Testing the effects of economic regulation on the cost efficiency of European airports using homogenous Stochastic Frontier Analysis

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Abstract

Over the past 15 years, the European airports market has changed considerably. The gradual commercialisation and privatisation of airports in the European Union, driven by the Single European Market objective, has increased the need for economic regulation of previously state-operated airports. It is therefore important for policymakers to understand how well theoretical regulatory incentives work in practice. Using a sample of 34 European airports between 2000 and 2009, this paper tests the effects of economic regulation on variable costs and variable cost efficiency, with the hypothesis that regulation would increase variable costs and make regulated airports less cost efficient than their unregulated counterparts. The results support the hypothesised effects of regulation on variable costs but also show the importance of airport size as a driver of variable costs. However, the hypothesis that regulated airports are less cost efficient than unregulated airports is rejected. Each type of regulation overall appears to be able to provide cost efficiency incentives as sharp as those faced by unregulated airports, although certain distinct theoretical incentives appear to not materialise in practice. Economic regulation may therefore be an effective policy tool as it does not appear a detrimental effect on the cost efficiency of European airports.

Keywords: Airports, Economic Regulation, Stochastic Frontier Analysis

1. Introduction

Over the past 15 years, the European airports market has changed considerably. The gradual commercialisation and privatisation of airports in the European Union, driven by the Single European Market objective, has increased the need for economic regulation of previously state-operated airports. It is therefore important for policymakers to understand how well theoretical regulatory incentives work in practice. Economic regulation is intended to resolve market failure and replicate a well-functioning competitive market and so could be expected to provide regulated airports with incentives to improve cost (and technical) efficiency. However, issues in the implementation of theoretical regulatory models mean that their intended incentives may not always materialise. Airport regulators may also have other objectives that may compete with cost efficiency incentives, including ensuring that an airport undertakes sufficient investment or that it operates in the intertemporal interests of all its users. The actual effects of regulation on airport cost efficiency may be then a priori less clear.

The aim of this paper is to build on the existing literature to analyse the effects of particular types of regulation on the variable cost efficiency of a sample of 34 European airports between 2000 and 2009 using Stochastic Frontier Analysis. The findings would also enable a comparison of the actual effects of each type of regulation with their theoretical incentives. This paper is structured as follows. Section 2 introduces the different models of economic regulation in use in Europe. Section 3 summarises the existing literature. Building on sections 2 and 3, the hypothesis to be tested in this paper is set out in section 4. Section 5, 6, 7, 8 introduce cost functions, stochastic frontier analysis, the model assessment criteria and the data set respectively. The regression results and efficiency scores are reported and analysed in sections 9. Section 10 discusses the results and concludes while also considering the methodological limitations and suggesting areas for further research.

2. Economic regulation of European airports

According to Niemeier (2009), there are two general motivations for the economic regulation of airports. A theoretical motivation lies in correcting market failure and accounting for positive network externalities that lead to economies of scale and density from increased passenger footfall and airline operations. A more pragmatic reason is to control the exertion of an airport's substantial market power, arising from an absence of close substitutes, (see for example DfT 2007). Similarly, Crew and Kleindorfer (1996) argued that economic regulation should resolve allocative inefficiency resulting from imperfect competition. It would then follow that airports facing competition should not require regulation because their competitive constraints would exert a downward pressure on price and create incentives to drive costs, service quality and efficiency towards the market-clearing level. By contrast, airports enjoying significant market power would face weaker competitive constraints, creating a rationale for implementing economic regulation.

In the European Union, ex ante economic regulation is typically used to restrict the maximum prices (revenue) per passenger that regulated airports can charge (earn), either through rate of return regulation or hybrid price caps.[1] Rate of return regulation, in theory, allows an airport to recover costs by setting an allowed rate of return that the airport can earn on its assets, which is calculated using a regulated asset base (RAB) generally based on historical cost accounting. Two major criticisms of this model are that it allows the airport to fully pass through all its costs to its users, and that it incentivises over-investment and gold-plating of assets, the Averch-Johnson (1962) effect, by shielding the airport from market risk. Tretheway (2001) described it as "something like having an unlimited expense account; if you could produce a receipt, you would be reimbursed." However, some mitigating measures such as negotiated settlements and certain forms of capital expenditure triggers could be used to reduce over-investment. Despite this, rate of return regulation would overall provide weak cost efficiency incentives.

Hybrid price caps loosely make use of the Littlechild (1983) RPI-X framework where a price cap rises at the rate of inflation (CPI or RPI) minus (or plus) a productivity adjustment (X). For example, the UK CAA sets the price cap as the maximum average revenue per passenger at the designated airport(s). Theoretically, price caps incentivise cost reduction since the airport can retain any profits earned by pricing at the cap while having a cost base below it. However, this incentive may have two detrimental consequences.

First, the incentive to reduce costs could result in under-investment. For this reason, price regulation is in practice often based in part on the value of an airport's RAB in order to

[1] Lighter-handed regulation such as price monitoring in Australia has not (yet) been implemented in Europe.

incentivise investment. Starkie (2004) argued that the inclusion of a RAB eliminates the difference between hybrid price caps and rate of return regulation, and Starkie (2006) added that three managerial incentives could actually lead to over-investment under a hybrid price cap, citing the example of BAA in the 1990s. First, managers generally prefer to avoid congestion and quality problems. Second, they would gold plate assets to manage larger, more prestigious airports. Third, managers may over-invest to show their market power to deter new entrants. Niemeier (2009) added that setting a price cap below the market-clearing level at a congested airport might distort efficiency and investment incentives. By contrast, Graham (2007) and Forsyth (2002) argued that a hybrid price cap gives greater efficiency incentives since it is set on a forward-looking basis. For both types of regulation discussed above, the length of the regulatory lag can act as an additional barrier to investment, due to a conflict between regulatory and investor time horizons. For example, quinquennial reviews of a price cap would create uncertainty for investors considering returns on investment over a time horizon of fifteen years. This is known as the regulatory commitment problem.

Second, the cost reduction incentive may also result in the airport supplying sub-optimal service quality. As a counter-measure, regulators often stipulate a minimum level of service quality which implies additional necessary operating expenditure. Since hybrid price caps are in practice often supplemented by other regulatory stipulations, the actual incentive to cost reduction and efficiency may no longer materialise.

Several other aspects of economic regulation can affect theoretical incentives. Pricing and investment incentives can also be affected by the regulatory till, which determines which charges are taking into account when setting a price cap. Starkie and Yarrow (2000) provide an overview of the relative merits of single and dual till regulation. Additional supplements to price regulation can include sliding scales, revenue drivers, and risk-sharing agreements. Regulatory independence from government may improve the effectiveness of regulatory incentives by increasing transparency (Niemeier 2009). In Europe, however, only the Austrian, Dutch and UK regulators are independent. For example, the French regulator did not disclose key figures such as the value of the RAB in its 2006 regulatory decision (Morgan Stanley 2006). However, analysing the precise effects of these regulatory details is beyond the scope of this paper.

