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The Technical Efficiency of UK Airports

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Abstract:

In this paper, the innovative random stochastic frontier model is used to estimate the technical efficiency of UK airports. These airports are ranked according to their total productivity for the period 2000-2005 and homogenous and heterogeneous variables in the cost function are disentangled, which leads us to advise the implementation of common policies as well as policies by segments. Economic implications arising from the study are also considered.

Keywords:

Airports, UK, efficiency, random frontier models, policy implications

1. Introduction

This paper explores the use of random technical efficiency as an instrument for assessing the technical efficiency of UK airports, combining operational and financial data. The random frontier model allows for heterogeneity in the data and is considered the most promising state-of-the-art modelling available by which to analyse cost functions (Greene, 2003, 2004, 2005). The advantage of this method over alternative models is twofold. First, it allows for the error term to combine different statistical distributions. Second, it uses random parameters; i.e., parameters that describe factors not linked to observed features on the cost function. This type of estimation disentangles the explanatory variables to determine which of them must be treated in a homogeneous way and which are heterogeneous and must be managed by segments.

The efficiency of airports is of interest in contemporary economics, because of their increasing strategic importance in the movement of people and cargo in the globalised world (Oum and Yu, 2004). Efficiency has been the focus of much recent research (see Pels et al., 2001, 2003; Oum and Yu, 2004; Yoshida, 2004; Yoshida and Fujimoto, 2004; Fung, Wan, Hui and Law, 2007; Barros, 2008). Moreover, the increased competition among airlines resulting from deregulation and liberalisation has placed airports in a much more competitive environment. As a result, airports are now under pressure to upgrade their efficiency relative to their competitors. Benchmarking analysis is one of the ways to drive airports towards the frontier of best practices (De Borger, Kerstens and Costa, 2002).

Previous research on airports has been conducted by several authors using either data envelopment analysis (DEA), such as Gillen and Lall (1997), Parker (1999), Pels, Nijkamp and Rietveld (2001, 2003), Adler and Berechman (2001), Fernandes and Pacheco (2002), Barros and Sampaio (2004) and Murillo-Melchor (1999), or the homogeneous stochastic frontier model (Pels et al., 2001, 2003; Oum and Yu, 2004; Yoshida, 2004; Yoshida and Fujimoto, 2004; Fung, Wan, Hui and Law, 2007; Barros, 2008). However, the stochastic frontier model used in these papers is the homogenous frontier model, which assumes all units as homogenous. Therefore, the present research is innovative in the context of airports.

The paper is organised as follows: section 2 describes the institutional setting; section 3 surveys the literature on the topic; section 4 presents the methodological framework; section 5 explains the method; section 6 displays the data; section 7 presents the results; section 8 discusses the findings; and finally, section 9 concludes.

2. Institutional Setting

British airports are owned and managed by one of three distinct entities, BAA (British Airports Authority), Manchester Airports PLC and TBI PLC.

BAA is the owner and operator of seven British airports and operator of several airports in Italy and the USA, making it one of the world's largest transport-sector companies. It also owns British Airline. BAA was established by the passing of the Airport Authority Act 1966, to take responsibility for four state-owned airports. In 1986, under Margaret Thatcher's policy to privatise government-owned assets, BAA was transformed into a PLC and has achieved expansion beyond the UK. This includes the acquisition of retail contracts at Boston Logan International Airport and Baltimore-Washington International Thurgood Marshall Airport (through subsidiary BAA USA, Inc.), and a total management contract with the City of Indianapolis to run the Indianapolis International Airport (as BAA Indianapolis, Inc.). In July 2006, BAA was taken over by a consortium led by the Spanish transportation group, Grupo Ferrovial. As a result, the company was delisted from the London Stock Exchange (where it had previously been part of the FTSE100 index) and the company name was subsequently changed from BAA plc to BAA Limited.

Manchester Airports PLC, formed in 1986, manages several English city airports and is characterised by being a public limited company owned by local authorities. Following the purchase of a majority shareholding in Humberside Airport in 1999 and the acquisition of East Midlands Airport and Bournemouth Airport in 2001, the company was restructured to create the Manchester Airport Group. Although Manchester Airport Group is registered as a public limited company, its shares are not quoted or for sale on the Stock Exchange. Manchester City Council has a majority shareholding (55%) with each of nine other councils holding 5% each.

TBI PLC is the owner of three regional airports in England, Wales and Northern Ireland. In 2004, TBI was acquired by a Spanish enterprise owned by AENA, the company that manages Spanish airports, and Abertis, a Spanish construction company. The company has also expanded into international airport management under contract.

Table 1 depicts some characteristics of these companies in relation to UK airports. This ownership status contributes to the competition among airports. The competition itself is fuelled by the steady increase in passengers and flights, which is both a cause and effect of the competition between the traditional national flag carrier airlines and the new wave of low-cost carriers. London's airports (Heathrow, Gatwick, Stansted, Luton and London City Airport) accounted for 62% of the total traffic in 2005.

