of MLEFFCH and MLTECH also provide information about the behaviour of airline operations. Assuming airlines are aware of measures that can reduce carbon emissions, airlines tend to adopt best-practice management measures rather than investing in new technologies for cost-cutting reasons. This is evident from the positive estimates of MLEFFCH where eighteen airlines posted positive MLEFFCH. Of these eighteen airlines, twelve had negative MLTECH, which suggest that most of these airlines have yet to adopt new technologies which increases desirable output with lower CO_2 levels.

Table 3 reports the annual productivity change, technical change, and efficiency changes under the regulated and unregulated production technologies. Under the regulated production technology, the annual change in productivity ranged from 1.02 percent in 2005-06 to -0.95 percent in 2006-07. The change in efficiency ranged from 2.01 percent in 2005-06 to 0.08 percent in 2007-08, while technical change ranged from -0.58 percent in 2007-08 to -1.16 percent in 2006-07. Under the unregulated production technology, the annual change in productivity ranged from 2.69 percent in 2005-06 to -0.09 percent decrease in 2007-08. The change in efficiency ranged from 2.71 percent in 2005-06 to 0.13 percent in 2007-08, while technical change ranged from -0.01 percent in 2005-06 to -0.75 percent in 2006-07.

Table 3: Annual comparisons of M and ML Productivity Index

	Accounting for undesirable output: CO_2			Ignoring undesirable output		
	ML	MLEFFCH	MLTECH	M	MLEFFCH	MLTECH
2005-2006	1.0102	1.0201	0.9903	1.0269	1.0271	0.9999
2006-2007	0.9905	1.0021	0.9884	1.0157	1.0235	0.9925
2007-2008	0.9950	1.0008	0.9942	0.9991	1.0013	0.9977

Notes: ML: Malmquist-Luenberger Index; M: Malmquist Index

What are the implications that can be drawn from the above results? It is evident that great strides have been undertaken by relevant stakeholders to improve aircraft efficiency in terms of airframe design, weight reduction, reformulated fuel, development of fuel-efficient engines, improved navigation and flight planning equipment. Overall, fuel efficiency, measured as the ratio of total distance flown (in kilometres) over total fuel consumed, showed an increase between 2004 and 2008, which suggests improvement in airline fuel efficiency. Hence, does it mean that airlines should start adopting fuel-efficient state-of-the-art aircraft? This is unlikely to happen since airlines have financial obligations and would not commit to huge capital outlay. Is it also not reasonable to impose a law that airlines must adopt fuel-efficient state-of-the-art aircraft. Just like the current EU's emissions trading scheme on airlines, numerous countries have shown their discontentment leading to discussions which have yet to come up with an agreement. Although the adoption of fuel-efficient state-of-the-art aircraft is costly and takes considerable time to replace old fleet, individual governments can contribute by providing subsidies as incentives for national carriers to gradually adopt new technologies. While policies take time to come into effect, Airlines can also reduce CO_2 emissions through best-practice management and operations such as adopting improved navigation and finding the optimal timings for landing and take-off in order to reduce time spent on the tarmac waiting for take-off and time spent circling waiting for approval to land.

Airlines may operate short-haul or long-haul flights or a combination of both. Understandably, short-haul operations tend to be less efficient than long-haul since the former engages in more flights over shorter-distance per day compared to long-haul which has fewer number of flights per day. This suggests that short-haul based airlines have more take-offs which consume more fuel each time. Furthermore, long-haul flights are able to compensate for heavier loads by achieving cruising speeds at higher altitudes which makes them more fuel efficient than short-haul flights.

5.0 Conclusions

The study focused on measuring productivity growth of airlines taking into account, both desirable and undesirable outputs into consideration. Using a dataset for the period, 2004-2008, the ML productivity index was employed to derive productivity change, , technical change, and changes in technical efficiency for twenty-two airlines. The average annual change in ML productivity was -0.15 percent, whichis s largely attributed to technical regression. When we ignore the undesirable output, CO_2 emissions, annual productivity growth was 1.38 percent suggesting that pollution abatement activities in airlines reduces productivity growth.

It should be noted that one of the main limitations of the current study is the small sample size. A larger sample size would have provided more robust results. A longer-time series would provide a better picture of productivity growth to demonstrate the impact of best-practice management and the adoption of new technologies on technical change. An important policy implication stemming from the results is that airlines with higher CO_2 emissions are likely to suffer due to higher penalties (costs) imposed by the regulatory authorities which is currently happening in Europe. Such action is likely to lower productivity growth of these airlines, raise the cost of airfares and possibly reduce the TKP. To address all these, it would be worthwhile for governments to consider subsidising airlines in the adoption of more fuel-efficient aircraft as well as the sharing of knowledge between airlines in terms of efficient flight paths, flight altitudes, ideal combination of short-haul and long-haul flights and other ways to improve operations with the aim to achieve economies of scale while minimising CO_2 emissions.

Nonetheless, this is a first step towards examining the level of productivity and efficiency of airlines while taking into account both desirable and undesirable outputs using the ML index which measures ‘true’ productivity growth. Future studies would aim at increasing the sample size, including sufficient number of low-cost carriers over a longer time-period for comparative analysis between types of carriers, as well as conduct a second stage regression analysis to quantify sources of inefficiency and productivity. In addition, the expansion of the data outputs may include other undesirable outputs such as noise pollution and airline delays.

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