Efficiency and productivity change in the European airlines industry in the post liberalization era

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Abstract: In recent years the European airlines industry has experienced critical restructuring and evolved from a highly regulated market predominantly operated by national airlines to a dynamic, liberalized industry where airline firms compete freely on prices, routes, and frequencies. In this study, we investigate the recent performance record of European airlines. The core of the analysis is a decomposition of total factor productivity change derived from the econometric estimation of an airline total cost function. We use panel data methods and incorporate time varying inefficiency that is specific to each airline. The results indicate the importance of the 9/11 shock and the recovery from it, and demonstrate that the industry's performance has been relatively strong despite the challenges of a very difficult decade.

1. Introduction

Interest in measuring the comparative performance of airline companies has developed considerably since the deregulation experience of the US airlines in the late 1970s. This had inspired the majority of the research to focus upon the consequences of the deregulation experience of the US. Some studies compared the efficiency differences between the deregulated US airlines and highly regulated European airlines, which has often been criticised on the grounds that it is inherently less efficient than US carriers (Good et al 1993).

In recent years however, the European airlines industry has experienced critical restructuring and evolved from a highly regulated market predominantly operated by national airlines to a dynamic, liberalized industry where airline firms compete freely on prices, routes, and frequencies. Liberalization reforms in European airlines industry created a new market environment which deserves a closer look to find out more on the recent performance record of the airlines. In this study, we measure the efficiency and productivity change in the European airlines industry post-liberalization over the period between 1999 and 2011. During our study period, the international air transport has experienced a turbulent episode due to a number of factors, such as the 9/11 shock in 2001 and the global financial crisis in 2008. We examine the impact of those major events on the performance of European airlines.

The industry provides a fascinating case study with the coexistence of full-service carriers with low cost carriers who have entered the liberalized market after the reforms were introduced. When compared to the US deregulation, the liberalization in European airlines industry was slow and gradual. Starting in 1987, subsequent reform packages were introduced to remove economic barriers, with an ultimate aim to establish a fully liberalized Single Aviation Market. Drastic measures in pricing and market access, however, came with the third liberalization package in 1993, and full deregulation only came into force during 1997. The reforms created a competitive environment which fosters growth in productivity and efficiency. European airlines in the new environment are expected to improve their efficiencies in order to remain competitive. Our paper examines this aspect to find out if there has been any efficiency and productivity change over time.

In the literature there are few studies devoted solely to efficiency and productivity analysis of European airlines. Our paper seeks to fill this gap by concentrating on the recent evolution of performance of airline firms in Europe and specifically analyse the impact of major events on the industry. Great majority of studies do not capture this as they mostly use data from the 1980s or 1990s. We contribute to the existing literature with our latest data set to capture the recent developments in the industry. We follow Good et al (1995) to construct our data set to include all the relevant inputs and output using both quantities and input prices. We use a number of sources, such as International Civil Aviation Organization (ICAO), Avmark and Platts to construct our comprehensive data set. The majority of papers in the literature exclude input prices and only use quantities (Assaf and Josiassen, 2012; Barbot et al. 2008; Schefczyk, 1993). Finally, according to our best knowledge, our paper is the first study which measures efficiency and productivity decomposition in European airlines post liberalization using panel data methods that incorporate time varying inefficiency specific to each airline.

The paper is organized as follows. Section 2 reviews the empirical literature. The modelling framework and estimation methods are detailed in Section 3 and 4. Section 5 gives a brief overview of the data used in the analysis while Section 6 discusses our empirical findings. Section 7 concludes.

2. Literature review

There is vast amount of literature which measures efficiency and productivity of airlines. Some early (TFP) applications assess US airlines productivity during 1970s (Caves, Christensen and Tretheway, 1981; 1983). Others examine the TFP for international airlines and compare US airlines under deregulation with non-US airlines (see Forsyth et al 1986; Caves, Christensen, Tretheway and Windle, 1987; and Windle, 1991). The results in general demonstrate that productive efficiency of US airlines grew after deregulation and the US airlines performed better than non-US carriers.

We identify another two strands of empirical literature which use frontier methodologies; nonparametric and parametric methods in airlines efficiency studies. Nonparametric data envelopment analysis (DEA) is more common (Schefczyk, 1993; Distexhe and Perelman, 1994; Oum and Yu, 1995; Coelli et al. 2002; Scheraga, 2004; and Barbot et al 2008). Except for Sheraga and Barbot et al, the rest of the studies use data prior to 1995. Barbot et al 2008 is the only study which includes low cost carriers into their analysis. Some of the DEA studies confirm that during 1980s the European carriers were technically less efficient than other carriers (Schefczyk, 1993; Distexhe and Perelman, 1994).

