MARGINAL COST ESTIMATIONS IN AIRPORTS. MULTIPRODUCTIVE COST FUNCTIONS AND STOCHASTIC FRONTIERS: AN INTERNATIONAL AIRPORTS CASE STUDY

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ABSTRACT

Regarding some regulation fields, such as optimal investments and pricing policies, marginal cost estimations for infrastructure intensive transport services is always a challenging effort in order to provide some basis for important areas of economic regulation. The lack of comparable data among airports is one of the causes which could explain the relative scarcity of this literature in the previous studies. In this paper, we estimate different specifications and methods, using mono and multi product translog specifications and a technical efficiency stochastic frontier. We also estimate long and short run cost functions, using a pooled database of financial data on 41 airports across Europe, North America, Asia and Australia for the period 1991-2005. We find significant economies of scale using Work Load Units (WLU) and Air Traffic Movements (ATM) as output measures. Additionally, we provide individual long and short run marginal costs estimates for each output measure, and for every airport under study. The variability of our marginal cost estimations lead us to further deviate from the assumption of neoclassical theory, and to study the existence of some important levels of inefficiency regarding airports performance. For this reason, we consider the stochastic frontier analysis which partially solves this matter.

Keywords: airport cost functions, stochastic frontier, marginal costs, translog system.

1. INTRODUCTION

Transport activities have been usually considered in the past as public services. Thus, authorities and regulators have questioned themselves different issues regarding efficiency, optimal investments, first best pricing policies and market structure. In the airport industry, the choice of any pricing policy provokes a direct effect on demand and congestion, and if prices are not optimally set, false market signals could misguide dynamic decisions about optimal capacity investments. Charging for the use of transport infrastructures is a central issue in European Transport Policy, which supports a pricing scheme based on social marginal costs. In such sense, the estimation of cost functions appears to be a suitable solution that will gain its momentum in the near future to study market structure, economies of scale or costs subadditivities. Link et al. (2006) sustain that the majority of cost function studies in aviation have rather been motivated by analytical issues which attempt to estimate infrastructure costs or marginal costs.

Thus, in the industries in which firms are price takers in input markets, the multi-product cost function is defined as the minimum cost incurred by the firm to produce the output Y at input prices ω, given actual technology. The firm, then, faces the problem of finding the set of inputs that minimize the expenditure needed to produce Y. Mathematically, the firm resolves the following problem:

$$\underset{X}{Min}\ \omega X^{'} = \omega_1 X_1 + ... + \omega_r X_r$$
$$\text{s. t. } F(X,Y) \geq 0$$

The solution to this problem is represented by the vector of conditional input demands $X^* = X^*(\omega, Y)$. Thus the multi product cost function is obtained by replacing X^* on the previous objective function. $C(\omega,Y) = \omega_1 X_1^*(\omega,Y) + ... + \omega_r X_r^*(\omega,Y)$ This is usually known as the long-run cost function, as all the inputs are considered variable in the period of time studied. However, if some inputs are restricted to be fixed, then the short run cost function $C(\omega_v, Y, \bar{X})$ could also be estimated considering now the variable factor prices and the fixed inputs.

2. ECONOMETRIC ESTIMATION OF COST FUNCTIONS

Cost function estimations require observations on costs, outputs, input prices and fixed factors, associated to firms whose behavior is assumed to be cost-minimizing. Some functional form has to be postulated in the stochastic specification of the cost function, namely

$$C = H(\omega, Y, \bar{X}) + \varepsilon$$

Where C, ω, Y and $\bar{X}$ are observed variables and ε is the error term. The function H is explicitly formulated through unknown parameters reflecting some type of relationship between C and the independent variables. The evaluation of these parameters is the objective of the econometric process.

2.1. Specification and estimation issues

Duality ensures that, under certain regularity conditions[1], the specification of *C* may be interpreted as the total cost function of some underlying production function or technology, even though we could not always express it explicitly. Diewert (1971) showed that it is possible to make very general specifications of *C* while maintaining all classical restrictions on the underlying structure of production. Thus, it is desirable to specify a form which be flexible (i.e., without some priori restrictions on its first and second order derivatives). Caves et al. (1980) established that, to be attractive for empirical applications, besides all previous duality conditions, a flexible functional form should also be parsimonious in parameters, and contain the value zero for output quantities, in order to properly assess economies of scope and incremental costs.

They discuss three flexible forms for a multi product cost functions: 1) “Hybrid Diewert” (Hall, 1973). It imposes CRS as its underlying production function is linear. Besides the important restriction about the underlying economies of scale, it is usually the large number of parameters which makes it unsuitable for estimation; 2) “Quadratic” (Lau, 1974). It does not satisfy the homogeneity condition *a priori*, however this can be imposed by parametric restrictions without sacrificing its flexibility. Additionally, fixed costs are not properly specified in order to catch its variability through different production subsets[2]; 3) Transcendental logarithmic “translog” (Christensen et al., 1973). Of all the functional forms which have been estimated over the last 30 years, this is probably the most frequently used. It provides a local second order approximation to any cost structure and allows a great variety of substitution patterns than any other

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[1] C must be nonnegative, real valued, nondecreasing, strictly positive for positive output, and linearly homogeneous and concave in w for each Y (Shephard (1953); McFadden (1978); and Uzawa (1964))

[2] This is solved using *dummy* variables. See Mayo (1984) for the flexible fixed costs quadratic function.

functional form which usually impose some pattern on the elasticities of substitution[3]. Linear homogeneity can be imposed by considering certain linear restrictions to the parameters, which also reduce significantly the number of them to be estimated. The general structure, with logged variables and being ε_i the disturbance term, is as follows:

$$\ln C=\alpha_o+\sum_j \alpha_j \ln y_j+\sum_i \beta_i \ln w_i+\sum_i\sum_j \gamma_{ij}\ln y_i \ln w_j+\frac{1}{2}\left[\sum_j\sum_h \delta_{jh}\ln w_j \ln w_h+\sum_i\sum_k \rho_{ik}\ln y_i \ln y_k\right]+\varepsilon_i$$