U.K. airports have been the subject of research by Parker (1999), who analyses the performance of the British Airports Authority before and after privatisation with data from the financial reports for the period 1979/80-1995/96, using a CCR-DEA model and a BCC-DEA model. In addition, Jessop (2008) analyses the performance of UK airports with a block model.

Table 1: Characteristics of the U.K. Airports in the Analysis (2005)

No.	Airport	Total Passenger arrivals (000)	Number of equivalent employees	Owned by BAA	Owned by Manchester Airports plc	Owned by TBI plc
1	Heathrow	67673	4052	1	0	0
2	Gatwick	32013	1877	1	0	0
3	Stansted	21268	1036	1	0	0
4	Southampton	1561	188	1	0	0
5	Glasgow	8620	445	1	0	0
6	Edinburgh	8057	406	1	0	0
7	Aberdeen	2699	233	1	0	0
8	Manchester	21324	1221	0	1	0
9	Bournemouth	502	123	0	1	0
10	Humberside	533	146	0	1	0
11	Nottingham	4436	259	0	1	0
12	Birmingham	8774	691	0	0	0
13	Newcastle	4749	332	0	0	0
14	Belfast	3543	205	0	0	1
15	Cardiff	1536	92	0	0	1
16	Luton	7532	430	0	0	1
17	Blackpool	348	102	0	0	0
18	Bristol	3718	200	0	0	0
19	Durham	844	142	0	0	0
20	Exeter	671	271	0	0	0
21	Highlands	952	309	0	0	0
22	Leeds	2450	243	0	0	0
23	Liverpool	3458	352	0	0	0
24	Biggin Hill	20	58	0	0	0
25	London City	1685	216	0	0	0
26	Norwich	447	204	0	0	0
27	Southend	4	48	0	0	0
	Mean	1420997	514	0.259	0.148	0.111
	Median	556032	243	—	—	—
	Standard Deviation	2667912	814	—	—	—

Note: airports not belonging to BAA, Manchester or TBI are independent city airports

3. Literature Survey

While there is extensive literature on benchmarking applied to a diverse range of economic fields, the scarcity of studies regarding European airports bears testimony to the fact that this is a relatively under-researched topic (Humphreys and Francis, 2002; Humphreys, Francis and Fry (2002), Graham, 2005).

In Table 2, we present the models, inputs and outputs used in the various papers.

Table 2: Research into Airport Efficiency

Papers	Method	Units	Inputs	Outputs
Gillen and Lall (1997)	DEA-BCC model and a Tobit model	21 US airports	i) *Terminal services model*: 1) Number of runways 2)Number of gates 3)Terminal area 4)Number of baggage collection belts 5) Number of public parking spots ii) *Movement model*: 1)Airport area 2)Number of runways 3) Runway area 4) Number of employees	i)*Terminal services model*: 1)Number of passengers 2)Pounds of cargo ii) *Movements model* 1)Air carrier movements 2)Commuter movements
Parker (1999)	DEA-BCC and CCR models	32 U.K. regulated airports, 1979/1980 to 1995/1996. In a second model, 22 airports are analysed from 1988/89 to 1996/97	1) Number of employees, 2) Capital input estimated as an annual rental based on a real rate of return of 8% each year applied to net capital stock, 3) Other inputs defined as the residual of total operating costs.	1) Turnover, 2) Passengers handled, 3) Cargo and mail business
Murillo-Melchor (1999)	DEA-Malmquist	33 Spanish civil airports, 1992 to 1994	1) Number of workers, 2) Accumulated capital stock proxied by amortisation, 3) Intermediate expenses	Number of passengers