While DEA can handle multiple inputs and outputs, one of the major criticisms of the method is its inability to accommodate neither measurement errors nor other noise in the data. Stochastic frontier analysis (SFA), on the other hand, is a parametric methodology that can address the limitations of the DEA. Mostly, the SFA studies compare the performance between US and European airlines (Good et al 1993; Good et al, 1995; Marin 1998) except Barla and Perelman (1989) and Inglada et al. (2006) focus on performance comparisons among international airlines. The impact of ownership on productivity is covered in the study by Ehrlich et al 1994. In our study, we extend the above literature and focus on European airlines using panel data methods. The core of our analysis is a decomposition of total factor productivity change derived from the econometric estimation of an airline total cost function. Studying the cost differences has potential of use for formulating relevant policies for the industry, which seeks to improve its performance as a strategic response to the new market environment.

3. Modelling

3.1 Modelling the technology and relative efficiency

The starting point is the definition of the production technology in terms of the input requirement set for a sample of multi-product firms producing *R* outputs from *K* inputs:

$$I(\mathbf{y},t)=\left\{\mathbf{x}:\mathbf{x}\ can\ make\ \mathbf{y}\ at\ time\ t,\mathbf{x}\in R_{+}^{K},\mathbf{y}\in R_{+}^{R}\right\}$$

We assume that this production technology has the properties of convexity, and weak disposability.

We write the long run cost function as follows:

$$c(\mathbf{y},\mathbf{w},t)=\min_{\mathbf{x}}\left\{\mathbf{w}'\mathbf{x}:(\mathbf{x},\mathbf{y}\in I)\right\}$$

Panzar and Willig (1977) derive the following result concerning the inverse of the elasticity of cost with respect to output:

$$E_{c\mathbf{y}}^{-1}=c\Big/\sum_{r=1}^{r=R}\left(y_r\left(\partial c/\partial y_r\right)\right)=1\Big/\sum_{r=1}^{r=R}\left(\partial\ln c/\partial\ln y_r\right)$$

Then $E_{c\mathbf{y}}^{-1}<1$ implies diseconomies of scale (decreasing returns), $E_{c\mathbf{y}}^{-1}=1$ implies constant returns to scale and $E_{c\mathbf{y}}^{-1}>1$ implies economies of scale (increasing returns).

The actual cost experienced by the firm is by definition:

$$C_t\equiv\mathbf{w}'\mathbf{x}$$

Consequently, cost efficiency at time *t* is:

$$CE_t = \{c(\mathbf{y}, \mathbf{w},, t)/C_t\} \in (0,1]$$

Using $\exp(-u), u \geq 0$ to transform the measure of cost efficiency from the interval: $(0,1]$ into a non-negative random variable with support on the non-negative real line: $[0,+\infty)$, yields:

$$\ln C_t = \ln c(\mathbf{y}, \mathbf{w}, t) + u$$

This function should be homogeneous of degree +1 and concave in input prices (Diewert and Wales 1987). Homogeneity is imposed by dividing through by one of the input prices, w_K. Therefore we re-define the variables in vector form as:

$$\begin{aligned} \mathbf{l\tilde{w}} &= \left(ln(w_1/w_K) \quad \ldots \quad ln(w_{K-1}/w_K)\right) \\ \mathbf{ly} &= \left(ln\, y_1 \quad \ldots \quad ln\, y_R\right) \end{aligned}$$

An econometric approach may be adopted by replacing the deterministic kernel of $\ln(C/w_K) = \ln c(\mathbf{y}, \tilde{\mathbf{w}}, t) + u$ by a fully flexible functional form such as the translog function with an additive idiosyncratic error term, v to capture sampling, measurement and specification error.

We write the translog approximation with additive error term as $TL(\mathbf{y}, \tilde{\mathbf{w}}, t) + v$. These steps give us the following result:

$$\ln(C/w_K) = \alpha_0 + \boldsymbol{\alpha}'\mathbf{ly} + \boldsymbol{\beta}'\mathbf{l\tilde{w}} + \tfrac{1}{2}\mathbf{ly}'\mathbf{A}\,\mathbf{ly} + \tfrac{1}{2}\mathbf{l\tilde{w}}'\mathbf{B}\,\mathbf{l\tilde{w}} + \mathbf{ly}'\boldsymbol{\Gamma}\,\mathbf{l\tilde{w}} + \tfrac{1}{2}\delta_2 t^2 + \boldsymbol{\mu}'\mathbf{ly}t + \boldsymbol{\eta}'\mathbf{l\tilde{w}}t + v + u$$