As output values enter in logarithmic form, the translog has no finite representation if any output has a zero value. However, this can be solved by estimating the equation in deviations with respect to an approximation point (usually the mean of the sample). This procedure allows a simple calculation of outputs' cost elasticities (α_j) and the Hessian values (ρ_{ik}), which are essential in identifying economies of scale (S) and cost subadditivities (See Jara-Díaz, 1983)

$$\left.\frac{\partial \ln C(w,y)}{\partial \ln y_i}\right|_{\overline{y}\overline{w}}=\alpha_i+\sum_{j=1}^{s}\rho_{ij}\ln(y_j)+\sum_{j=1}^{m}\gamma_{ij}\ln(w_j)\Bigg|_{\overline{y}\overline{w}}=\alpha_i \qquad S=\frac{C(w,y)}{\sum_i \frac{\partial C(w,y)}{\partial y_i}y_i}=\frac{1}{\sum_i \alpha_i}$$

The translog cost equation is linear in parameters and can therefore been estimated, upon making the necessary assumptions about the stochastic error terms, by classical least squares regression techniques. Nevertheless, the translog function is commonly estimated jointly with the cost minimising input cost share equations by means of a seemingly unrelated equations (SUR) regression (Zellner, 1962) and using maximum likelihood estimators. Cost minimising factor shares can be obtained by applying Shephard's lemma. This procedure allows researchers to including *(m-1)* additional equations to the cost function where *m* is the number of inputs[4] that have been considered in the model specification. As no additional parameters are included, the estimation becomes more efficient.

$$s_i=\frac{w_i X_i}{C}=\frac{\partial C}{\partial w_i}\frac{w_i}{C}=\frac{\partial \ln C}{\partial \ln w_i}=\beta_i+\sum_{j=1}^{m}\delta_{ij}\ln w_j+\sum_{j=1}^{s}\gamma_{ji}\ln y_j$$

Additionally, for panel data, it would be also interesting to account for technological change and technological bias (both in inputs and in scale) in order to test Hicks' neutrality[5]. Technological development is defined as an *inward movement in input space of the production-isoquant frontier* (Stevenson, 1980). Viewing the time variable (t) as a proxy for the level of technological development (T_d), it can be measured as (1)

$$(1)\, T_d=\left.\frac{\partial \ln C}{\partial t}\right|_{Y,w} \quad (2)\, I_b=\left.\frac{\partial S_i}{\partial t}\right|_{Y,w} \quad (3)\, S_c\big|_w=\frac{\partial \ln C}{\partial \ln Y} \quad (4)\, S_{bi}=\left.\frac{\partial S_c}{\partial t}\right|_{Y,w} \quad 5)\, \frac{\partial^2 S_i}{\partial t \partial w_j}$$

Given the existence of technological advancement, the measure of input bias is (2), where S_i is the cost share of the ith input[6]. T_d may also give biased results with respect to scale characteristics of the production process. Such biases could alter the increasing returns to scale (IRS) range and therefore it could be the cause of some important policy

[3] This family of functional forms is usually referred as the constant-elasticity of substitution family (CES family). The well-known Cobb-Douglas form is a particular case of this family. McFadden (1963) and Uzawa (1963) show that this family is very restrictive for more than one output or two inputs.
[4] This is necessary in order to avoid the singularity of the disturbance covariance matrix.
[5] Neutrality implies that technological change does not alter factor proportions or factor cost shares.
[6] A positive value implies that T_d is probably affecting the use of factor proportions.

implications. The scale measure is given by (3) and the scale bias is obtained by (4)[7]. Following Stevenson (1980), one would expect all cross sectional parameters to change over time, allowing us to test for price-induced technological input bias (5).[8] Therefore, if our data supports all new parameters to be estimated, we should incorporate time (t) into the model by specifying a truncated third-order translog function. The proposed model is as follows:

$$\ln C = \mathrm{H} + \phi_1 t + \frac{1}{2}\phi_2 t^2 + \sum_i \psi_i t \ln w_i + \frac{1}{2}\sum_i \sum_j \psi_{ij} t \ln w_i \ln w_j + \sum_k \theta_k t \ln y_k + \frac{1}{2}\sum_k \sum_l \theta_{kl} t \ln y_k \ln y_l + \sum_i \sum_k \theta'_{ik} t \ln w_i \ln y_k$$

, where H represents the set of terms of a second-order translog specification.

Up to this point, researchers need to evaluate whether this approximation could be or not a second-order local approximation $\hat{G}(\omega, Y)$ of the real world cost relationship $G(\omega, Y)$, because it can be that, due to the existence of some firms inefficiencies, this estimations are biased and they really overestimate the real cost function $C(\omega, Y)$. Therefore, and assuming that Taylor remainders are not quite significant, it is mandatory to find a way to properly include the effect of each firm inefficiency into the specification. This topic can be further analyzed using stochastic frontiers[9].

The study of costs inefficiencies arises from the certainty that, in the real world, the minimum cost estimations do not agree with the firms actual expenditures. So the estimations obtained by the methodology described above are biased because real world firms do not show this presumable optimizing behaviour. In fact, a producer is said to be inefficient if it fails to produce the maximum possible output given an optimal input allocation for some input prices. Stochastic frontier methods are always related to the structure of the disturbance term ε_i:

$$\varepsilon_{at} = u_{at} + v_{at}$$

$$\text{a) } u_{at} = u_a \xrightarrow{iid} N^+(\mu, \sigma_\mu^2) \quad and \quad v_{at} \xrightarrow{iid} N(0, \sigma_v^2) \ ,$$

$$\text{b) } u_{at} = \exp\{-\eta(t - T_i\} u_a \text{ where } u_a \xrightarrow{iid} N^+(\mu, \sigma_\mu^2)$$

where u_a is a random disturbance term that captures the "firm effect" derived from the possible technical and allocative inefficiency of airports[10], and the v_{at} is the white noise disturbance term of the model. It is worth noting that all inefficiency components should follow a truncated distribution, since they can only take positive values[11]. The model that presents the structure under (a) was introduced by Schmidt and Lowell (1979), and the model (b) was proposed by Battese and Coelli (1992). In this last model, the firm effects are assumed to be truncated normal random variables, and they can also systematically be varied with time.