Gillen and Lall (2001)	DEA-Malmquist	22 major US airports, 1989 to 1993	i) *Terminal services model*: 1) Number of runways, 2) Number of gates, 3) Terminal area, 4) Number of employees, 5) Number of baggage collection belts, 6) Number of public parking places. ii) *Movement model*: 1) Airport area, 2) Number of runways, 3) Runway area, 4) Number of employees	i) *Terminal services model*: 1) Number of passengers, 2) Number of pounds. ii) *Movement model*: 1) Air carrier movements, 2) Commuter movements.
Pels, Nijkamp and Rietveld (2001)*	DEA-BCC model.	34 European airports, 1995 to 1997	1) Terminal size in square meters, 2) Number of aircraft parking positions at the terminal, 3) Number of remote aircraft parking positions, 4) Number of check-in desks, 5) Number of baggage claims.	i) *Terminal model*: 1) Number of passengers. ii) *Movement model*: 1) Aircraft transport movements.
Pels, Nijkamp and Rietveld (2001)*	Stochastic frontier model.	34 European airports, 1995 to 1997	1) Constant, 2) Number of baggage claim units, 3) Number of parking positions at the terminal, 4) Number of remote parking positions.	i) *Terminal model*: 1) Number of passengers. ii) *Movement model*: 1) Aircraft transport movements.
Adler and Berechman (2001)	DEA-BCC with Principal Component Analysis.	26 European airports	1) Passenger terminals, runways, 2) Distance to city centres, 3) Minimum connecting times in minutes.	1)Principal components obtained from a questionnaire on airlines.
Martin and Román (2001)	DEA-CCR DEA-BCC	Spanish airports, 1997.	1)labor 2)capital 3)material	1)Passengers 2)Cargo 3)ATM
Martín-Cejas (2002)	Translog cost frontier model	40 Spanish airports, 1996-1997	WLU, labour price and capital price.	total cost
Fernandes and Pacheco (2002)	DEA.	16 Brazilian airports, 1998	1) Airport surface area in m2, 2) Departure lounge in m2, 3) Number of check-in counters, 4) Curb frontage in meters, 5) Number of vehicle parking spaces, 6) Baggage claim area in m2.	Domestic passengers.
Pels, Nijkamp and Rietveld (2003)**	DEA-BCC model.	33 European airports, 1995 to 1997	i) *Terminal model*: 1) Airport surface area, 2) Number of aircraft parking positions at terminal, 3) Number of remote aircraft parking positions, 4) Number of	i) *Terminal model*: 1) Annual number of domestic and international movements ii) *Movement model*: 1) Annual number of domestic and international passengers.

			runways; 5) Dummy z variables for slot-coordinated airports and 6) Dummy z variable for time restrictions. ii) *Movement model*: 1) Number of check-in-desks, 2) Number of baggage claim units; 3) Annual number of domestic and international movements.	
Pels, Nijkamp and Rietveld (2003)**	Stochastic frontier model	As above.	As above.	As above.
Sarkis (2000)	Several DEA models, including the CCR and BCC models.	43 US airports from 1990-1994.	1) Operating costs, 2) Employees, 3) Gates, 4) Runways.	1) Operating revenues, 2) Aircraft movements, 3) General aviation, 4) Total passengers, 5) Total freight.
Sarkis and Talluri (2004)	DEA-CCR and cross-efficiency DEA model from Doyle and Green (1994)	43 US airports from 1990-1994.	1)Operating costs, 2) Employees, 3) Gates, 4) Runways.	1) Operating revenue, 2) Aircraft movements, 3) General aviation, 4) Total passengers, 5) Total freight.
Barros and Sampaio (2004)	DEA - allocative Model.	10 Portuguese airports 1990-2000.	1) Number of employees, 2) Capital proxied by the book value of physical assets, 3) Price of capital, 4) Price of labour.	1) Number of planes, 2) Number of passengers, 3) General cargo, 4) Mail cargo, 5) Sales to planes, 6) Sales to passengers.
Yoshida (2004)	Endogenous-Weight method	43 Japanese airports, 2000.	1) Runway length, 2) Terminal size.	1) Passenger loading, 2) Cargo handling, 3) Aircraft movement.
Yoshida and Fujimoto (2004)	DEA-CCR, DEA-BCC and Input distance function.	43 Japanese airports, 2000.	1) Runway length, 2) Terminal size, 3) Monetary access cost, 4) Time access cost, 5) Number of employees in terminal building.	1)Passenger loading, 2)cargo handling, 3)aircraft movement.
Lin and Hong (2006)	DEA-CCR, DEA-BCC DEA-FDH	20 major world airports, 2003	1) number of employees 2) number of check counters 3) number of runways 4) number of parking spaces 5) number of baggage collection belts 6) number of aprons 7) number of boarding gages 8) termina area	1)Number of passengers 2)cargo 3) movement
Barros and Dieke (2007)	Multiple DEA models	31 Italian airports, 2001-2003	1) Labour cost, 2) Capital invested, 3) Operational costs excluding wage costs.	1) Number of planes, 2) Number of passengers, 3) General cargo. 4) Handling receipts, 5) Aeronautical sales, 6) Commercial sales.

Fung, Wan, Hui and Law (2007)	Malmquist DEA model	25 regional Chinese airports, 1995-2004.	1) Runway length, 2) Terminal size.	1) Passengers handled, 2) Cargo handled, 3) Aircraft movements.
Barros (2008)	Homogenous stochastic frontier model	10 Portuguese airports, 1990-2000	1) Operating costs, 2) Price of capital, 3) Price of labour.	1) Sales to planes, 2) Sales to passengers, 3) Non-aeronautical fee.
Barros and Dieke (2008)	DEA two-stage model	31 Italian airports, 2001-2003	1) Labour costs 2) Capital invested 3) Operational costs excluding labour costs. *Second-stage variables*: 4) Hub 5) WLU 6) Private 7) North.	1) Number of Planes 2) Number of Passengers 3) General Cargo 4) Handling receipts 5) Aeronautical sales 6) Commercial sales.