The vectors of elasticity functions (equivalent in the case of the input prices to the share equations by Shephard’s lemma) are derived by differentiating the translog quadratic form:

$$\begin{bmatrix} \boldsymbol{\varepsilon}_y \\ \boldsymbol{\varepsilon}_{\tilde{w}} \\ \varepsilon_t \end{bmatrix} = \begin{bmatrix} \boldsymbol{\alpha} & \mathbf{A} & \boldsymbol{\Gamma} & \boldsymbol{\mu} \\ \boldsymbol{\beta} & \boldsymbol{\Gamma}' & \mathbf{B} & \boldsymbol{\eta} \\ \delta_1 & \boldsymbol{\mu}' & \boldsymbol{\eta}' & \delta_2 \end{bmatrix} \begin{bmatrix} 1 \\ \mathbf{ly} \\ \mathbf{l}\tilde{w} \\ t \end{bmatrix}$$

3.2 Productivity growth decomposition

We derive a total factor productivity decomposition as follows, see Bauer (1990), Orea (2002) and Lovell (2003). Differentiating both sides of the cost equation $\ln C_t \equiv \ln(\mathbf{w}'\mathbf{x}) = \ln c(\mathbf{y}, \mathbf{w}, t) + u$ with respect to *t* and rearranging the result, we obtain:

$$E^{-1}\boldsymbol{\varepsilon}'_y\dot{\mathbf{y}} - \mathbf{s}'\dot{\mathbf{x}} = (1 - E/E)\boldsymbol{\varepsilon}'_y\dot{\mathbf{y}} + (\mathbf{s} - \boldsymbol{\varepsilon}_{\tilde{w}})'\dot{\mathbf{w}} - \varepsilon_t - (du/dt)$$

In this expression which is a general statement for the multiple output case, E^{-1} is the elasticity of scale, $\boldsymbol{\varepsilon}_y$ is the vector of cost elasticity functions with respect to the outputs, with typical element: $\varepsilon_{yr} = \partial \ln c(\mathbf{y}, \tilde{\mathbf{w}}, t)/\partial \ln y_r$; $\boldsymbol{\varepsilon}_{\tilde{w}}$ is the vector of cost elasticity functions with respect to the input prices, with typical element: $\varepsilon_{\tilde{w}k} = \partial \ln c(\mathbf{y}, \tilde{\mathbf{w}}, t)/\partial \ln \tilde{w}_k$; ε_t is the cost elasticity function with respect to the time based index of technological progress: $\varepsilon_t = \partial \ln c(\mathbf{y}, \tilde{\mathbf{w}}, t)/\partial lt$; (du/dt) is the rate of change of inefficiency. The left hand side of this expression is by definition a measure of total factor productivity change with weights that sum to unity: by construction in the case of outputs and by linear homogeneity in the case of inputs. Hence the right hand side is a complete decomposition of the total factor productivity index.

The five components of the total factor productivity change on the right hand side of the equation can therefore be interpreted as follows:

a) $(1 - E/E)\boldsymbol{\varepsilon}'_y\dot{\mathbf{y}}$: *scale efficiency change*; if $E = 1$ i.e. CRS, there is zero scale efficiency change in the total factor productivity change, *TFPC*, decomposition

b) $(\mathbf{s} - \boldsymbol{\varepsilon}_{\tilde{w}})'\dot{\mathbf{w}}$: *allocative efficiency change*: if actual input cost shares and optimal input cost shares are equal, there is no potential for allocative efficiency change: $\mathbf{s} - \boldsymbol{\varepsilon}_{\tilde{w}} = \mathbf{0}$

c) $-\varepsilon_t$: *technological change*; if the elasticity of cost with respect to time as a proxy for the technological change is negative, $\varepsilon_t < 0$, then this term will raise productivity.

$-\left(du/dt\right)$: *cost efficiency change*: if this term, including the sign, is positive then efficiency change contributes positively to total factor productivity growth.

These components of total factor productivity change, $TFPC$, are shown in total differential form; however by application of the quadratic lemma, Caves, Christensen and Diewert (1982), we can use them in index number form, as follows:

a) $\frac{1}{2}\sum_{r}\left[\left(\left(1-E^{t+1}\right)\varepsilon_{yrt+1}/E^{t+1}\right)+\left(\left(1-E^{t}\right)\varepsilon_{yrt}/E^{t}\right)\right]\left(\ln y_{rt+1}-\ln y_{rt}\right)$ is the effect of scale efficiency change

b) $\frac{1}{2}\sum_{k}\left[\left(s_{kt+1}-\varepsilon_{\tilde{w}kt+1}\right)+\left(s_{kt}-\varepsilon_{\tilde{w}kt}\right)\right]\left(\ln w_{kt+1}-\ln w_{kt}\right)$ is the effect of the bias in using actual cost share weights instead of optimal cost shares based on shadow prices, i.e. allocative efficiency change.