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[7] A positive value implies the minimum efficient size can be attained at a lower level of output.

[8] This is reflected by the parameter ψ_{ij}. We can test for the influence of output size in scale bias (θ_{kl})

[9] Stochastic frontier framework was introduced by Aigner et al. (1977) and Meeusen and van den Broeck (1977). This topic is also analyzed by Koop and Diewert (1982), and Kumbhakar (1991).

[10] Recent results in Kumbhakar and Wang (2006) show that, aggregating both effects in the error specification provoked biased estimations of parameters, returns to scale, price elasticities and inefficiencies. This section is not intended to describe the state-of-the-art in SF but to briefly describe the specifications used in this paper. For a further analysis, see Kumbhakar (1997), Kumbhakar and Lovell (2000), Kumbhakar and Tsionas (2005)

[11] Many other distributions have been proposed. Meeusen and van den Broeck (1977) used an exponential distribution. Aigner et al. (1977) used a half-normal. Stevenson (1980) used a gamma distribution.

3. THE CASE OF AIRPORTS

The identification of scale economies from production or costs functions, as previously mentioned, is a basic tool in order to regulate adequately an industry. Jeong (2005) show that only a few studies have dealt with the costs of airport infrastructure services, and that the use of very different data and methodologies provides inconsistent findings, mainly related to: 1) major limitations about capital costs and input levels; 2) a partial view of the airport activity, especially while dealing with the output definition; and 3) the difficulty in collecting comparable data across different airports size and location.

Keeler (1970) used ordinary least squares models (OLS) to estimate two Cobb-Douglas (C-D) partial cost functions[12] for both capital and operating costs, using air transport movements (ATM) as output. He found constant returns to scale (CRS) in airport operations using pooled time series and cross sectional data from 13 U.S. airports between 1965 and 1966. However, these results are limited by a very small database, and, as mentioned, by its partial rather than total approach.

Doganis and Thompson (1973, 1974) estimated a C-D[13], and also parameterised models for capital and operating costs separately. They used work load units (WLU)[14] as output variable. They found increasing returns to scale (IRS) that were exhausted above 3 million WLUs. They use cross sectional data from 18 British Airports for 1969. However, their results suffer the same limitations as Keeler.

Tolofari et al. (1990) used a pooled cross section-time series data for seven BAA Airports for 1979-87 to model a short run total cost (SRTC) function with fixed capital stock. A constant which represents the cost of capital is included to give long run total costs. They adopt the translog function, whose variables were output (WLU), the input prices of labour, equipment, and residual factors, capital stock, pax per ATM, percentage of international passengers, percentage of terminal capacity used and a time trend. Using seemingly unrelated regressions SUR (Zellner, (1962)), they found that there were IRS up to 20.3 million WLUs. A significant finding, however, it could not be easily generalized because only one airport in the sample (Heathrow) operated more than 20 million WLU.

Main et al. (2003) constructed four C-D, using WLU or PAX as output , and including depreciations or not. Other variables were price of staff, price of other costs, passengers divided by air transport movements, the percentage of passengers classified as international and total assets. The price of staff was estimated by dividing staff costs by the number of fully equivalent employees. Prices of ‘other costs’ were estimated as expenditure on other costs divided by the value of tangible assets. They found IRS till 5M WLU or 4M PAX, using a dataset of 27 airports in the United Kingdom for 1988 and other dataset of 44 airports around the world between 1998 and 2000.

In order to examine economies of output scale under the given state of capital infrastructure and facilities, Jeong (2005), estimated a translog specification for total operating costs, using three different output definitions: Passengers, WLU or an output index. Additionally, he used a similar aggregated input index (excluding capital costs)

[12] Tolofari et al. (1990) argued that all these separate estimations would result in biased estimates because the error terms are likely to be correlated, failing then to model adequately this issue.
[13] They categorized expenses into total, capital, maintenance, labour, administrative and operating costs. Besides, they considered investments in development and air traffic control services into the cost figures
[14] WLU is equivalent to one passenger or 100kg of cargo (Doganis, 1992).

and a cost-of-living index as a proxy for the factor price[15]. The models also include other characteristics which may affect operating costs, such as the percentage of international passengers, the percentage of delays, the percentage of cargo volume in WLU, and the share of contractual costs as a function of the total operating cost. This study found that economies of output scale in the airport industry were present up to 2.5M PAX or 3M WLU, using a cross-sectional database of 94 U.S. airports for 2003.

The study of airports inefficiencies is also limited in literature, especially in the cost side. In a very interesting work, Pels et al. (2003) proposed two stochastic production frontiers both for ATM and air passenger movements (APM), using the first predictions as an intermediate input for the second. They found that European airports were relatively inefficient, and most airports displayed CRS in ATM but exhibited IRS in APM. They used data from 34 European airports for the period 1995-1997[16]. Rendeiro (2002) estimated a translog total cost function, using WLU as output measure and considering capital and labour costs, using a *pool* of data of 40 Spanish airports for the period 1996–1997. Results show that those airports whose traffic volumes are between 1-3M WLU were relatively more efficient.

Regarding other regulation areas such as infrastructure pricing, Morrison (1983) estimated various cost functions including maintenance, operation and administration, runway construction, land acquisition, capacity rental, and delay expenditures in order to compute optimal long-run toll costs. He estimated the marginal maintenance, operations and administrative costs of airports to be $12.34 (1976 dollars) per ATM.

Link et al. (2006) make use of an alternative approach to traditional cost function analysis. Focusing on staff costs and using time series instead of cross sectional data, they specified a SARMA model to identify a relationship between the number of scheduled person-hours in service area and the traffic measured as ATMs. This study gives some interesting results, such an estimation of the marginal cost (MC) for an extra ATM of € 22.60[17]. However, for international departures this MC ranges between € 25 and € 72[18].