* The paper by Pels, Nijkamp and Rietveld (2001) presents two methods for analysing efficiency. We therefore present the paper in two separate entrie s in order to explain the techniques.

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We can observe that a conventional approach to the analysis of airports is to separate activities into terminals and movements (Gillen and Lall, 2001; Pels, Nijkamp and Rietveld, 2001; Pels, Nijkamp and Rietveld, 2003). Several papers compare the DEA model with the frontier model (Pels, Nijkamp and Rietveld, 2001; Pels, Nijkamp and Rietveld, 2003, Hooper and Hensher, 1997), while others combine principal component analysis with a DEA model (Adler and Berechman, 2001). Furthermore, others rely on the homogenous stochastic frontier models to analyse airport efficiency (Pels, Nijkamp and Rietveld, 2001, 2003). Therefore, our use of the random frontier model is innovative in this context.

4. Theoretical Framework

In this paper, two economic efficiency models are adopted as theoretical references. The first of these is the strategic-group theory (Caves and Porter, 1977), which justifies differences in efficiency scores as being due to differences in the structural characteristics of units within an industry, which in turn lead to differences in performance. In the case of UK airports, units with similar asset configurations pursue similar strategies, with similar results in terms of performance (Porter, 1979). While different strategic options can be found among the different sectors of an industry, not all options are available to each airport due to mobility impediments, causing a spread in the efficiency scores of the industry.

The second theoretical reference is the resource-based theory (Barney, 1991; Rumelt, 1991; Wernerfelt, 1984), which justifies different efficiency on the grounds of heterogeneity of resources and capabilities on which airports base their strategies. These resources and capabilities may not be perfectly mobile across the industry, resulting in a competitive advantage for the best-performing airport.

These two theoretical frameworks are rooted in economics (the strategic-group theory) and in management (resource-based theory) and are adequate to support efficiency analysis, whenever there are variations in the efficiency among the units observed. Moreover, both theories have been previous used to support efficiency analysis (Warning, 2004; Taymaz, 2005).

Purchasable assets cannot be considered to represent sources of sustainable profits. Indeed, critical resources are not available in the market. Rather, they are built and accumulated on the airport's premises, their non-imitability and non-substitutability being dependent on the specific traits of their accumulation process. The difference in resources thus results in barriers to imitation (Rumelt, 1991) and in the airport managers' inability to alter their accumulated stock of resources over time. In this context, unique assets are seen as exhibiting inherently differentiated levels of efficiency; sustainable profits are ultimately a return on the unique assets owned and controlled by the airport (Teece et al., 1997).

5. Method

The methodological approach adopt here is the stochastic cost econometric frontier. The frontier is estimated econometrically and measures the difference between the inefficient units and the frontier by the residuals, which are assumed to have two components: noise and inefficiency. The general frontier cost function is of the form:

$$C_{it} = C(X_{it}) \cdot e^{v_{it}+u_{it}} \; ; \forall \;\; \mathrm{i}=1,2,\ldots N; \forall \; \mathrm{t}=1,2,\ldots T \qquad (1)$$

Where C_{it} represents a scalar cost of the decision-unit i under analysis in the t-th period; X_{it} is a vector of variables including input prices and output descriptors present in the cost function. The error term v_{it} is assumed to be i.i.d. and represents the effect of random shocks (noise). It is independent of u_{it}, which represents technical inefficiencies and is assumed to be positive and to follow a $N(0, \sigma_u^2)$ distribution. The disturbance u_{it} is reflected in a half-normal independent distribution truncated at zero, signifying that the cost of each airport must lie on or above its cost frontier, implying that deviations from the frontier are caused by factors controlled by the airport management authority.

The total variance is defined as $\sigma^2 = \sigma_v^2 + \sigma_u^2$. The contribution of the different elements to the total variation is given by: $\sigma_v^2 = \sigma^2 / (1+ \lambda^2)$ and $\sigma_u^2 = \sigma^2 \lambda^2 / (1+ \lambda^2)$; where $\lambda = \sigma_u / \sigma_v$, which provides an indication of the relative contribution of u and v to $\varepsilon = u + v$. Because estimation of equation (1) yields merely the residual ε, rather than u, the latter must be calculated indirectly (Greene, 2003). For panel data analysis, Battese and Coelli (1988) used the expectation of u_{it} conditioned on the realised value of $\varepsilon_{\mathrm{it}} = u_{\mathrm{it}} + v_{\mathrm{it}}$, as an estimator of u_{it}. In other words, $\mathrm{E}[u_{\mathrm{it}+}\nu_{\mathrm{it}}| \; \varepsilon_{\mathrm{it}}]$ is the mean productive inefficiency for airport i at time t. But the inefficiency can also be due to the airports' heterogeneity, which implies the use of a random effects model:

$$c_{it} = (\beta_0 + w_i) + \mathbf{\beta}'\mathbf{x}_{it} + v_{it} + u_{it} \tag{2}$$

where the variables are in logs and w_i is a time-invariant specific random term that captures individual heterogeneity. A second issue concerns the stochastic specification of the inefficiency term u, for which the half-normal distribution is assumed. For the likelihood function we follow the approach proposed by Greene (2005), where the conditional density of c_{it} given w_i is:

$$f(c_{it} \mid w_i) = \frac{2}{\sigma}\phi\left(\frac{\varepsilon_{it}}{\sigma}\right)\Phi\left(\frac{\lambda\varepsilon_{it}}{\sigma}\right) \ , \ \varepsilon_{it} = c_{it} - (\beta_0 + w_i) - \mathbf{\beta}'\mathbf{x}_{it} \tag{3}$$

Where ϕ is the standard normal distribution and Φ is the cumulative distribution function. Conditioned on w_i, the T observations for airport i are independent and their joint density is:

$$f(c_{i1},...,c_{iT} \mid w_i) = \prod_{t=1}^{T}\frac{2}{\sigma}\phi\left(\frac{\varepsilon_{it}}{\sigma}\right)\Phi\left(\frac{\lambda\varepsilon_{it}}{\sigma}\right) \tag{4}$$

The unconditional joint-density is obtained integrating the heterogeneity out of the density.

$$L_i = f(c_{i1},...,c_{iT}) = \int_{w_i}\prod_{t=1}^{T}\frac{2}{\sigma}\phi\left(\frac{\varepsilon_{it}}{\sigma}\right)\Phi\left(\frac{\lambda\varepsilon_{it}}{\sigma}\right)g(w_i)dw_i = E_{w_{ii}}\left[\prod_{t=1}^{T}\frac{2}{\sigma}\phi\left(\frac{\varepsilon_{it}}{\sigma}\right)\Phi\left(\frac{\lambda\varepsilon_{it}}{\sigma}\right)\right] \tag{5}$$

The log likelihood is then maximised with respect to β_0, $\mathbf{\beta}$, σ, λ and any other parameter appearing in the distribution of w_i. Even if the integral in expression (5) is intractable, the right-hand side of (5) leads us to propose computing the log likelihood by simulation. Averaging the expectation over a sufficient number of random draws from the distribution of w_i will produce a sufficiently accurate estimate of the integral shown in (5) to allow estimation of the parameters (see Gourieroux and Monfort, 1996; Train, 2003). The simulated log likelihood is then:

$$\log L_s(\beta_0, \mathbf{\beta}, \lambda, \sigma, \theta) = \sum_{i=1}^{N} \log \frac{1}{R} \sum_{r=1}^{R} \left[\prod_{t=1}^{T} \frac{2}{\sigma} \phi\left(\frac{\varepsilon_{it} \mid w_{ir}}{\sigma} \right) \Phi\left(\frac{\lambda \varepsilon_{it} \mid w_{ir}}{\sigma} \right) \right] \tag{6}$$

where θ includes the parameters of the distribution of w_i and w_{ir} is the r-th draw for observation *i*. Based on our panel data, Table 4 presents the maximum likelihood estimators of model (1), as found in recent studies (see Greene, 2004 and 2005).

6. Data

We use a balanced panel comprising twenty-seven UK airports during six years from 2000/01 to 2004/05 (162 observations) obtained in Cruickshank, Flannagan and Marchant's *Airport Statistics* [CRI - Centre For The Study of Regulated Industries, University of Bath (several years)]. The variables were transformed as described in Table 3, where monetary magnitudes are expressed in £'000 pounds, deflated by the GDP deflator and denoted at prices of 2002.

Table 3: Descriptive Statistics of the Data

Variable	Description	Minimum	Maximum	Mean	Standard Deviation
LgCost	Logarithm of operational cost in pounds at constant price 2002=100	6.6685	8.9475	7.4633	0.4104
LgPL	Logarithm of price of workers, measured by dividing total wages between the number of workers	4.61378	6.8152	5.7316	0.3782
LgPK1	Logarithm of price of capital-premises, measured by the amortisations divided by the value of the total assets	0.00453	0.3959	0.0689	0.0486
logPK2	Logarithm of price of capital-investment, measured by the cost of long-term investment divided by the long-term debt	0.0252	0.278	0.083	0.012
LgPassengers	Logarithm of the passengers at each airport in pounds at constant price 2002=100	5.6367	8.3703	7.2507	0.4537
LgAircraft	Logarithm of the aircraft movements at each airport	1.4313	1.9542	1.7216	0.0988