c) $-\frac{1}{2}\left[\left(\partial\ln c\left(\mathbf{y},\mathbf{w},z_0,t+1\right)/\partial t\right)+\left(\partial\ln c\left(\mathbf{y},\mathbf{w},z_0 t\right)/\partial t\right)\right]$ is the effect of cost reducing technical progress

d) $\left[CE_{t+1}-CE_{t}\right]$ is cost efficiency change

4. Estimation

The stochastic frontier analysis (SFA) regression to be estimated, with the error components: v representing idiosyncratic error and u representing inefficiency can be expressed succinctly as follows:

$$\ln\left(C/w_K\right)_{it}=\alpha_0+\mathbf{x}_{\mathbf{it}}'\boldsymbol{\theta}+v_{it}+u_{it}\quad i=1\ldots N,t=1\ldots T$$

Here $\mathbf{x}'_{it}$ is a $(K+R+2)$ vector of explanatory variables representing the input prices, outputs, time and the level of the fixed input equity capital. The range of panel data SFA models reflects different assumptions about the nature of the composed error terms. We briefly describe a number of these specifications that have been widely used in the literature. Because experience suggests that parameter values can be sensitive to the form of the stochastic frontier analysis model that is fitted, we shall use a number of different types of these models.

The SFA models all assume two component error terms, one to measure idiosyncratic error and one to measure inefficiency. One of these composed error models is due to Schmidt and Sickles (1984) who treated the inefficiency term as time-invariant, an assumption that may be especially applicable to short samples where: $N > T$. In a fixed effects (FE) formulation, their assumed error terms are: $v_{it} \sim iid(0, \sigma_v^2)$ and u_i is a constant randomly distributed across firms so that the intercept is $\alpha_0 + u_i = \alpha_i$. The inefficiency component is then obtained by interpreting the usual heterogeneity effect as inefficiency and using Least Squares Dummy Variable LSDV or 'within' regression estimation. We refer to this FE model as SS (84). Both Pitt and Lee (1981) and Schmidt-Sickles (1984) suggested random effects (RE) formulations as well, with time invariant inefficiency; Pitt and Lee specify normal and half-normal distributions for the idiosyncratic and inefficiency components: $v_{it} \sim Nid(0, \sigma_v^2)$ and $u_i \sim Nid^{+}(0, \sigma_u^2)$ and use maximum likelihood estimation (MLE) for the parameter set: $(\alpha_0, \boldsymbol{\theta}', \sigma_v^2, \sigma_u^2)$. We call this model *time-invariant inefficiency*. Both of the Schmidt-Sickles and Pitt-Lee models assume that inefficiency is time-invariant over the sample, and they differ only in the formulation of the time invariant inefficiency component. Therefore it is useful to compare these with two time-varying efficiency models. The first is due to Battese and Coelli (1992) who extended the Pitt-Lee model to allow for time-varying inefficiency by combining a truncated normal distribution $u_i \sim Nid^{+}(\mu, \sigma_u^2)$ for the inefficiency component with a deterministic function of time incorporating a single parameter covering the whole sample:

$u_{it} = u_i\, exp(-\eta(t-T)), u_i \sim Nid^+(\mu, \sigma_v^2)$. MLE is used for the parameter set: $(\alpha_0, \boldsymbol{\theta}', \mu, \eta, \sigma_v^2, \sigma_u^2)$. The test for whether the inefficiency is time varying has null hypothesis: $H_0 : \eta = 0$ and is an asymptotic t-test. We refer to this model as *cross-sample time varying inefficiency.*

The second model is due to Cornwell Schmidt and Sickles (1990) and is further developed in Sickles (2005). This is an FE model with firm-specific linear dependence on time of the fixed effects representing the inefficiency component. It maintains the assumption that the fixed effects reflect inefficiency of performance but allows these to be determined by exogenous variables including time. This yields a model with firm specific time-varying parameters:

$$\ln(C/w_K)_{it} = \mathbf{x}'_{\mathbf{it}}\boldsymbol{\theta} + \mathbf{w}'_{it}\boldsymbol{\beta}_{it} + v_{it} \quad i = 1 \ldots N, t = 1 \ldots T$$

Estimation of the general model can be complex, see Sickles (2005) and generally requires a balanced sample, but the Cornwell Schmidt and Sickles (1990) model adopts a specific version which is relatively straightforward. The fixed effects used to measure inefficiency in Schmidt and Sickles (1984) are permitted to be time-varying by using a polynomial function of time. For example:

$$\beta_{it} = \theta_{0i} + \theta_{1i}t + \theta_{2i}t^2$$

We call this model *firm-specific time varying inefficiency*.

The computation of the estimated inefficiency component varies amongst the different models. For the models where time invariant or firm-specific time varying cost inefficiency is measured by a fixed effects approach, the estimated inefficiency for the typical firm is

$$\hat{u}_{it} = \hat{\beta}_{it} - \min_j(\hat{\beta}_{jt})$$

In each period there is one firm that is 100 percent efficient, but the identity of this efficient form may differ in different time periods[1]. For the MLE models, the inefficiency for the typical firm is computed as the estimated conditional mean of the inefficiency density function given the realization of the composed error term, i.e. the MLE residual:

$$\hat{u}_{it} = E\left(u_{it} \middle| e_{it}\right)$$

5. Sample

The sample of data is not balanced since not all airlines that are operating over the period report the relevant data in every year to the data source. Therefore a compromise has to be made about the coverage of the airlines in the sample.