4. SOME METHODOLOGICAL NOTES

4.1. Output definition

An airport's primary function is to provide an interface between aircraft and the passengers or freight (Doganis, 1992). Therefore, an analysis of output requires, at a least level, data of passengers and ATMs. From this very simple perspective the output of an airport could be composed by: 1) ATMs, according to Link and Nilsson (2005), considering traffic volumes leads to a problem of output separation, as vehicles are different, they have a different impact on infrastructure damage. Regarding aircraft, a well-defined separation criterion should be the weight *(w)* of the aircraft, i.e., between *wide* and *narrow body*[19]. However, neither aircraft's origins nor destinations (*od*) are to

[15] As he mentions, an important shortcoming of his approach is that he uses consumer rather than producer prices.
[16] However, they did not include labour inputs into the model.
[17] These figures are comparable with those (€32.97 - adjusted for 2000 euros) obtained by Morrison (1983).
[18] When comparing these results with other airports it has to be borne in mind that the person-hours should also include all the outsourced activities.
[19] A wide-body aircraft has a fuselage diameter of about 5 to 6 meters. Passengers are usually seated 7 to 10 abreast in a normal configuration of 2 aisles (up to 600 pax). A traditional narrow-body aircraft has a diameter of 3 to 4 meters, a single aisle, and seats arranged from 4 to 6 abreast (up to 280 pax).

be considered, as long as different costs are hardly imposed to the airport infrastructure. Additionally, according to what many pricing policies suggest, every output has to be subject to peak off-peak congestion considerations[20] ; 2) The passengers/baggage flow systems may impose very different costs depending primarily on the composition of different origins and destinations, and also on peak considerations; 3) The cargo is mainly measured in tons of freight and mail, and the same consideration applied to passengers and baggage flows can also be valid for this item; 4) The commercial revenues which are beginning to be a more important source of revenues in the perimeter area of an airport. In this rubric we have different rental concessions like restaurants, rent a car, parking space and others; and 5) the noise level or other important environmental cost measured in the vicinity area. This issue is beginning to be more important in the calculus of social marginal cost in which all the externalities are to be internalized. Thus, an output vector in the business of airports should have theoretically the following components:

$$y = \left\{ ATM_p^w, PAX_p^{od}, FRE_p^{od}, REV, NOI \right\}$$

However, in practice, the lack of adequate data obliges researchers to have usually estimated marginal costs for only one or two outputs: ATMs and WLUs, respectively.

Nevertheless, the fact that ATMs are not affected by a spatial dimension poses some doubts on its, apparently correct, definition as an output of a transportation firm[21]. On this subject, there is an interesting proposal in Pels et al. (2003). They propose that the airport can also be regarded as an interface between airlines and passengers. As the carriers can adjust load factors, there is not an exact positive relationship between ATMs and passengers which can directly be attributed to airports performance. Hence, ATMs is not necessarily endogenous and it can be considered as an intermediate good that is "produced" and then "consumed" in the "production" of air passengers. Given the terminal capacity and load factors, a high value of ATMs (runway efficiency) corresponds to a high value of APM (terminal efficiency). As their work is related to production frontiers, a similar approach could also be carried out using a dual approach.

Econometrically, however, multi-output definition is constrained by data sources and degrees of freedom. Additionally, the specification of many variables so highly correlated such as ATMs and passengers could also lead to some multicolinearity problems, and non-efficient estimators may mislead the structural analysis which can be done. Hence, previous literature has been primarily focused in mono-production estimations, using aggregate measures such as WLU, which explanatory effect is, at first sight, a very limited approximation to the very complex aspects of airport productivity issues.

4.2. Input prices

According to Doganis (1992), labour costs are the most important single cost element. This is due to the fact that handling activities are particularly labour intensive. It includes *direct remuneration to personnel, as well as expenses for social and medical insurance, remuneration in kind, travel subsistence allowances, employee trainig and similars* (ICAO, 2006*)*. Therefore, labour costs produce some additional heterogeneity as they depend on each region's social policies. Current methodology seeks for labour expenses in the airport operator accounts, and prices are obtained by dividing its figure

[20] CAA (2001) provides an interesting estimation of the cost difference, an international peak passenger costs at Heathrow were £25.69 - £29.52 while off-peak passengers would only cause costs of £0.76 - £0.92 (in 1982/83 prices).

[21] Do airports show the same characteristics of other transportation firms?

by the full time equivalents employees (FTEE). However, the main limitation that appears frequently is related to the outsourcing practices, which can put labour expenses into the materials and other concepts. So, it is really important to adjust the data according to the different activities in which airports are actually involved. Additionally, some firms/activities are really in transportation core activities, and are not included in the consolidated annual balances of airports. Airport complexity usually implies a very difficult engineering approach in order to compare the airports performance.

The second major cost element is capital costs, which encompass interest paid, economic depreciation and, specially regarding land requirements use of runways and other major facilities, some measure of opportunity cost. However, this last value is hardly included in financial accounts, and a methodology for its proper valuation at a international scale using some homogeneous criteria would deserve special attention in the international forums, such as, IATA or ICAO. As known, book values are very different of economic value, and interest payments do not represent the true opportunity costs (Oum and Waters, 1996). Additionally, it is a major challenge to accurately value capital assets and collect consistent and comparable information on capital expenditures because: 1) Investments over many years may be "hidden" in the published figures; 2) facilities at airports may be built and operated by airlines or other enterprises (US airports); 3) Some financing sources may not appear in the airports accounts, especially governmental aids, whose related assets may not be charged at a depreciation cost; 4) Taxation, interest rates and accounting practices are also heterogeneous. Thus, practitioners have used a very pragmatic approach collecting depreciation and interest figures from accounting official books, and calculating prices according to some ratio of these figures over an output measure (e.g., WLU or ATM). This approach has been commonly used in the previous empirical exercises. Another alternative approach has been generating own capital stock series using perpetual inventory methods. Christensen and Jorgenson (1969) proposed the following scheme:

$$K_{it} = I_{it} + (1-\mu_i)K_{i,t-1} \qquad\qquad P_{it} = K_{it}(r_{it} + \delta_{it})$$

Where K is the end of period capital stock, I is the quantity of investment occurring in the period and μ is the rate of replacement for the *ith* stock. In the right equation, the input price (p) can be calculated accounting for interest (r) and depreciation (δ) rates[22]. Other alternative, in order to homogenize capital costs, consist in separating some common capital components, such as, runways, aprons and terminal buildings, and apply a uniform depreciating scheme to them taking into account any general maintenance schedule[23], which systematically changes their useful lives and net values. The last alternative is to estimate short-run total cost functions (SRTC) given a fixed (or quasi-fixed) capital stock, and use this estimation to derive the long run cost function by minimizing SRTC with respect to the fixed factor[24].