Outside the European Union, airports in Europe still tend to be directed by their respective state governments, raising questions concerning their incentives. While economic theory suggests that public enterprises maximise social welfare instead of profits and are therefore less efficient, the empirical evidence does not always confirm this. Bhattacharyya (1994) found public US water utilities to be more efficient than their private counterparts, while Caves and Christensen (1980) did not find a significant difference between public and private Canadian railroad efficiency. Conversely, Button and Weyman-Jones (1992) supported economic theory and an extensive study by Oum (2006) concluded that public and majority-publicly owned airports were significantly less efficient than those majority-privately owned.

3. Literature Review

Most of the existing literature studying airport efficiency used variants of non-parametric Data Envelopment Analysis (DEA) to analyse technical efficiency using production functions on datasets ranging from individual countries and continents to airports worldwide. A thorough summary of previous empirical work is available in Barros (2008a). Comparatively fewer papers have made use of Stochastic Frontier Analysis (SFA) in analysing the airports sector. SFA is a parametric approach which can be used to estimate either production or cost functions to derive efficiency scores relative to a frontier firm. Despite imposing a functional form, which introduces the risk of misspecification, an advantage of SFA is that the statistical significance of each cost driver can be tested. Pels (2001, 2003) provided a homogenous stochastic frontier analysis of 34 European airports for the years 1995-97 using a production function. Scotti (2010) analysed the impact of airport competition on technical efficiency for Italian airports. Oum (2007) investigated the effects of ownership on airport efficiency for a worldwide sample. Cost efficiency was analysed by Barros (2007, 2008a). The first paper used a homogenous SFA model on 10 Portuguese airports between 1990 and 2000 while the second used latent class stochastic frontier analysis for UK airports between 2000 and 2006 to capture airport heterogeneity and obtain more precise cost efficiency estimates. Another example is the translog cost frontier model used by Martín-Cejas (2002) for 40 Spanish airports for 1996-7.

The effects of regulation on airport cost efficiency appear to be an under-researched area in the existing literature. Since DEA does not allow the inclusion of control variables, it cannot be used to test the effects of regulation. Oum (2003) compared different types of regulation using productivity indices using a sample of worldwide airports. In terms of capital input productivity, price caps gave greater efficiency incentives than rate of return regulation, largely due to their under-investment incentive. Similarly, total factor productivity was lower for rate of return regulation. These findings supported economic theory.

By contrast, Bel and Fageda (2010) and Bilotkach (2010) partly supported Starkie (2004) by finding that aeronautical charges do not vary markedly according to type of regulation. The imposition of economic regulation in itself seemed to create a downward pressure on charges, which would suggest that all regulation overall gives the same incentives. In contrast, Barros (2008b) found that imposing regulation increased UK airport costs and decreased efficiency, suggesting that regulation may be implemented to protect the interests of consumers and not always to reduce airport costs and inefficiency.

Only Barros and Marques (2008) have used SFA to consider the effect of each type of price regulation on cost efficiency, using both homogenous and heterogenous SFA on a translog cost model on a sample of European airports for 2001 to 2004. However, only labour and capital costs were used as input variables, which ignored other operating costs such as maintenance and energy. Further, their regulation dummy variables base group contained only two airports, which raises questions regarding the robustness of the dummy variable coefficient estimates. The results of that paper may therefore not be entirely reliable.

4. Hypothesis

Following Barros (2008b), all types of regulation are expected to be associated with larger variable costs, reflecting the practical imperfections of regulatory cost efficiency incentives and possible conflicting regulatory objectives. Economic theory suggests that state-direction of an airport should increase variable costs by the greatest amount, as it would be likely to maximise social welfare over profit, followed by rate of return and then hybrid price cap regulation. However, it is not clear that the relative size of the coefficients will follow economic theory. Nevertheless, the variable cost efficiency scores would be expected to show that price regulated airports are less efficient than their unregulated counterparts, while state-directed airports would be expected to be least efficient.

5. The variable cost model

A Cobb-Douglas variable cost model will be estimated, which describes the minimum input costs of producing a given level of output, holding fixed the prevailing factor input prices. Although it would be in principle preferable to estimate a long-run total cost model, which allows all factors to vary, Oum and Fu (2008) and Bottasso and Conti (2010) argued that doing so would be unsuitable since it assumes that the airport is able to (instantaneously) vary its capital stock. Additions to airport infrastructure can often take over a decade to complete, as with Heathrow Terminal 5.[2] Forsyth (1997) added that an airport's long run cost function tend to be irregular because the cost of capacity expansion varies on a case-by-case basis. Faced with capital fixity, an airport would then usually operate with short run excess capacity in response to a negative external demand shock, which suggests that a variable cost model would more accurately describe an airport's costs over a decade.

The log-linearity of a Cobb Douglas variable cost model means that, in this paper, it takes the form:

$$\ln(VC) = \alpha + \beta_1 \ln(p_1) + \beta_2 \ln(p_2) + \beta_3 \ln(fixedcapitalstock) + \beta_4 \ln(Q)$$

The input price coefficients are their cost shares, which are the proportions in which they enter into the cost function. The inputs' constant own-price elasticities can be calculated as $\varepsilon_{ii} = \beta_i - 1$ where i = 1, 2. Since the Cobb-Douglas restrictions are over-identifying, linear homogeneity will be imposed to set the sum of the input price coefficients to one, $\beta_1 + \beta_2 = 1$.

The coefficient on the output variable represents the scale elasticity, from which the returns to scale can be inferred. Due to the log-linear functional form and assuming fixed proportions, these are the reciprocal of the scale elasticity:

$$RTS = \frac{1}{\frac{\partial \ln(C)}{\partial \ln(Q)}} = \frac{1}{\varepsilon_Q}$$

[2] After 3 years and 10months of planning, Heathrow Terminal 5 was approved by the Secretary of State in September 2001 with phase 1 opening in March 2008 (a total of 11 years 10months project time) and phase 2 scheduled to open in 2011 (a total of 14years 10months).
http://www.airport-technology.com/projects/heathrow5/

Values greater (smaller) than one indicate increasing (decreasing) returns to scale while a unitary value indicates constant returns to scale.

The main advantage of the Cobb-Douglas specification is that it uses few, easily interpretable, parameters, which leads to efficient estimation. However, the model's parsimony restricts the description of a firm's economic behaviour in a way unrelated to cost minimisation or technology. For example, linear homogeneity restricts own-price and cross-price input elasticities to negative and positive values respectively. This assumes that the inputs are substitutes, which would overlook any input complementarity. Further, it imposes a common elasticity of scale at all levels of output. This means that average cost curve is allowed to be falling, flat, or rising but cannot have all three properties, which precludes a U-shaped curve. Further, the curvature restrictions only allow the inclusion of one output variable.