The full unbalanced sample contains information about 86 airlines operating at some point over the period 1999-2011, totalling 523 panel observations. This sample is 66 per cent balanced in terms of the ratio of the average number of time-series observations per cross-section relative to the maximum (12). This sample includes many tiny operations which return data for only one to three periods and then disappear or are absorbed by larger organizations. On the other hand, restricting the sample to be 100 per cent balanced reduces the coverage to 72 observations of six airlines, almost all national carriers and excludes several important low-cost airlines.

With an 80 per cent balanced sample and at least 7 time-series observations per cross-section, we have 358 observations, where the number of small operations is still significant since the minimum revenue-tonne-kilometre value is only $184 billion-kilometres. This panel includes all the well-known low cost airlines as well as national carriers. With at least 9 time-series observations per cross-section the panel is 90 per cent balanced while the number of observations is 243 with a minimum

[1] The model is discussed in further detail in Kumbhakar and Lovell (2003: 108-9).

revenue-tonne-kilometre value of $12577 billion-kilometres. Very small carriers are excluded but so are one or two low cost carriers with incomplete data returns. Balancing these arguments we experimented with several samples and found the parameter estimates to be relatively consistent across the different unbalanced samples. Since in this paper we are primarily interested in the performance of the European airlines as a whole, we will focus most attention on the 90 percent balanced sample where there are at least nine time series observations per airline.

A separate sampling issue is how to accommodate the shock to the data arising from the tragic events of the terrorist attack on the World Trade Center on September 11, 2001 which hugely disrupted airline activity all over the world. One approach would be to treat the data for 2001 as a special case and use, for example, a dummy variable for that year. An alternative is to work with the unadjusted data and monitor the results for evidence of the effect of the shock. This is what we have done and we are able to observe with clarity the impact of the nine-eleven shock on the European airlines through their measured productivity performance.

6. Results

We now apply the three theoretical models of (i) *time-invariant inefficiency* (Pitt-Lee (1981) and Schmidt-Sickles (1984), (ii) *whole sample time varying inefficiency* (Battese-Coelli (1992) and (iii) *firm-specific time varying inefficiency* (Cornwell Schmidt and Sickles (1990) to our data on European airlines for 1999-2011. We report the results for the 90 per cent balanced sample. The specification is a translog total cost function with one output, revenue tonne kilometres, and three input prices: labour, capital and materials including fuel expenses. The cost function is normalised on the price of materials to impose linear homogeneity in input prices on the cost function. Additional variables are time and exogenous operating characteristics. Time (t) represents the shifting cost frontier as technological progress evolves. We may interact this with the other variables to allow for non-neutral technological progress but we find that parameter estimates on other variables show greater precision when technological progress is restricted to be Hicks-neutral. Five exogenous operating characteristics are used to locate the firm specific cost frontier and these are described more fully in the section of the paper dealing with the data sources. In summary they are: *stage length*, *load factor*, *size* (average airplane seating capacity), *jet* (the percentage of the airline's fleet comprising jets, and *wide* (the percentage of the airline's fleet that is wide-bodied).

In table 1 below we report the estimation results for the three cost function models with different inefficiency error component terms using the 90 percent balanced sample with 243 observations. We report first order coefficients from estimating the translog function using demeaned data which fully identifies the frontier at the sample mean[2]. The results confirm the monotonicity conditions on the output and input prices and indicate that there are considerable economies of scale available in the European airlines industry over this sample period. These results are robust to all the different specifications modelled. The cost frontier does display a positive rate of Hicks-neutral technological progress but this is not substantial and it is weak in terms of statistical significance. The operating characteristics indicate that *jet-based* fleets and *wide-bodied* fleets are not significantly less costly given their output levels and input prices than the other technologies. However, *stage length, load factor* and *siz*e do impact on the location of the cost frontier to a varying degree.

<u>Table 1 Here</u>

In table 1 we see that the output and input price elasticity results are relatively consistent across the three different models of the way in which inefficiency is allowed to vary (or not) over time. There are important economies of scale yet to be exploited. The rate of Hicks-neutral technological progress indicates a lowering of the cost frontier over time, but this is at a relatively slow rate

[2] There are of course numerous second order and cross-product coefficients in the estimation as well which are not reported to save space.

suggesting that airlines may have been over-capitalised at the beginning of the sample period and carried out limited investment in new capacity during this twelve year period. Materials input including fuel expenses is the main factor driving up costs from the input side, however the productivity narrative reported later in the paper indicates that scale and allocative efficiency changes could have compensated for this. Increased load factor has a statistically significant impact on total cost in all three models, with a relatively high numerical elasticity. The other exogeneous operating characteristics, although they indicate opportunity for cost reduction, are not statistically significant.