Other operating costs, under the label of "Materials and OS Work" include *the cost of spare parts and consumables that the airport actually incorporates or expends in providing facilities or services i.e. operation and maintenance of fixed assets (not listed*

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[22] Different capital prices could be aggregated using a Divisia price index.

[23] Runway maintenance is carried out usually in five-year programs, closing them for 2/3 weeks in summer. The maintenance cost is added to the runway net value and depreciated during the new useful life. As every runway needs maintenance, this could be used to elicit a homogeneous depreciation rate for one of the most important capital component (the runway/taxiway/platform system).

[24] See Oum and Zhang (1991) and Caves et al. (1981).

as depreciable assets), cost of services and supplies such as heating, air conditioning, cleaning, laundry, sanitation... (ICAO, 2006). This amount greatly depends on the concession contracts (in outsourcing cases). In this case, prices are usually obtained by dividing total costs of the activities which are outsourced by an output indicator, or using some proxy price, such as, energy or water as a representative price of this component.

Additional factors to account for could be the passengers' time, as a very important input for every transport activity. This generalized cost approach has inspired some marginal cost estimations which have been cited above. Finally, the consideration of noise as an output would also require considering the silence of the surrounding communities as an input, and the externalities of the noise should be evaluated according to some methodology, but such a problem lies for the moment out of the scope of our research.

5.INTERNATIONAL AIRPORTS CASE STUDY

Availabiliy of good financial data on European airports is very restricted, and it is difficult to find a unique source to gather all the necessary information to estimate marginal costs. In fact, we have used different sources, such as, Annual Airports Reports, Balance Sheets, and some official statistics of governmental offices. In some cases, we have directly contacted some airport authorities to request some basic information in order to complete the database. In other cases, airports web sites include enough detailed information of traffic activity, such as, ATMs, passenger enplanements, and cargo. We have also consulted different databases in the Centre of Documentation of the Spanish Airport Authority (AENA). Regarding the figures for the US airports, we have used the database provided by the Federal Aviation Agency in its database of the financial reporting program (CATS database). Some traffic figures were completed using the ICAO / ATI Airport Traffic Summary reports, which provide data for airports around the world between 1992 and 2004. Further details were consulted in the 2003 edition of IATA / ACI / ATAG Airport Capacity and Demand profiles. Other interesting sources were Wikipedia or the Google Earth software (www.earth.google.es).

Data collection has been completed for the following variables: Labour expenses (Salaries and employee benefits), Materials expenses (Energy, consumables and Outsourced work), Capital costs (Amortization and Interest), Full-time equivalent employees, other fixed assets (Terminal surface and runway length) and Traffic figures: Passengers, ATMs and tons of Cargo. We have formed an unbalanced pooled database for 41 airports in EU, US, Canada, Australia and Asia for the period 1991-2005 (see Table 5). Airport size ranges from 206.000 passengers (Liege) to 83 million passengers (Atlanta) with the following average figures: 15.970.000 passengers and 216.000 ATMs. All the variables related to costs and prices were converted to 2005 Purchasing Power Parity (PPP) USD using OCDE published indicators. Labour prices were obtained dividing their respective costs over FTEE, and materials and capital prices were obtained dividing over WLUs and ATMs, respectively. Additionally, in order to provide an easy calculation of output cost-elasticities, all explanatory variables[25] are transformed with respect to the average logged variable, i.e.

$$y = \ln(Y) - \overline{\ln(Y)}$$

[25] This procedure has been done for each variable but time which has been transformed with respect to the nominal average.

For this case study, we have estimated both long and short run, mono and multi product cost functions using always the well known translog cost system, which includes cost share equations in order to get more degrees of freedom. The model has been estimated using the SURE procedure with the method of maximum likelihood. In the section 5.4, we also estimate a stochastic cost frontier model, using different specifications for the disturbance term. Finally, all marginal cost estimations are easily calculated as follows:

$$\frac{\partial C}{\partial y_i} = \frac{\partial \ln C}{\partial \ln y_i}\frac{C}{y_i} = \frac{AC(\omega,Y)}{S_i} \ ,$$

where S_i is the scale factor of the cost function for the output *i*.

5.1. Long–run monoproduction

In order to compare our results with those that have been obtained in the previous literature, our translog cost function includes WLU as the single output variable, the prices of capital (WC), materials (WM), and labour (WP), and finally a time variable (T) to study potential technological changes in the period of time which is under analysis. The system is completed with the cost share equations and other common regularity restrictions such as homogeneity of degree 1 in prices[26]. To estimate the model we use EVIEWS software with seemingly unrelated regression (SURE) procedure. Estimation results are shown in Table 1. (R^2=0.90891)

Table 1. Mono product LR cost function. Estimation results.

	Coefficient	*Std. Error*	*t-Statistic*	*Prob.*
constant	*11.92354*	*0.021587*	*552.3431*	*0.0000*
wlu	*0.713981*	*0.013161*	*54.24999*	*0.0000*
capital	*0.333639*	*0.005977*	*55.81654*	*0.0000*
material	*0.377507*	*0.006987*	*54.03088*	*0.0000*
personnel	*0.293305*	*0.005094*	*57.57430*	*0.0000*
wlu capital*	*0.010967*	*0.005414*	*2.025629*	*0.0430*
wlu material*	*0.036832*	*0.005750*	*6.405586*	*0.0000*
wlu personnel*	*-0.046502*	*0.004806*	*-9.676379*	*0.0000*
*material * capital*	*-0.069808*	*0.006155*	*-11.34200*	*0.0000*
material^2	*0.086876*	*0.007656*	*11.34694*	*0.0000*
capital^2	*0.095865*	*0.007997*	*11.98828*	*0.0000*
*material * personnel*	*-0.010245*	*0.005853*	*-1.750279*	*0.0803*
*capital * personnel*	*-0.028904*	*0.006015*	*-4.805660*	*0.0000*
personnel^2	*0.031924*	*0.009916*	*3.219382*	*0.0013*
wlu^2	*-0.034353*	*0.016605*	*-2.068817*	*0.0387*
time	*-0.022949*	*0.004844*	*-4.737539*	*0.0000*
*time * capital*	*0.008817*	*0.001413*	*6.240803*	*0.0000*
time personnel*	*-0.008804*	*0.001358*	*-6.482980*	*0.0000*