The specification of the cost function follows microeconomic theory (Varian, 1987). The costs are regressed in input prices and output descriptors. The empirical specification of the cost function is the translog. We have chosen a flexible functional form in order to avoid imposing unnecessary *a priori* restrictions on the technologies to be estimated. Each explanatory variable is divided by its geometric mean. In this way, the translog can be considered as an approximation to an unknown function and the first order coefficients can be interpreted as the production elasticities evaluated at the sample geometric mean. We also include both a time trend and a squared time trend in order to obtain some temporal changes. The equation to estimate is:

$$\ln(Cost_{it}) = \tau_0 + \tau_1 t + \frac{1}{2}\tau_2 t^2 + \sum_{k=1}^{m} \alpha_k \ln y_{kit} + \sum_{j=1}^{n} \beta_j \ln w_{jit} +$$
$$\frac{1}{2}\left[\sum_{k=1}^{m}\sum_{r=1}^{m} \pi_{kr} \ln y_{kit} \ln y_{rit} + \sum_{j=1}^{n}\sum_{s=1}^{n} \delta_{js} \ln w_{jit} \ln w_{snt}\right] + \sum_{k=1}^{m}\sum_{j=1}^{n} \theta_{kj} \ln y_{kit} \ln w_{jit} + (V_{it} - U_{it})$$
(7)

where y is the output measured as points, w denotes input price, t is a time trend, v is a random error which reflects the statistical noise and is assumed to follow a normal distribution centred at zero, while u reflects inefficiency and is assumed to follow a half-normal distribution. Each explanatory variable was divided by its geometric mean. In this way, the translog can be considered as an approximation to an unknown function and the first order coefficients can be interpreted as the production elasticities evaluated at the sample geometric mean. We also included a time trend and a squared time trend in order to get some temporal changes. Therefore the equation to estimate is:

Table 4: Stochastic panel cost frontier (Dependent Variable: Log Cost)

Variables	**Translog Non-Random Frontier Model**	**Translog random Frontier model**
Non-random parameters	**Coefficient (t-ratio)**	**Coefficient (t-ratio)**
Constant	0.555 (0.528)	0.342 (0.127)
Trend	2.302 (5.012)*	1.021 (3.219)*
Trend^2	-0.287 (-4.361)*	-0.158 (-4.218)*
LogPL	0.515 (1.812)	0.532 (4.329)*
Log PK1	0.210 (3.219)	0.212 (3.294)*

LogPK2	0.248 (5.186)*	0.148 (4.218)*
LogPassengers	0.488 (7.894)*	—
LogAircraft	-0.104 (-1.167)	—
$(\log PL)^2$	0.016 (1.577)	0.345 (5.318)*
$(\text{LogPK1})^2$	0.563 (2.218)	0.018 (3.892)*
$(\text{LogPK2})^2$	1.218 (1.215)	0.967 (3.321)*
$(\text{Log Passengers})^2$	0.053 (2.031)	0.067 (5.321)*
$(\text{Log Aircraft})^2$	-0.078 (-2.129)	-0.021 (-2.167)
Trend*log PL	0.267 (3.178)*	0.124 (3.289)*
Trend*logPK1	0.056 (0.021)	0.002 (1.005)
Trend*logPK2	0.078 (0.127)	0.021 (0.032)
Trend*logPassengers	0.564 (2.563)	0.218 (3.656)*
Trend*logAircraft	-0.035 (-0.127)	-0.021 (-0.023)
LogPL*logPK1	0.127 (2.563)	0.041 (1.027)
LogPL*logPK2	0.189 (1.028)	0.039 (0.219)
LogPL*logPassengers	-0.559 (-4.089)*	-0.008 (-0.789)
logPL*logAircraft	0.437 (2.960)	0.032 (1.673)
Log PK1*logPK2	0.128 (1.027)	0.025 (3.218)[a]
LogPK1*logPassengers	0.053 (2.125)	0.026 (3.142)*
LogPK1*LogAircraft	0.095 (1.219)	0.071 (3.219)*
LogPK2*logPassengers	0.053..(1.214)	0.019 (0.218)
LogPK2*logAircraft	0.026 (0.278)	0.004 (0.021
Log Passengers*log Aircraft	-0.301 (-8.262)*	-0.021 (-3.218)*
BAA	0.346 (2.184)*	0.218 (3.672)*
Manchester	0.147 (0.963)	0.128 (3.218)*
TBI	0.310 (1.009)	0.289 (3.210)*
Mean for Random Parameters		
LgPassengers		0.478 (3.219)*
LgAircraft	–	-0.052 (-3.937)*
Scale Parameters for Distribution of Random Parameters		
LgPasseng	–	0.984 (4.218)*
LgPasseng	–	0.021 (3.219)*
Statistics of the model		
$\sigma = (\sigma_V^2 + \sigma_U^2)^{½}$	0.507 (9.112)*	0.318 (5.219)*
$\lambda = \sigma_U / \sigma_V$	0.772 (3.012)*	0.248 (3.218)*
Log likelihood	-116.289	-116.521
Chi Square Degrees of freedom Probability	132.214 3 0.000	141.210 3 0.000
Observations	162	162

t-statistics in parentheses (* indicates that the parameter is significant at 1% level).