6. Stochastic frontier analysis

The variable cost function will be modelled in homogenous Stochastic Frontier Analysis (SFA), which is estimated using Maximum Likelihood Estimation (see Greene 2003). First developed for production functions frontiers by Aigner, Lovell and Schmidt (1977), SFA was extended to cost functions by Schmidt and Lovell (1980). The distinguishing feature of SFA is the inclusion of an asymmetrically distributed efficiency error term. After estimation, cost efficiency scores for each sampled firm are calculated and ranked relative to a "frontier, most efficient, airport" constructed from the sample. Since panel data are used in this paper, the general form of the cost model can be written, following Kumbhakar and Knox Lovell (2000), as

$$\ln(c_{it}) = \beta_0 + \beta_q \ln(q_{it}) + \sum_{j=1}^{k} \beta_j \ln(p_{jit}) + v_{it} + u_{it}$$

where q_{it} is the output of the ith firm in the tth period, and p_{jit} is the jth input price of the ith firm in the tth period. The sign on the efficiency error term is positive since inefficiency raises costs. The random error v_{it} is assumed to follow a normal distribution such that $v_{it} \sim N[0, \sigma_v^2]$, while the efficiency error term u_{it} is assumed to be independently identically distributed according to a strictly non-negative asymmetric normal distribution, i.i.d. $u_{it} \sim N^+[\mu, \sigma_u^2]$. The composite error term contains both terms, $\varepsilon_{it} = v_{it} + u_{it}$.

In principle, both fixed and random effects models could be estimated. Fixed effects estimation includes airport-specific fixed effects that are assumed to be correlated with the independent variables, forcing efficiency to be time-invariant. Unbiased efficiency estimates can be calculated under few distributional assumptions. However, the Fixed Effects method suggested by Schmidt and Lovell (1980) would score airports in terms of relative efficiency, instead of against a frontier airport. Further, as none of the preliminary fixed effects regressions converged after 100 iterations, this paper focuses on random effects modelling.

Random effects models impose the stronger assumption that the airport-specific term is not correlated with the explanatory variables, which should hold as most of the variation in the explanatory variables occurs across cross-sections instead of time (NERA 2006). Time-invariant explanatory variables can also be included. Estimation is also more efficient than fixed effects though consistent and not unbiased.

All regressions in this paper were performed in STATA, assuming the efficiency term to follow a strictly non-negative truncated-normal distribution.[3] Random effects SFA models can assume either time-varying or time-invariant efficiency. The time-varying random effects model (Battese and Coelli, 1992) is the most unrestricted specification, allowing efficiency to vary over time. The efficiency error term u_{it} in this case takes the form

$$u_{it} = \exp\{-\rho(t - T_i)\}u_i$$

where $u_{it} \sim N^{+}(\mu, \sigma_u^2)$, ρ is the rate of inefficiency decay for airport *i* in time period *t* and T_i is the last time period in the i^{th} panel and the base efficiency level for the airport.
The log-likelihood function is

$$\ln L = -\frac{1}{2}\left(\sum_{i=1}^{N} T_i\right)\{\ln(2\pi) + \ln(\sigma_s^2)\} - \frac{1}{2}\sum_{i=1}^{N}(T_i - 1)\ln(1-\theta)$$

$$-\frac{1}{2}\sum_{i=1}^{N}\ln\left\{1 + \left(\sum_{t=1}^{T_i}\rho_{it}^2 - 1\right)\theta\right\} - N\ln\left\{1 - \Phi(-\tilde{z}) - \frac{1}{2}N\tilde{z}^2\right\}$$

[3] As well as the truncated normal distribution, STATA allows the selection of a number of other assumed distributions for the asymmetric inefficiency term.

$$+\sum_{i=1}^{N}\ln\left\{1-\Phi(-z_i^*\right\}+\frac{1}{2}\sum_{i=1}^{N}z_i^{*2}-\frac{1}{2}\sum_{i=1}^{N}\sum_{t=1}^{T_i}\frac{\varepsilon_{it}^2}{(1-\theta)\sigma_s^2}$$

where $\varepsilon_{it}=y_{it}-\beta' x_{it}$, $\sigma_s=\left(\sigma_u^2+\sigma_v^2\right)^{\frac{1}{2}}$, $\theta=\frac{\sigma_u^2}{\sigma_s^2}$, $\rho_{it}=\exp\left\{-\rho(t-T_i\right\}$, $\tilde{z}=\frac{\mu}{\left(\theta\sigma_s^2\right)^{\frac{1}{2}}}$,

$z_i^*=\dfrac{\mu(1-\theta)+\theta\left(\sum_{t=1}^{T_i}\rho_{it}\varepsilon_{it}\right)}{\left[\theta(1-\theta)\sigma_s^2\left\{1+\left(\sum_{t=1}^{T_i}\rho_{it}^2-1\right)\theta\right\}\right]^{\frac{1}{2}}}$ and $\Phi(.)$ is the cumulative distribution function of the normal distribution. The time-invariant model (Pitt and Lee, 1981) is a restricted form of this model which imposes a constant level of efficiency, setting $\rho_{it}=1$ and $\rho=0$.

The efficiency score for the i^th airport is calculated by taking the expected value of the efficiency error term conditional on the composite error term, that is

$$E\left(u_i\mid\varepsilon_{it}\right)=\tilde{\mu}_i+\tilde{\sigma}_i\left\{\frac{\phi\left(-\frac{\tilde{\mu}_i}{\tilde{\sigma}_i}\right)}{1-\Phi\left(-\frac{\tilde{\mu}_i}{\tilde{\sigma}_i}\right)}\right\}$$

where $\tilde{\mu}_i=\dfrac{\mu\sigma_v^2+\sum_{t=1}^{T_i}\rho_{it}\varepsilon_{it}\sigma_u^2}{\sigma_v^2+\sum_{t=1}^{T_i}\rho_{it}^2\sigma_u^2}$ and $\tilde{\sigma}_i=\dfrac{\sigma_v^2\sigma_u^2}{\sigma_v^2+\sum_{t=1}^{T_i}\rho_{it}^2\sigma_u^2}$.

The time-varying model is more flexible than its time-invariant counterpart because efficiency can vary over time. However, a shortcoming of the model is that the inefficiency can only decay monotonically, meaning that inefficiency cannot fall over some periods and rise again. If the inefficiency decay term is (not) statistically significant, then the time-varying (-invariant) efficiency model would be preferred.

Note on heterogeneity

Stochastic Frontier Analysis in this paper assumes that the firms in the sample are homogenous. However, there is a considerable amount of heterogeneity in the airports industry, which may be incorrectly captured in the efficiency error term and create bias in cost efficiency scores. There are two kinds of heterogeneity. Observed heterogeneity can be captured through control variables, such as airport size which influences an airport's ability to experience economies of scale and/or density. By contrast, unobserved heterogeneity cannot. Possible causes can include underlying economic conditions, such as business cycles and market level characteristics (Bottasso and Conti 2010), and the limited mobility of certain input factors. Non-regulatory factors may also cause cost inefficiency at airports. ATRS (2008) found that the degree to which airports outsource operations could have an effect on efficiency by changing airports' cost structure. Operations that could be outsourced include car parking, utility sales, ground handling services, consultancy and surface transport. Other operational barriers outside the airport operator's control, which are difficult to explicitly control for, include the quality of access infrastructure, low population density in the airport's catchment area, and environmental barriers such as location weather and land scarcity. Airline inefficiency, such as delays and low load factors, could also be directly detrimental to the airport. The institutional framework in which airports operate may also be important. Government policy based on "dubious impact analysis" (Niemeier, 2009), non-economic regulations and inadequate ownership structures could also create inefficiency, as well as constituting unobserved heterogeneity.