It can be seen that this specification shows correct signs and that the parameters are significant. Some degree of technological progress is also observed. Additionally, it holds all mathematical assumptions to be a proper specification of the total cost function. We also obtain important economies of scale in the average airport (S = 1,40). However, this figure seems to be a little bit high, and it gives some idea about the necessity of including a second output measure, which also increases the global signification of the model, as we suspect that the variability of total costs is not well explained by a single output. Only for a comparative purpose, we calculate marginal

[26] In this case, it can be imposed by restricting the sum of the 3 first-order price coefficients to be one.

costs for this specification, which are shown in the fourth column of Table 5, and whose average value is 12,57 USD per WLU.

5.2. Long–run multiproduction

Using a similar specification as the previous example, the cost function now includes both ATM and WLU as output variables:

$$\ln TC=\alpha_1+\alpha_2 atm+\alpha_3 wlu+\beta_4 wc+\beta_5 wm+\beta_6 wp+\gamma_7 atm*wc+\gamma_8 atm*wm+\gamma_9 atm*wp+\gamma_{10} wlu*wc+$$
$$+\gamma_{11} wlu*wm+\gamma_{12} wlu*wp+\delta_{13} wm*wc+\delta_{14} 0.5*wm*wm+\delta_{15} 0.5*wc*wc+\delta_{16} wm*wp+\delta_{17} wc*wp+$$
$$+\delta_{18} 0.5*wp*wp+\rho_{19} 0.5*atm*atm+\rho_{20} 0.5*wlu*wlu+\phi_{21} t+\psi_{22} wp*t+u_i$$

$$S_C=\beta_4+\gamma_7 atm+\gamma_{10} wlu+\delta_{13} wm+\delta_{15} wc+\delta_{17} wp$$
$$S_P=\beta_6+\gamma_9 atm+\gamma_{12} wlu+\delta_{16} wm+\delta_{17} wc+\delta_{18} wp+\psi_{22} t$$
$$\beta_4+\beta_5+\beta_6=1$$

Results are presented in Table 2. (R^2=*0.97133)*

Table 2. Multi product LR cost function. Estimation results.

	Coefficient	Std. Error	t-Statistic	Prob.
constant	11.90753	0.013456	884.9149	0.0000
atm	0.446550	0.024829	17.98467	0.0000
wlu	0.432750	0.019257	22.47238	0.0000
capital	0.359618	0.003052	117.8380	0.0000
material	0.374822	0.005298	70.74285	0.0000
personnel	0.271473	0.005411	50.17427	0.0000
atm* capital	0.127053	0.008644	14.69839	0.0000
atm* material	-0.161966	0.018388	-8.808232	0.0000
atm* personnel	0.059264	0.013197	4.490628	0.0000
wlu* capital	-0.116098	0.007438	-15.60837	0.0000
wlu* material	0.169917	0.019724	8.614823	0.0000
wlu* personnel	-0.092171	0.011063	-8.331174	0.0000
material * capital	-0.163793	0.004967	-32.97857	0.0000
material^2	0.114709	0.025136	4.563613	0.0000
capital^2	0.174501	0.005202	33.54438	0.0000
material * personnel	-0.017759	0.007197	-2.467699	0.0137
capital * personnel	-0.038298	0.006480	-5.910081	0.0000
personnel^2	0.081256	0.012719	6.388449	0.0000
atm^2	-0.113788	0.022437	-5.071506	0.0000
wlu^2	0.066817	0.016738	3.991845	0.0001
time	-0.012754	0.002640	-4.830512	0.0000
time* personnel	-0.004471	0.001021	-4.376858	0.0000

It can be seen, at first sight, that this specification shows a very good performance, correct signs and a valid significance of parameters, and, as expected, global significance of the model measured by R^2 has been positively increased. We also check the regularity conditions of the cost functions, finding that the estimation satisfy all of them. In summary, the homogeneity conditions for the input price vector *(w)* respect each output have been tested using a Wald Test, whose Null Hypothesis is clearly accepted.

Null Hypothesis: Homogeneity $\gamma(7)+\gamma(8)+\gamma(9)=0$

	γ (10)+ γ (11)+ γ (12)=0		
Chi-square	*3.287670*	*Probability*	*0.193238*

From the two last parameter estimates, we have shown that some degree of technological progress exists for the average airport of our sample in the period of time analyzed, and that this technological progress is highly related with the labour price. Regarding the analysis of economies of scale, our estimation also shows that there still exist important increasing returns to scale as the inverse of the sum of output cost elasticities is 1,13 in the mean[27]. The Wald test on the sum of ATM and WLU first order parameters also shows evidence that the constant returns to scale (CRS) null hypothesis can be rejected.

Null Hypothesis:CRS	*α(2)+ α (3)=1*		
Chi-square	*114.1751*	*Probability*	*0.000000*

Translog cost model is a flexible functional form where elasticities of scale are not constant for each airport, therefore individual estimation for scale elasticities can be calculated (see the Table 5). It can be seen that: 1) The mono product specification consistently overestimate the economies of scale for each airport; and 2) Increasing returns to scale do not seem to be exhausted at any output level in the sample, and even Atlanta Hartsfield presents economies of scale. Additionally, individual estimates for marginal costs are also provided both in the Table 5 and in the Figure 3. The Figure 3 shows the density kernel plots, for both, WLU and ATM marginal cost estimates, whose means are about 8.02 and 582.04 US dollars, respectively. It can be seen that, as expected, marginal costs for an additional WLU using this specification are clearly lower than for the mono product estimations, as a new output has been considered.