Table 4 presents the results obtained for the stochastic frontier, using GAUSS and assuming a half-normal distribution specification for the cost function frontier.

Regularity conditions require the cost function to be linearly homogeneous, non-decreasing and concave in input prices (Cornes, 1992).

Turning to the number of observations and exogenous variables, we use the translog model with a half-normal distribution, a choice that is supported by the data analysis. Having estimated two rival models, the homogeneous and heterogeneous translog frontier models and heterogenous frontier model, we apply the likelihood test and conclude that the heterogeneous frontier is the most adequate functional form. In addition, we computed the Chi-square statistic for general model specification, which also advocates using the heterogeneous frontier.

Finally, in order to differentiate between the frontier model and the cost function, we consider the sigma square and the lambda of the cost frontier model. They are statistically significant, meaning that the traditional cost function is unable to capture adequately all the dimensions of the data. Furthermore, the random cost function fits the data well, since both the R^2 and the overall F-statistic (of the initial OLS used to obtain the starting values for the maximum-likelihood estimation) are higher than the standard cost function. Lambda is positive and statistically significant in the stochastic inefficiency effects, and the coefficients have the expected signs.

The variables have the expected signs since all price elasticities are positive. Moreover, instead imposing homogeneity in prices we have tested it. Therefore we accept the hypothesis that the cost function is homogeneous in prices for both models. It can be seen that the labor elasticity is 0.532. Cost increases along the trend and decreases with the square trend and moreover, increases significantly with the price of labour, the price of capital-premises, the price of capital-investments and passengers. The cost decreases with aircraft. Moreover, passengers and aircraft are heterogeneous statistically significant variables. The statistically significant random parameters vary along the sample. The identification of the mean values of random parameters implies taking into account heterogeneity when implementing cost control measures.

7. Efficiency Scores

The motivation and scope of this paper derive from the fact that random frontier models generally succeed at describing the costs structure of UK airports. In particular, our analysis suggests that homogenous frontier models should be abandoned since they do not capture relevant aspects of the examined context. On the contrary, random frontier models allow the homogenous and heterogeneous variables to be disentangled.

Based on the new frontier, the alternative ranking is shown in Table 5, which reports the cost average cost efficiency for each airport across the sample. The cost efficiency is defined as the ratio between the minimum cost and the actual cost, implying that it takes values between 0 and 1. Hence, the closer to 1 is the ratio, the more efficient the airport is. Given that the dependent variable has been transformed in logarithms, we compute:

$$EC = exp(-\hat{u}) \qquad (8)$$

where the estimated value of the inefficiency ($\hat{u}$) is separated from the random error term ($\hat{v}$), using the Jondrow et al. (1982) formula.

Table 5: Average Cost Efficiency

Obs	Homogeneous Translog Frontier model Airports	Efficiency Scores	Heterogenous or random Frontier model Airports	Efficiency Scores
1	Manchester	1	Luton	1
2	Norwich	0.997412	Newcastle	0.943234
3	Aberdeen	0.905293	Leeds	0.82459
4	Highlands	0.806273	Liverpool	0.82163
5	Bournemouth	0.741081	Southampton	0.793113
6	Glasgow	0.664058	Nottingham	0.777509
7	Edinburgh	0.629182	Glasgow	0.728814
8	Heathrow	0.619693	Durham	0.699758

9	Southampton	0.580381	Edinburgh	0.693839
10	Stansted	0.514696	Aberdeen	0.692494
11	Biggin Hill	0.495779	Bristol	0.645951
12	Humberside	0.457946	Belfast	0.644606
13	Exeter	0.400579	Cardiff	0.616626
14	London City	0.377534	Blackpool	0.60452
15	Gatwick	0.366874	Bournemouth	0.563627
16	Liverpool	0.347218	Stansted	0.559322
17	Luton	0.292624	Humberside	0.558515
18	Belfast	0.288681	Birmingham	0.539144
19	Newcastle	0.259474	Southend	0.514662
20	Birmingham	0.258734	Exeter	0.513048
21	Leeds	0.221948	Biggin Hill	0.507398
22	Cardiff	0.221086	London City	0.469465
23	Durham	0.202662	Highlands	0.455206
24	Bristol	0.197178	Norwich	0.446059
25	Nottingham	0.150964	Manchester	0.442023
26	Blackpool	0.150225	Gatwick	0.435297
27	Southend	0.146651	Heathrow	0.417867
	Mean	0.455342	Mean	0.626234

The results displayed in Table 5 demonstrate that each of the frontier specifications produce different scores, with the homogenous frontier model displaying a higher level of relative efficiency. The average efficiency is 0.62 on the random or heterogenous frontier but only 0.45 in the homogenous frontier. A comparison of both models reveals that the homogeneous scores present larger variances than those computed from the heterogeneous frontier, which signifies that heterogeneity in variables contaminates the scores.