However, Bel and Fageda (2010) argued that the European Union, Switzerland and Norway together tend to be relatively a homogenous area for which Pels (2003) found no region-specific effects. Testing for these in the present sample would not have produced robust results because of insufficient variation within certain region dummy variables. Nevertheless, homogenous SFA can with some degree of confidence be used in this paper, bearing in mind its limitations.

7. Model assessment criteria

Several criteria are used to evaluate the models. The primary statistical criteria were the log-likelihood, Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC).

The log-likelihood is the measure of fit for maximum likelihood estimation, giving the probability of observing the sample being distributed according to the parameters in the model. However, although a larger value would indicate a better fit, the log-likelihood tends to increase with each additional parameter.

The AIC and BIC estimate the level of “information” in the model. They are defined as:

$$AIC = -2(LL) + 2k$$

$$BIC = -2(LL) + (\ln(N) \cdot k)$$

where LL is the model’s log-likelihood, k is the degrees of freedom in the model and N is the number of observations. The BIC corrects for the degrees of freedom in a model and so penalises additional parameters more strongly than the AIC. For both statistics, the model with the smallest AIC and BIC would tend to be preferred.

There are several additional non-statistical considerations. First, the coefficient estimates would need to be reasonable. For example, a model that scores well statistically but has unrealistic coefficients would not be preferred to a model with worse statistical scores but more reasonable coefficients. Secondly, the statistical significance of the efficiency error variance is important. As Stata (2009) states,

“Our simulation results indicate that this estimator requires relatively large samples to achieve any reasonable degree of precision in the estimates of μ and σ_u^2.”

This shows that variance estimates need to be very precise. Since they are used to calculate efficiency scores, they must be statistically significant to produce reliable results. The sample of 254 observations used in this paper may restrict the level of statistical significance of the efficiency error variance. However, a 5% significance level would be sufficient to not affect the analysis. Further, according to Diana (2010),

“the greater the variance in u_{it}, the more significant the inefficiency of some observations relative to others. As the [efficiency] error variance goes toward zero, so does inefficiency.”

The *gamma* estimate should therefore decrease as fit improves, reflecting that some of the heterogeneity erroneously captured in the estimation as efficiency has been controlled for in the improved specification. Accordingly, the error variances should also be smallest in the preferred model. Therefore, the model forming the basis of the cost efficiency calculations will be selected after consideration of all the above criteria.

8. Data set

The data set is an unbalanced panel of 34 European airports specialising in commercial aviation between 2000 and 2009, a total of 254 observations. Increases in capacity and changes in technology are sufficiently infrequent in the airport industry for it to be reasonable to estimate one "average" cost function across ten years of panel data.

Due to variations in the availability of financial data, there are 18 UK and 16 other European airports, as shown in table 8.1. The UK data are a balanced panel of 18 airports for the financial years from 2000 to 2008. The data are sourced from *Cruickshank's Airport Statistics* obtained from the Centre for the Study of Regulated Industries. All monetary values are in £000s while the air traffic movement and passenger counts are in unit terms. The monetary data were deflated using the GDP deflator obtained from the HM Treasury website, with 2002 as the base year.

Several airports listed in the *Airport Statistics* could not be included in the sample due to comparability issues. The cost figures for the Highland and Islands airports are aggregates for many small Scottish airports, making them incomparable to individual airports. For some other airports, commercial movements constitute less than 50% of total air traffic movements. Since non-commercial aviation imposes different cost requirements on airports, the costs for these airports would not be comparable to the rest of the sample.

The data for the other European airports are an unbalanced panel of 16 airports from 2000 to 2009, sourced from the airports' annual reports. Monetary data in different currencies were converted to pound sterling using the 2004 average exchange rate for each currency, obtained from the Bank of England website. The converted values were deflated to £2002 and expressed in £000s, to make them comparable to the UK data.

The panel is unbalanced due to the varying availability of airports' annual reports. For example, Zurich airport provides an archive from 2000 to 2009 whereas Hannover only supplies 2006 to 2008. The reason for the missing data, which makes the panel unbalanced, is therefore not correlated with the stochastic error term and should not bias estimates, since it is not related to shifts in efficiency.

The sample size was also limited by some airport groups only publishing consolidated financial data. For example Aéroports de Paris issues consolidated financial accounts for Charles de Gaulle, Orly and Le Bourget airports. Similarly, Aeroporti di Roma publishes consolidated accounts for Rome Fiumicino and Ciampino airports. These airport groups were nevertheless included due to the airports' importance and the fact that their consolidated figures only include the value of assets used at those airports. However, interpretation of their results would need to be made with caution. By contrast, other airport groups such as Amsterdam Schiphol, Berlin, and Fraport (for Frankfurt) publish consolidated accounts that include assets held in subsidiaries. Furthermore, some countries operate their airports as a network, for example Finland, Portugal and Spain. The financial accounts therefore aggregate the entire network's costs. Their cost figures would then not be representative of the costs and assets of the airport. Consequently, these airports could not be included in the sample. Other countries with state-owned and operated airports, such as Belarus, do not make any financial information publicly available. The size of the data set used in this paper was therefore restricted by the lack of suitable financial data for many airports.

Variables

All variables used in this paper are in logarithms. Table 8.2 provides the descriptive statistics. The variable cost model uses variable cost (*lvc*) as the dependent variable, representing operating costs net of depreciation. The labour input price is the staff costs divided by the average number of workers for each year (*lscwk)*. As the variable cost model holds the capital stock fixed, the average total fixed asset value for each year (*ltfa)* is used instead of the cost of capital. After testing other possible variables, other costs as a proportion of total annual passengers (*locpax*) were chosen to account for other operating costs, such as maintenance and energy.

Total air traffic movements (*latm*) and total passenger numbers (*lpax*) are the possible output variables. Since the Cobb-Douglas specification only allows one output variable, they will be tested for inclusion. Total annual cargo tonnage is another output produced at some airports, but was not considered since passengers are the primary output at commercial airports and Cobb-Douglas specifications are limited to one output variable. Consequently, cost efficiency scores may be understated for airports with large cargo operations.

Table 8.3 contains the correlations coefficients between the variables. The correlations between variable costs and the input prices are positive, as expected, since an increase in input prices for a given quantity would increase costs. The output variables, air traffic movements and passengers, are strongly positively correlated with variable costs, as expected. The variable cost base model takes the following form:

$$\ln(VC_{it}) = \alpha_i + \beta_{1t}\ln(scwk) + \beta_{2t}\ln[ocpax] + \beta_{3t}\ln(tfa) + \beta_{4t}\ln[output] + u_{it} + v_{it}$$

Table 8.4 details the categorisation of the sampled airports into dummy variable groups to control for the effects of each type of economic regulation. The base group consists of unregulated airports while dummy variables are included in the regression for the groups of price capped (*pricecap)*, rate of return (*ror*) regulated and state-directed (*state*) airports. Information on the types of regulation for each airport was obtained from Gillen and Niemeier (2006), Gillen (2007), and Marques and Oliveira-Brochado (2007).