Since the cost function describes the technology, we can also analyse the degree of substitutability among the production factors by means of Allen elasticities of substitution. These elasticities are defined as:

$$\sigma_{AES\,ij} = \frac{\lambda_{ij}}{s_j} \text{ where } \lambda_{ij} = \frac{\partial x_i}{\partial w_j}\frac{w_j}{x_i} \text{ and } s_j = \frac{w_j x_j}{C}$$

Table 3 shows the Allen elasticities of substitution of the production factors considered in our study. The estimated Allen elasticities suggest somehow that there exist some possibilities for substitution among the different pairs of production factors, being materials and personnel the two factors which are more substitutable among them. Looking at the own price elasticities, it can be seen that in all the cases the expected signs are correct, and that the demand for labour is by far the most elastic production factor demand.

Table 3. Allen elasticities of substitution. Mean (std. dev.)

	wc	*wm*	*wp*
wc	*-0,45978 (0.350)*	*0,04275 (0.5050)*	*0,49815 (0.345)*
wm	*0,04275 (0.5050)*	*-0,87593 (0.1857)*	*0.80000 (0.666)*
wp	*0,49815 (0.345)*	*0.80000 (0.666)*	*-1,68390 (0.857)*

[27] Due to the logarithmic transformation, results should be evaluated around the sample's geometric mean (8.494.444 passengers; 144.323 ATM; 118.891 tons of cargo)

5.3. Short–run estimates.

Although this issue would require some serious discussion, the airport's capital assets are supposed to be fixed so they can not be easily adjusted to meet capacity requirements in the short run. Therefore, in order to make this estimation, capital costs figures were eliminated, and we only use variable costs (VC = Materials + labour costs) as the dependent variable and a fixed factor measure was taken into account. A first attempt was conducted using both Terminal floor area (ter) and runway/s length. Nevertheless, estimation results were extremely poor and led us to eliminate the second one as the very high correlation between them distorted the estimates. Taking into account this preliminary discussion, we estimate the following equation:

$$\ln VC=\alpha_1+\alpha_2 sur+\alpha_3 atm+\alpha_4 wlu+\beta_5 wm+\beta_6 wp+\gamma_7 atm*wm+\gamma_8 atm*wp+\gamma_9 wlu*wm+\gamma_{10} wlu*wp+$$
$$+\delta_{11}0.5*wm*wm+\delta_{12} wm*wp+\delta_{13}0.5*wp*wp+\rho_{14}0.5*atm*atm+\rho_{15} atm*sur+\phi_{16}t+\psi_{17} wp*t+u_i$$

$$S_P=\beta_6+\gamma_8 atm+\gamma_{10} wlu+\delta_{12} wm+\delta_{18} wp+\psi_{19}t$$
$$\beta_5+\beta_6=1$$

Where, the total surface of the terminal buildings (ter) was considered fixed, and we only include the prices of the inputs that were considered variable. We also include the cost share equation of labour in order to estimate the model.

The results of the final estimation are shown in Table 4. (R^2=0.9391).

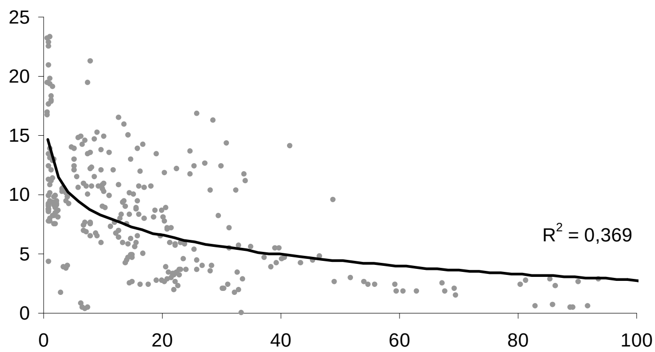
Table 4. Short Run variable cost function. Estimation results.

	Coefficient	*Std. Error*	*t-Statistic*	*Prob.*
constant	*11.51866*	*0.018122*	*635.6340*	*0.0000*
ter	*0.065056*	*0.016317*	*3.987001*	*0.0001*
atm	*0.191664*	*0.035545*	*5.392186*	*0.0000*
wlu	*0.555930*	*0.030242*	*18.38253*	*0.0000*
wm	*0.582328*	*0.008003*	*72.76807*	*0.0000*
wp	*0.424994*	*0.006614*	*64.26038*	*0.0000*
atm wm*	*-0.046560*	*0.022907*	*-2.032613*	*0.0424*
atm wp*	*0.139409*	*0.013593*	*10.25587*	*0.0000*
wlu wm*	*0.041924*	*0.020286*	*2.066608*	*0.0391*
wlu wp*	*-0.175116*	*0.011337*	*-15.44605*	*0.0000*
*wm*wm*	*-0.087531*	*0.032720*	*-2.675153*	*0.0076*
*wm*wp*	*-0.107372*	*0.007344*	*-14.62064*	*0.0000*
*wp*wp*	*0.085440*	*0.017152*	*4.981463*	*0.0000*
atm^2	*-0.273270*	*0.036538*	*-7.479018*	*0.0000*
*ter*atm*	*0.092113*	*0.015300*	*6.020472*	*0.0000*
time	*-0.028899*	*0.004163*	*-6.942036*	*0.0000*
*time*wp*	*-0.012547*	*0.001809*	*-6.935761*	*0.0000*

Many second order parameters, such as, ter/wlu became non-significant and therefore, they were accordingly dropped out from the final specification. However, we highlight that the significance of the two surviving fixed factor parameters implies some degree of short run disequilibrium for some airports in the sample. In spite of that, correct signs of the estimated parameters, significant returns to scale and technological progress still remain. Marginal cost estimates for the mean airport are about 170,78 and 6,5 $ for ATM and WLU respectively, the last two columns of the Table 5 show individual estimates, which obviously are considerably lower than all previous specifications as we are not accounting for capital costs. This last point is especially remarkable for marginal ATM costs, which are drastically reduced. A very interesting interpretation of these results relates to the optimal charge decomposition, i.e. which is the amount of capital component that any hypothetical landing charge should bear? Evaluating the difference between LR and SR estimates in the average airport, landing charges should be composed of a 70,65 % of capital costs as materials and staff costs theoretically suppose only the 29,35 % of the MC of an extra ATM .