It can be observed that taking into account heterogeneity, the rankings change and the best practice is achieved by a small UK airport, Luton, which is a TBI airports specialised in low cost airlines. Moreover, the four top positions are achieved by the independent city airports, while the weakest position is achieved for the most important UK airports, Heathrow, Gatwick and Manchester.

8. Discussion

This article has proposed a simple framework for the comparative evaluation of UK airports and the rationalization of their operational activities. The analysis was carried out through implementation of a Random or heterogenous stochastic frontier model, which allows for the incorporation of multiple inputs and outputs in determining the relative efficiencies and the inclusion of heterogeneity in the data.

The main policy implication of the findings of the present analysis is that heterogeneity must be considered a major issue in the UK airports. Accordingly, public policies towards airports should take into account such heterogeneity. For instance, the authorities could implement policies by segments defined by passengers and aircraft with the aim of regulating aircraft and passenger movements in the UK airports. The planned "open skies" between the USA and the UK is one such policy, since it will have an adverse effect on London's airports and be more beneficial to other British airports. Understandably, BAA is now blocking the accord. New slots allocation in congested airports is another policy move. Airport capacity is expressed in slots (i.e. an expression of capacity representing the permission given to a carrier to operate an air service at a slot-controlled airport on a specific date and time for the purpose of landing and take-off) and is allocated within the framework of voluntary guidelines developed and evolved over the years by IATA. Slot allocation in European Union airports falls within the scope of the European Union Single Market, thus being subject to a common regulatory framework under European Council Regulation. Under the congestion pricing strategy (Madas and Zografos, 2008), historic slot rights will be abandoned and a congestion-based scheme with fees varying with congestion throughout the day will be set by an administrative authority. Each carrier could operate at any time or slot by paying the corresponding scarcity rent (i.e., congestion fee). During recent years, the European Commission (1993, 2001, 2004) has pursued a radical revision of the existing slot allocation regime, aiming to deal with the scarcity of airport capacity. However, IATA regulation 95/93 denies the use of market-based mechanisms to allocate slots. The European Commission proposes several market-based slot allocation mechanisms (Madas and Zagrafos, 2008). This will be a natural area for cluster regulation, using different market–based slot allocation mechanisms based on the characteristics of the UK airports.

Relative to results of the model, the cost increases alongside with the trend, which hints that there are not technological improvements during the period to drive the costs down? However, costs increases at decreasing rate. Moreover, the cost significantly increases homogenously with price of labour, price of capital-premises and capital-investment. It also rises with passengers and aircrafts, but in a random way. The significant random parameters vary along the sample. The identification of the mean values of random parameters implies having into account the heterogeneity when implementing policies for cost control.

What is the rationality of this result? This is an intuitive result, since airports are not homogenous. There are small and large and medium sized airport. These visible characteristics translate into different performances obtained in the market, resulting in different clusters within the market. These clusters are distinguished from each other based on the passenger and aircraft. This result also signifies that other inputs are relatively homogenous on the labour and capital. With regard to labour and capital, this means that competition over resources drives the market and translates into homogenous dynamics in the labour and capital market.

How can we explain the efficiency rankings? This is an endogenous result of the model, which can be explained by congestions and other managerial problems that the bigger airports are facing in contemporary world which affect their performance.

In comparison with the previous literature in this area, our research overcomes the bias towards DEA models in studies on airports. Relative to the stochastic frontier model, all published papers have adopted models using homogenous frontiers and no clear comparisons can be made. The comparison between homogenous and heterogeneous frontier models is undertaken in the present research, concluding that heterogeneity better captures the cost structure of the UK airports, based on the log likelihood test. Possibly, the main limitation of the present research relates to the data span, which is, to some extent, short for econometric purposes. The prevalence of DEA models in this research field exhibits the problem of the short data span at European level. Therefore, a larger data set is needed to confirm the validity of the present results.

The main limitations of the present research are related to the short data span. Since the data set is short, the conclusions are limited. In order to generalise, a larger panel data set would be necessary. Future extensions of the present research include the analysis of the effects of competition, regulation and the Spanish presence on the efficiency of airports in the UK, Oum, Adler and Yu (2006).

9. Conclusion

Common policies can be defined for UK airports based on the average values of the homogeneous variables, whereas segmented policies may be prescribed to account for heterogeneous variables. Given that the scale parameters of heterogeneous variables are statistically significant, we recognise such heterogeneity, which entails managerial insights and policy implications.

More research is needed to confirm the present conclusions.

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