9. Results

To assess the suitability of regression estimates, guidance figures for cost shares of the labour and other cost inputs is obtained from the cost data. These benchmarks are calculated as the mean average proportions of staff costs and other costs to variable costs in the sample. The expected cost shares for labour and other costs are 40.8% and 59.2% respectively.

The regression results are reported in table 9.1. For each model, the time-invariant form of efficiency is reported, as the decay term was not found to be statistically significant at the 10%. The second column gives the base model results. The cost shares in the chosen base model are close the benchmark with the staff cost and other cost inputs comprising 38.7% and 61.3% of variable costs respectively, both significant at the 1% level. Changes in the fixed capital stock do not appear to greatly influence variable costs, a 1% increase leading to a 0.08% rise in cost, but the effect is statistically significant at the 1% level. This could be due to the greater operating costs of additional infrastructure, for example more staff and other resources, being offset by a degree of technological substitutability between capital and labour. For example, a self-check-in facility may replace both a manned check-in desk and the labour required to operate it. The output coefficient estimates that a 1% increase in passengers increases variable costs by 0.704%, indicating that on average an airport experiences increasing returns to scale with regards to the number of passengers it handles. The *gamma* term is significant at the 1% level, which indicates the presence of variable cost inefficiency. For the base model, inefficiency is estimated to explain 93.8% of the error variance.

The results of the *regulation* model are shown in the third column of table 9.1. The coefficients on the regulation dummy variables are individually and jointly significant at the 1% level. Their positive coefficients indicate that regulation is associated with higher variable costs, but not in the order expected by economic theory. The coefficients appear to be considerably affected by the size of the airports in the dummy variable groups as they each only contain five or six airports. This reveals a lack of robustness in estimation. The estimated effect on variable costs and average annual passenger numbers for the price-capped airports is 42.2% and 40.2million, 17.4% and 17.6million for the rate of return group, and 27.9% and 23.7million for the state-directed airports.

Since the **type** of regulation should not be associated with airport size, the *pricecap* and *ror* variables were combined into a price regulation dummy variable (*pricereg*) in order to improve the statistical robustness of the regulation dummy variables. In a regression with the *pricereg* and the *state* dummy variables, in the fourth column of table 9.1, price regulated and state-directed airports are significant at the 5% level and are estimated to increase variable costs by 21.3% and 23.1% respectively[4], which partly supports Oum (2006). Combining all dummy variable groups, into one all regulation (*allreg*) dummy variable group of 17 airports, suggests that regulation overall increases variable costs by 22% compared to unregulated airports, again significant at the 5% level. It would appear from these results that regulation is associated with larger variable costs compared to unregulated airports. A possible explanation

[4] Using $[\exp(\beta)-1]*100 = \%\Delta\log(y)$.

could be that regulation in practice does not provide effective cost efficiency incentives, either due to practical implementation difficulties or because of competing regulatory objectives. However, there could also be a degree of endogeneity between an airport's regulated status and its size as larger airports would be more likely to have substantial market power and consequently would be more likely to be regulated.

To establish whether airport size alone has an effect on variable costs, an interaction term was created to interact the fact that an airport is denoted as large with the annual passenger output variable. The "large" airports group comprises those with over 10million annual passengers, classified as Category A airports by the EC. When included without any regulation dummy variables, the results in the sixth column of table 9.1 show that a 1% increase in passengers at an airport with over 10million annual passengers increases variable costs by 0.027% more than an identical increase at a smaller airport.

Interestingly, the significance of the regulatory dummy variables' coefficients falls in every regression where the interaction term is included alongside a set of regulatory variables, while the interaction term's coefficient is slightly smaller but always significant at the 1% level (columns 7, 8, 9 of table 9.1). These results could suggest that size has a more important effect on an airport's variable costs than the incentives of any form of economic regulation. However, the relatively strong positive correlation between the three dummy groups that include price capped airports (*pricecap*, *pricereg*, *allreg*) and the interaction term could be leading a degree of multicollinearity.[5] This would confirm the suspicion that larger airports, which would have greater variable costs, would also be those more likely to hold substantial market power and consequently be regulated.

Another effect of including the interaction term is that the coefficient on the average total fixed assets variable, representing capital stock, becomes statistically insignificant. The strong positive correlation between the two variables could also indicate multicollinearity[6], as a larger airport would tend to have larger infrastructure, and consequently capital stock, in order to accommodate a greater number of annual passengers. This multicollinearity, since it is a form of misspecification, was captured as increased inefficiency, which is reflected in the larger *gamma* terms of the regressions that include the interaction term.

[5] Each correlation coefficient was above 0.666.
[6] The correlation coefficient is 0.834.

In order to investigate the effects of airport size without explicitly controlling for it, a regression was run controlling for the effects of regulation overall (*allreg*) and an interaction term to control for the effects of an airport being regulated but with fewer than 10million annual passengers. The result, in the tenth column of table 9.1, showed that the *allreg* variable has a positive coefficient, significant at the 1% level, while the coefficient for regulated airports with fewer than 10million annual passengers (*nonlargeallreg*) was negative and statistically significant at the 1% level. These estimates suggest that while regulation overall is associated with 50.1% greater variable costs, the smaller airports in that group have 12.2% greater variable costs than unregulated airports. The difference between large and smaller regulated airports would appear to demonstrate that airport size has an important impact on an airport's variable cost than whether or not it is regulated.[7] However, despite the impact of an airport size on variable costs, it also appears that regulation is still associated with an increase in variable costs compared to unregulated airports, which would lend support to this paper's hypothesis and the results of Barros (2008b).[8]

The efficiency scores were based on the *regulation* regression, as it scored best statistically and had the lowest *gamma* term which estimated that 91.8% of the error variance was inefficiency. The variable cost efficiency of the mean and median airports were 45% and 40% lower than that of the frontier airport. The range of efficiency scores suggests that there is considerable, though realistic, variable cost inefficiency in the airport industry.

Table 9.2 shows the variable cost efficiency rankings based on the *regulation* model.[9] Cardiff airport, which is unregulated, is the most variable cost efficient airport, with costs 2.6% above the frontier airport.[10] The rest of the airports constituting the top 5 also cover the three different types of regulation studied in this paper: Stansted (hybrid price cap), Oslo and Turin (rate of return) and Zagreb (state-directed), as well as Brussels (formerly state-directed now subject to rate of return). The Paris airport aggregate is, perhaps as expected due to it

[7] Other regressions were run to control for year-specific effects. The results showed that these were not jointly significant at the 10% level.

[8] Analysis of the effects of regulatory independence on variable costs was impeded by the strong correlation between the group of independently regulated airports and the airports subject to a hybrid price cap, which is a group suffering from size bias.