The models estimated provide us a range of choices for computing the total factor productivity change in the European airlines industry over the period following liberalisation. We can use the first and second order parameters of these models to generate the total factor productivity decomposition as described earlier in the paper. Here we do this with the most general firm-specific time-varying inefficiency model based on the Cornwell-Schmidt-Sickles stochastic frontier analysis using the time-related fixed effects approach (column three in table 1). We do this by applying the Divisia index decomposition described earlier distinguishing the components of scale efficiency change (SEC), allocative efficiency change (AEC), technical or cost efficiency change (EFC), and finally Hicks-neutral technological change (TC). Total factor productivity change is the sum:

$$TFPC = SEC + AEC + EFC + TC\,.$$

In the tables and charts reporting the results we express the outcomes in index number form by exponentiating the *TFPC* decomposition, so that an index number of 1.0 indicates no change, an index number < 1.0 indicates productivity regress and an index number > 1.0 indicates productivity improvement. We are interested in the average performance of the European airline industry as a whole. In the tables and charts we distinguish two forms of sample average index number: (i) unweighted geometric mean index numbers and (ii) geometric mean index numbers weighted by share of industry output, revenue tonne kilometres, i.e. market share. The second form gives a picture of how the market dominant airlines performed relatively to the industry as a whole.

The underlying component in the econometric results is the basic rate of Hicks-neutral technical change which is estimated at just under half of one per cent per year. However, the industry shows a total factor productivity change that is considerably larger than this in some years in the sample. The variability therefore is in the other components of the decomposition: scale efficiency change (SEC), allocative efficiency change (AEC) and technical efficiency change (EFC).

We begin in figure 1 with the pattern of technical efficiency change because it is in this component of the index that we see most clearly the impact of the 9/11 terrorist attacks in the US on the performance of the European airlines. In 2011 this impact appears as a greater than 30 percent drop in performance compared with 2000. There is however a relatively rapid recovery with this component of the TFPC index showing positive efficiency change averaging around 5 per cent per year until the impact of the financial crisis in 2008.

Figure 1 Here

The component of TFPC associated with changes in input intensity and responsiveness to relative input prices (in particular the impact of relative fuel price changes) is the Allocative Efficiency Change (AEC) shown in figure 2. This is positive for most of the period except for the middle years and shows in particular that there was a major attempt to improve allocative efficiency after the financial crisis. The AEC index number increases at 15 per cent per year between 2007 and 2009. As was the case with the technical efficiency change component, the larger airlines weighted by output underperformed the sample as a whole.

Figure 2 Here

The final component to consider is Scale Efficiency Change (SEC). This has been much less volatile than the two reactive market components of allocative and technical efficiency despite the econometric evidence of the existence of unexploited economies of scale. Larger airlines slightly underperform the sample average, but this appears to be an area where further efficiency gains can be found. The European market may therefore be lagging behind at this time compared with the consolidation gains observed in the US market. Figure 3 demonstrates these scale effects.

Figure 3 Here

Finally in figure 4, we bring these components together to display the estimate total factor productivity change for the sample of European airlines over the period 1999-2011. Three factors stand out. First, the industry has shown marked productivity growth in the post liberalisation period of between 5 and 10 per cent per year at the end of the period. This is composed of different components with different degrees of volatility. The second notable factor is the severe shock of 9/11 attacks but the relatively rapid recovery from these, with the volatility of the EFC component being the chief shock absorber. Finally, the third factor, particularly at the end of the period is that the smaller airlines are leading in performance and the larger airlines (by output) underperform the sample average.

Figure 4 Here

7. Conclusions

In this paper we set out to measure the efficiency and productivity trends in the European airlines industry post liberalization. The paper described how the main thrust of the liberalization programme in the industry progressed up to the year 2000. The period since then has been one of adjustment to the new market conditions. We chose to measure the total factor productivity change (TFPC) decomposition of the industry over the period 1999-2011 by estimation of a flexible function form for the long run cost function using panel data methods. This allowed us to decompose TFPC into technical change, scale efficiency change, allocative efficiency change (on the input side) and technical efficiency change. We compared three approaches to the estimation problem, each of which distinguished a particular model of inefficiency measurement: time-invariant inefficiency, time varying inefficiency at a constant rate across the sample, and, most generally, time-varying inefficiency at different rates specific to each airline.

The estimation results showed the potential for further economies of scale and the key role of materials input prices including fuel expenses in a three input, one output translog cost function. We found that there was a small amount of technical change during this difficult decade which included both the impact of 9/11 and the financial crisis. The major impacts on the industry's performance, which was a relatively strong one, came from allocative, scale and technical efficiency change. The technical efficiency change component was a major shock absorber displaying a massive drop following 9/11 but recovering remarkably quickly until the impact of the financial crisis. Scale efficiency change was positive but, given the potential for economies of scale, was relatively muted. Allocative efficiency change, along with technical efficiency change displayed most volatility and gives an indication of the nature of the industry's response to the liberalization initiatives that stemmed from the commencement of the sample period. Finally, although large and small airlines responded similarly, it appears that the larger airlines underperformed relatively to the sample average.

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Tables and figures

Table 1 Estimation results for the cost function for European airlines

Total cost translog regression (first order coefficients at the sample mean)			
variable	time-invariant inefficiency model	whole sample time-varying inefficiency model	firm-specific time-varying inefficiency model
output (RTK)	0.549***	0.540***	0.411***
input price of labour	0.280***	0.290***	0.257***
input price of capital;	0.286***	0.289***	0.317***
input price of materials (incl. fuel)	0.434 (interpolated)	0.431 (interpolated	0.426 (interpolated)
time Hicks-neutral technical progress	-0.020***	-0.004	-0.003
stage length	-0.092	-0.076	0.164
load factor	-0.320***	-0.321***	-0.246**
size	-0.181	-0.045	-0.147
jet	-0.001	-0.001	-0.002
wide-bodied	-0.004*	-0.003	0.001
Log likelihood	49.034	53.13	136.718
chi-square/F	2512.41***	131.69***	643.96***
σ	0.363	0.348	0.158
N	243	243	243
* p<0.05; ** p<0.01; *** p<0.001			

Figure 1 Technical Efficiency Change (EFC) component of Total Factor Productivity Change (TFPC)

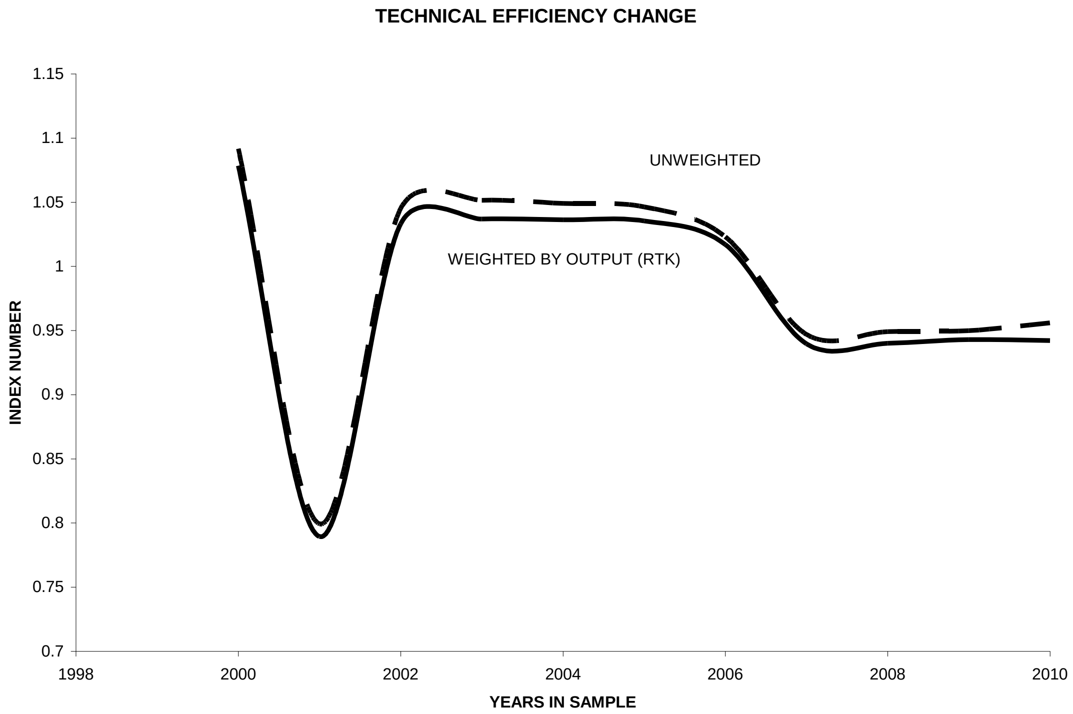

Figure 2 Allocative Efficiency Change (AFC) component of Total Factor Productivity Change (TFPC)