[9] Though the rankings vary slightly according to the particular specification used to calculate the efficiency scores, the principal conclusions remain valid regardless of the model specification used.

[10] The frontier airport's cost efficiency is normalised to 1. The cost efficiency gap between a given airport and the frontier is calculated using gap = (score – 1). For example, Cardiff airport is (1.026 – 1)*100 = 2.6% less cost efficient than the frontier.

representing three airports, the least efficient “airport” with costs 137.8% above the frontier. As with the top of the rankings, the four other least efficient airports are each subject to a different form of regulation. From least to most efficient, they are Billund (unregulated), Munich (rate of return, Vienna (hybrid price cap) and Zagreb (state-directed).

It can be seen from table 9.2 that airports with each type of regulation are distributed relatively evenly throughout the rankings, interspersed with unregulated airports. Overall, it cannot then be said that one form of regulation clearly gives sharper incentives for cost efficiency than another. This may be evidence that the theoretical incentives of regulatory models tend to become blurred as they are implemented, and is line with the findings of Bel and Fageda (2010, Bilotkach (2010) and Starkie (2004). Additionally, these rankings indicate that the economic regulation, on the whole, would provide variable cost efficiency incentives no worse than those facing unregulated airports.

10. Discussion and Conclusion

This paper tested the effects of economic regulation on variable costs and cost efficiency, with the hypothesis that regulation would increase variable costs and make regulated airports less cost efficient than their unregulated counterparts. Overall, the regression output has shown that regulated airports tend indeed to have larger variable costs than unregulated airports, which supports the findings of Barros (2008b). However, the results also show that airport size in terms of the number of annual passengers also increases variable costs, and that the effects of airport size and regulation are closely linked as larger airports are more likely to have substantial market power and as a result to be subject to regulation.

While the regression results would tend to support the hypothesis with regard to the size of variable costs, the cost efficiency score rankings suggest that regulatory efficiency incentives may be no worse than those faced by unregulated airports. Additionally, no particular type of regulation can be said to be conducive to higher cost efficiency than another. These results seem to support the possibility that regulators have objectives that compete with inducing cost efficiency. The efficiency incentives could be acting alongside other regulatory objectives, such as furthering the interests of both current and future airports users. Further, there are a number of factors both within and outside the airport operator’s control that may also interfere with an airport’s cost efficiency.

There are a number of limitations to the above analysis. The sample size was restricted by the unavailability of, or the unsuitability of the available, financial data for certain airports, which will have limited the statistical significance of the efficient error variance estimates as this requires a large sample (Stata 2009). The limited sample size also weakened the econometric robustness of the coefficient estimates for the original regulation dummy variables (*pricecap*, *ror*, *public*). A greater number of observations could allow more robust coefficient estimation for certain dummy variable groups and the analysis of the effects of single and dual till and regulatory independence. It is possible that other regulatory aspects could also potentially be robustly investigated with a sufficiently large sample size.

The Cobb-Douglas specification of the variable cost model restricted the shape of the cost curve, and linear homogeneity was imposed. A more flexible alternative approach could be the less transcendental log specification and to test for linear homogeneity instead of imposing it. Unobserved heterogeneity was also not completely captured due to the use of homogenous SFA. A solution would be to estimate latent class SFA (Barros 2008a) models to better capture the heterogeneity between airports. More generally, the analysis is inherently subject to the underlying assumptions of SFA, including the distribution assumption for the efficiency error, and random effects modelling. Specialist software such as LIMDEP would make possible the estimation of a fixed effects model. Lastly, since the modelling in this paper focused on passenger processing, the efficiency scores of airports with a large proportion of cargo movements may have been understated. Although cargo tonnage could have been converted into passenger numbers, this would have introduced measurement error. Overall, however, the estimation in this paper remains relatively robust.

The results in this paper, while supporting the hypothesised effects of regulation on variable costs, reject the hypothesis that regulated airports are less cost efficient than unregulated airports. Further, each type of regulation overall appears to be able to provide cost efficiency incentives as sharp as those faced by unregulated airports, although certain distinct theoretical incentives appear to not materialise in practice. Economic regulation may therefore be an effective policy tool as it does not appear a detrimental effect on the cost efficiency of European airports.

11. Table s

Table 8.1: Sampled airports

Country	Airport	Regulator	Approach	Till
Austria	Vienna	Independent	CPI-X price cap with tariff basket and sliding scale	Single
[redacted]	Graz	None	n/a	n/a
Belgium	Brussels	Dependent	Public until 2005. From 2006: Rate of return regulation with profitability of regulated activities linked to average of reference airports for five years.	Single with stepwise change to dual till
Croatia	Zagreb	Dependent	Public	n/a
Denmark	Billund	None	n/a	n/a
France	ADP (Paris Orly, Roissy, Le Bourget)	Dependent	Public until 2005. From 2006: Hybrid average revenue-based price cap with adjustments for investment (lumpy and incremental treated separately) and quality	Single with loosely defined dual characteristics for 2011-2015
Greece	Athens	Dependent	Public	n/a
Germany	Hannover	None	n/a	n/a
[redacted]	Munich	Dependent	Rate of return	Single
Italy	Naples	Dependent	Rate of return	Dual
[redacted]	Rome (Ciampino and Fiumicino)	Dependent	Rate of return	Dual
[redacted]	Turin	Dependent	Rate of return	Dual
Norway	Oslo Gardemoeren	Dependent	Rate of return	Single
Slovakia	Bratislava	Dependent	Public	n/a
Switzerland	Geneva	None	n/a	n/a
[redacted]	Zurich	None	n/a	n/a
UK	London Heathrow, London Gatwick, London Stansted (BAA)	Independent	RPI-X	Single
[redacted]	Manchester	Independent	RPI-X	Single
[redacted]	Aberdeen, Edinburgh, Glasgow, Southampton (BAA)	None	n/a	n/a
[redacted]	Belfast, Cardiff, London Luton (TBI)	None	n/a	n/a
[redacted]	Birmingham	None	n/a	n/a
[redacted]	Bristol	None	n/a	n/a
[redacted]	East Midlands	None	n/a	n/a
[redacted]	Leeds/Bradford	None	n/a	n/a
[redacted]	Liverpool	None	n/a	n/a
[redacted]	London City	None	n/a	n/a
[redacted]	Newcastle	None	n/a	n/a

Table 8.2: Descriptive statistics of variables

Variable	Description (logarithms)	Observations	Mean	Std Dev	Min	Max
lvc	Variable costs	254	10.705	1.186	8.249	14.095
lscwk	Staff costs per worker	253	3.388	0.378	1.281	4.694
locpax	Other costs per passenger	254	-5.590	0.444	-8.444	-4.382
ltfa	Average total fixed assets	254	12.307	1.521	8.393	15.866
lpax	Total annual passengers	254	15.743	1.150	13.534	18.282
latm	Total annual air traffic movements	254	11.627	0.798	9.220	13.569

All figures rounded to 3 decimal places.