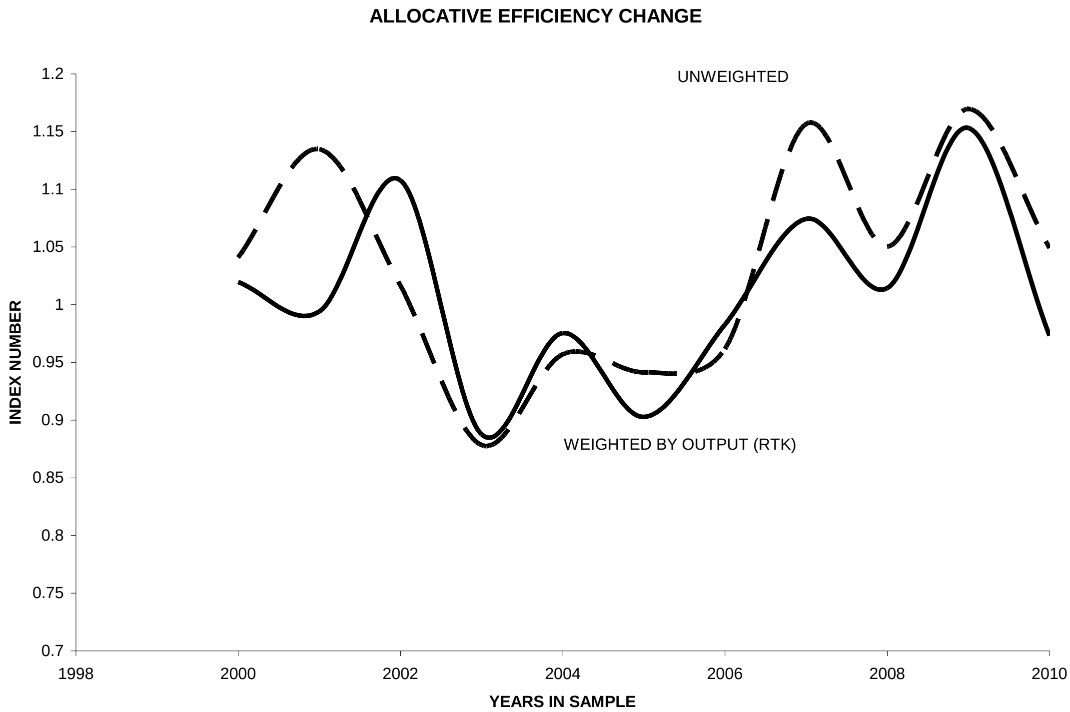

Figure 3 Scale Efficiency Change (SEC) component of Total Factor Productivity Change (TFPC)

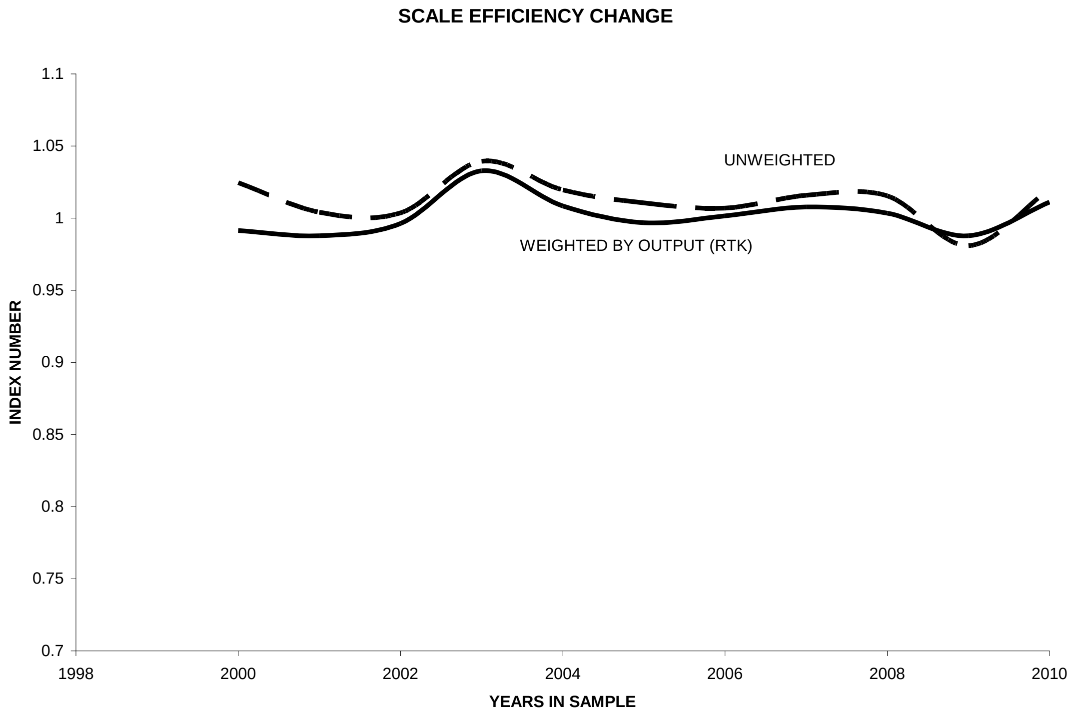

Figure 4 Overall Total Factor Productivity Change (TFPC)