Table 8.3: Correlations between variables

	lvc	lscwk	locpax	ltfa	lpax	latm
lvc	1.000					
lscwk	0.451	1.000				
locpax	0.359	0.183	1.000			
ltfa	0.846	0.313	0.063	1.000		
lpax	0.945	0.448	0.094	0.879	1.000	
latm	0.929	0.496	0.201	0.832	0.938	1.000

All figures rounded to 3 decimal places.

Table 8.4: Regulation dummy variable groups

Airport	Country	Price cap (*pricecap*)	Rate of Return (*ror*)	State-directed (*state*)	Unregulated (base group)
Aberdeen	United Kingdom	0	0	0	1
Athens	Greece	0	0	1	0
Belfast Intl	United Kingdom	0	0	0	1
Billund	Denmark	0	0	0	1
Birmingham Intl	United Kingdom	0	0	0	1
Bratislava	Slovakia	0	0	1	0
Bristol	United Kingdom	0	0	0	1
Brussels until 2005	Belgium	0	0	1	0
Brussels from 2006	Belgium	0	1	0	0
Cardiff Intl	United Kingdom	0	0	0	1
East Midlands	United Kingdom	0	0	0	1
Edinburgh	United Kingdom	0	0	0	1
Gatwick	United Kingdom	1	0	0	0
Geneva	Switzerland	0	0	0	1
Glasgow	United Kingdom	0	0	0	1
Graz	Austria	0	0	0	1
Hannover	Germany	0	0	0	1
Heathrow	United Kingdom	1	0	0	0
Leeds/Bradford	United Kingdom	0	0	0	1
Liverpool	United Kingdom	0	0	0	1
London City	United Kingdom	0	0	0	1
London Luton	United Kingdom	0	0	0	1
Manchester	United Kingdom	1	0	0	0
Munich	Germany	0	1	0	0
Naples	Italy	0	1	0	0
Newcastle	United Kingdom	0	0	0	1
Oslo	Norway	0	1	0	0
Paris until 2005	France	0	0	1	0
Paris from 2006	France	1	0	0	0
Rome	Italy	0	1	0	0
Southampton	United Kingdom	0	0	0	1
Stansted	United Kingdom	1	0	0	0
Turin	Italy	0	1	0	0
Vienna	Austria	1	0	0	0
Zagreb	Croatia	0	0	1	0
Zurich	Switzerland	0	0	0	1
Total		**6**	**6**	**5**	**19**

Table 9.1: Regression output

Dependent variable: log of variable costs

Variables	Base	Regulation	Price Reg	All Reg	Airport size	Size Reg	Size Price Reg	Size All Reg	Size effect
constant	0.317	0.550	0.505	0.522	1.247***	1.241***	1.247***	1.249***	1.049**
	(0.429)	(0.408)	(0.400)	(0.392)	(0.428)	(0.425)	(0.426)	(0.424)	(0.408)
lscwk	0.387***	0.393***	0.390***	0.390***	0.408***	0.406***	0.407***	0.407***	0.403***
	(0.024)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
locpax	0.613***	0.607***	0.610***	0.610***	0.592***	0.594***	0.593***	0.593***	0.597***
	(0.024)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
ltfa	0.080***	0.075***	0.079***	0.078***	0.044	0.043	0.046	0.046	0.052*
	(0.029)	(0.028)	(0.028)	(0.028)	(0.037)	(0.029)	(0.029)	(0.029)	(0.029)
lpax	0.705***	0.688***	0.688***	0.687***	0.656***	0.658***	0.654***	0.654***	0.665***
	(0.039)	(0.038)	(0.037)	(0.037)	(0.037)	(0.037)	(0.037)	(0.037)	(0.037)
pricecap		0.352***				0.216**			
		(0.100)				(0.100)			
ror		0.160***				0.102			
		(0.063)				(0.081)			
state		0.246***	0.208**			0.140	0.114		
		(0.078)	(0.088)			(0.091)	(0.090)		
pricereg			0.193**				0.112		
			(0.082)				(0.081)		

allreg				0.199**				0.113*	0.410***
				(0.095)				(0.080)	(0.095)
large*lpax					0.027***		0.021***	0.021***	
					(0.006)		(0.007)	(0.006)	
nonlargeallreg									-0.295***
									(0.110)
sigma2	0.114**	0.085**	0.086**	0.085**	0.121*	0.103**	0.106**	0.106**	0.103**
	(0.051)	(0.038)	(0.037)	(0.038)	(0.064)	(0.052)	(0.053)	(0.053)	(0.047)
gamma	0.938***	0.918***	0.919***	0.918***	0.945***	0.935***	0.937***	0.937***	0.934***
	(0.029)	(0.037)	(0.036)	(0.037)	(0.030)	(0.034)	(0.032)	(0.032)	(0.031)
sigma u2	0.107**	0.078**	0.079**	0.078**	0.114*	0.096*	0.100*	0.100**	0.096**
	(0.051)	(0.037)	(0.037)	(0.038)	(0.064)		(0.053)	(0.053)	(0.047)
sigma v2	0.007***	0.007***	0.007***	0.007***	0.007***	0.007***	0.007***	0.007***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
LL	198.051	203.988	201.935	201.894	206.553	208.279	207.179	207.178	205.484
AIC	-382.103	-387.977	-385.870	-387.788	-397.107	-394.559	-394.359	-396.357	-392.969
BIC	-357.369	-352.643	-354.070	-359.520	-368.840	-355.692	-359.025	-364.556	-361.168

Figures rounded to 3 decimal places.
**** indicates significance at the 1% level. ** at the 5% and * at the 10% using p-values*
Standard errors are in brackets.

Table 9.2: Cost efficiency rankings

Cost efficiency	Airport	Regulation	Over 10million
1.026	Cardiff		
1.047	Stansted	Price cap	Yes
1.054	Oslo	Rate of return	Yes
1.054	Athens	Public	Yes
1.070	Turin	Rate of return	
1.084	Brussels Intl	Public/Rate of return	Yes
1.180	Bristol		
1.187	East Midland		
1.199	Belfast Intl		
1.230	Southampton		
1.248	Naples	Rate of return	
1.251	Aberdeen		
1.253	Geneva		Yes
1.282	Gatwick	Price cap	Yes
1.284	Manchester	Price cap	Yes
1.296	Graz		
1.344	Leeds/Bradford		
1.408	Edinburgh		
1.419	Zurich		Yes
1.459	London City		
1.462	Glasgow		
1.515	Rome	Rate of return	Yes
1.523	Liverpool		
1.533	Newcastle		
1.589	Heathrow	Price cap	Yes
1.616	London Luton		
1.633	Bratislava	Public	
1.681	Birmingham Intl		
1.840	Hannover		
1.903	Zagreb	Public	
1.973	Vienna	Price cap	Yes
2.165	Muenchen	Rate of return	Yes
2.167	Billund		
2.378	Paris	Public/Price cap	Yes

12. Bibliography

Aigner, D.J., Lovell, C.A.K., and Schmidt, P. (1977) "Formulation and estimation of stochastic frontier production function models," Journal of Econometrics, 6, pp.21-37

Air Transport Research Society (ATRS) (2008) "Air Benchmarking Report – 2008: global standards for airport excellence", ATRS, Vancouver.

Averch, H. and Johnson, L. (1962) "Behaviour of the firm under regulatory constraint," American Economic Review, 52, pp.1052-1069

Barros, C.P. (2007) "Technical efficiency in Portuguese airports with a stochastic cost frontier model," Working Paper, Technical University of Lisbon

Barros, C.P. (2008a) "The measurement of efficiency of UK airports, using a stochastic latent class frontier model," Transportation Reviews, vol.29, No.4, pp.479-98

__________ (2008b) "Regulation, ownership and heterogenous technical efficiency of UK airports: 2000-06," Working paper, Technical University of Lisbon.

Barros, C.P. and Marques, R.C. (2008) "Performance of European airports: regulation, ownership and managerial efficiency," Working paper, Technical University of Lisbon.

Battese, G.E. and Coelli, T.J. (1992) "Frontier production functions: technical efficiency and panel data: with application to paddy farmers in Indonesia," Journal of Productivity Analysis, 3, pp.153-69

Bhattacharyya, A., Parker, E., Raffiee, K. (1994) "An examination of the effect of ownership on the relative efficiency of public and private water utilities," Land Economics, Vol.70, No.2, pp.197-209

Bel, G. and Fageda, X. (2010) "Factors explaining charges in European airports: competition, market size, private ownership and regulation," Journal of Regulatory Economics, forthcoming.

Bilotkach, V., Clougherty, J.A., Müller, J., Zhang, A. (2010) "Regulation, privatisation and aeronautical charges: panel data evidence from European airports," Working Paper, University of California

Bottasso, A. and Conti M. (2010) "An assessment on the cost structure of the UK airport industry: ownership outcomes and long run cost economies" Working paper, University of Torino

Button, K.J. and Weyman-Jones, T.G. (1992) "Ownership structure, institutional organisation and measured X-inefficiency," American Economic Review, 82, pp439-445

CAA (2008) "Economic regulation of Heathrow and Gatwick airports – CAA decision" March 2008 www.caa.co.uk

Caves, D.W. and Christensen, L.R. (1980) “The relative efficiency of public and private firms in a competitive environment: the case of Canadian railroads,” Journal of Political Economy, 88, pp.958-76

Crew, M.A. and Kleindorfer, P.R. (1996) “Incentive regulation in the United Kingdom and United States: some lessons,” Journal of Regulatory Economics, 9, pp.211-225

Diana, T. (2010) “Can we explain airport performance? A case study of selected New York airports using a stochastic frontier model,” Journal of Air Transport Management, 16, pp.310-314

Department for Transport (2007) “Decision on proposed designation and de-designation criteria for airports” Department for Transport, London

Forsyth, P. (1997) “Price regulation of airports: principles with Australian applications,” Transportation Research Part E: Logistics and Transportation, vol.33, No.4, pp.297-309

_________ (2002) “Replacing regulation: airport price monitoring in Australia” Working paper, Monash University

Gillen, D. (2007) “The evolution of airport ownership and governance” Working Paper, University of British Columbia

Gillen, D. and Niemeier, H (2006) “Airport economics, policy and management: the European Union” Working Paper, Comparative Political Economy and Infrastructure Performance: the case of airports 2006

Greene, W. (2004) “Distinguishing between heterogeneity and efficiency: stochastic frontier analysis of the World Health Organisation’s panel on national health care systems”, Health Economics, 13, pp.959-980

________ (2005) “Fixed and random effects in stochastic frontier models,” Journal of Productivity Analysis, 23, pp.7-32

Littlechild, S (1983) “The regulation of British Telecommunication profitability,” Department for Industry, London

Malighetti, P., Martini, G., Paleari, S. and Redondi, R. (2007) “An empirical investigation on the efficiency, capacity and ownership of Italian airports,” Rivista di Politica Economica, 47, pp.157-88

Marques, R.C. and Oliveira-Brochado, A. (2007) “Airport regulation in Europe: Is there a need for a European Observatory?,” Transport Policy, 15, pp.163-72

Martín-Cejas, R.R. (2002) “An approximation to the productive efficiency of the Spanish airports network through a deterministic cost frontier,” Journal of Air Transport Management, 8, pp.233-38

Morgan Stanley (2006) “Aéroports de Paris Attractive Catalysts…But in 2010,” July 31, 2006 London

NERA (2006) "Cost benchmarking of air navigation service providers: a stochastic frontier analysis" www.nera.com

Niemeier, H. (2009) "Regulation of large airports: status quo and options for reform," Discussion Paper, International Transport Forum, Leipzig 2009

Oum, T.H., Adler, N. and Yu, C. (2006) "Privatisation, corporatisation, ownership forms and their effects on the performance of the world's major airports," Journal of Air Transport Management, 12, pp.109-121

Oum T.H. and Fu X. (2008), "Impacts of airports on airline competition: focus on airport performance and airport-airline vertical relations," Discussion Paper, OECD Joint Transport Research Centre

Oum, T.H., Yan, J. and Yu, C. (2007) "Ownership forms matter for airport efficiency: a stochastic frontier investigation of worldwide airports," Working Paper, Washington State University

Oum, T.H., Zhang, A. and Zhang, Y. (2003) "Alternative forms of economic regulation and their efficiency implications for airports," Journal of Transport Economics and Policy, 38, pp.217-246

Pels, E., Nijkamp, P. and Rietveld, P. (2001) "Relative efficiency of European airports," Transport Policy, 8, pp.183-192

________________________________ (2003) "Inefficiency and scale economies of European airport operations," Transportation Research Part E: Logistics and Transportation, 39, pp.341-361

Pitt, M. and Lee, L. (1981) "The measurement and sources of technical inefficiency in Indonesian weaving industry," Journal of Development Economics, 9, pp.43–64

Schmidt, P. and Lovell, C.A.K. (1980) "Estimating stochastic production and cost frontiers when technical and allocative inefficiency are correlated," Journal of Econometrics, Vol.13, No.1, pp.83-100

Scotti, D., Malighetti, P., Martini, G. and Volta, N. (2010) "The impact of airport competition on technical efficiency: a stochastic frontier analysis applied to Italian airports," Working Paper, University of Bergamo

Starkie, D. and Yarrow, G. (2000) "The single till approach to the price regulation of airports" Working Paper, Civil Aviation Authority

Starkie, D. (2004) "Testing the regulatory model: the expansion of Stansted airport," Fiscal Studies, 25, pp.389-413

_________ (2006) "Investment incentives and airport regulation," Utilities Policy, Vol.14, No.4, pp.262-265

Tretheway, M.W. (2001) "Airport ownership, management and price regulation," Report to the Canadian Transport Act Review Committee, Ottawa

Books

Greene, W. (2003) *Econometric Analysis* 5th edition (Upper Saddle River, NJ: Prentice Hall)

Kumbhakar, S. and Knox Lovell, C.A. (2003) *Stochastic Frontier Analysis* (Cambridge: Cambridge University Press)

STATA (2009) *Stata documentation 2009* www.stata.com