Some airports in the sample, specially the larger ones, present some inconsistencies in the estimations of the short run marginal costs, and the main conclusion which can be made by these estimates is that there still exists an important variability (see the Figure 1). This is especially relevant for the middle size airports, and casts some doubts about the neoclassical assumption of the cost functions in which all the firms are considered efficient because they produce a certain level of output at the minimum cost. To present more evidence about this matter, we plot the marginal costs for WLU vs. the level of service of airports measures by the number of WLUs, and an adjusted logarithm trend which presents a very poor adjustment (R^2= 0.36). It can be seen that the variability of the estimations may be the result of the potential existence of inefficiencies that each airport in the sample can experience. For this reason, we further investigate this issue in the next section applying a model which takes into account this problematic, using a stochastic frontier cost method.

Figure 1. Long run WLU marginal cost estimation



5.4. Technical Efficiency (TE) Stochastic frontier

In this section, we estimate a Technical Efficiency Stochastic Frontier as described above, following the specification of Schmidt and Lowell (1979), i.e. assuming that the disturbance term ε_i has the following structure:

$$\varepsilon_i = u_i + v_i$$

$$u_i = u_i \xrightarrow{iid} N^+(\mu, \sigma_u^2) \quad and \quad \mathrm{v}_{at} \xrightarrow{iid} N(0, \sigma_v^2)$$

The random disturbance term u_i follows a truncated normal distribution (with mean μ). This term is usually interpreted as an indicator of the technical inefficiency of each airport. However, these effects capture not just the potential technical inefficiencies TE, but also incorporate the allocative inefficiency and potential influence of other variables that have not been fully specified into the model and that do not usually change over the sample period, such as type of ownership and the geographic location of each airport. These variables can have an effect on the indices of TE, and in this case they will be incorporated in these random disturbance effects.

All regularity conditions for the cost function were defined as parameter restrictions before starting the numerical procedure to estimate the model. The results are shown in the Table 6. We highlight that the inclusion of the new structure of the error term has significantly altered the estimation of the parameters.

Table 6. Stochastic Frontier total cost function. Estimation results.

	Coefficient	*Std. Error*	*t-Statistic*	*Prob.*
constant	*11,70601*	*0,009429*	*1241.54*	*0,000*
atm	*0,469569*	*0,028017*	*16.76*	*0,000*
wlu	*0,483206*	*0,025286*	*19.11*	*0,000*
wc	*0,412798*	*0,010976*	*37.61*	*0,000*
wm	*0,536174*	*0,008465*	*63.34*	*0,000*
wp	*0,051027*	*0,012984*	*3.93*	*0,000*
wc^2	*0,084046*	*0,026766*	*3.14*	*0,002*
wm^2	*0,197103*	*0,037119*	*5.31*	*0,000*
wp^2	*-0,108668*	*0,025997*	*-4.18*	*0,000*
*wc*wm*	*-0,194909*	*0,026884*	*-7.25*	*0,000*
*wc*wp*	*0,110862*	*0,024857*	*4.46*	*0,000*
*wm*wp*	*-0,002194*	*0,019945*	*-0.11*	*0,911*
atm^2	*0,035551*	*0,107730*	*0.33*	*0,738*
wlu^2	*0,165777*	*0,097516*	*1.70*	*0,090*
*atm*wlu*	*-0,130252*	*0,094386*	*-1.38*	*0,167*
*atm*wc*	*0,108912*	*0,044820*	*2.43*	*0,015*
*atm*wm*	*-0,237594*	*0,041393*	*-5.74*	*0,000*
*atm*wp*	*0,128683*	*0,040466*	*3.18*	*0,001*
*wlu*wc*	*-0,121232*	*0,043452*	*-2.79*	*0,005*
*wlu*wm*	*0,216141*	*0,049688*	*4.35*	*0,000*
*wlu*wp*	*-0,094917*	*0,034641*	*-2.74*	*0,006*
time	*-0,014529*	*0,002505*	*-5.80*	*0,000*
mu	*0,18391*	*0,018633*	*9.87*	*0,000*

We can see that the economies of scale are significantly lower (S=1.05 in the average airport), and some degree of technological progress still remain. The μ parameter, introduced to measure technical and allocative inefficiency, is statistically significant showing that the hypothesis of efficiency should be discarded as the average airport presents about a 20% level of inefficiency and the estimation of translog models without considering TE and AE can be considered biased approximations. Point estimation of technical efficiencies follows Jondrow et al. (1982) specification, which uses the conditional distribution of the inefficiency term in ε. Additionally, individual estimates of marginal costs account now for predicted (i.e. in its efficient level) instead of actual costs for computing average costs in the formula. Thus, we use the following formulas to calculate technical inefficiencies and marginal costs estimations:

$$TE_i = E\left\{\exp[(u_i / \varepsilon_i)]\right\} \qquad \frac{\partial C}{\partial y_i} = \frac{\partial \ln C}{\partial \ln y_i}\frac{\tilde{C}}{y_i} = \frac{\tilde{A}C}{S}$$

Last three columns of Table 5 show the point estimation of economic efficiency and marginal costs for each airport of the sample. The average values of marginal costs for ATMs and WLUs are now 460,25 $ and 7.48 $, respectively. As expected, these values are lower than those obtained supposing that the neoclassic theory is valid because some part of the actual expenditures (inefficiency cost) is not considered for the calculation. It can also be seen that economic efficiencies are significant for almost all airports during this period, being London Luton and Oslo the most efficient airports in our sample. Furthermore, marginal costs estimates show lower variance and the logarithmic downward trend line present a slightly better adjustment to the observations. (Figure 2)

Table 5. Scale elasticities, Marginal costs and inefficiencies. Individual airport estimations.

Airports	*Pax (10^6)*	*Scale*	*Mono LR*	*Multi. LR*		*Multi. SR*		*Stochastic Frontier*		
			wlu	*atm*	*wlu*	*atm*	*wlu*	*eff*	*atm*	*wlu*
DARWIN	1,19	1,12	2,30	280,63	0,47	54,19	0,60	0,94	303,61	0,45
PERTH	6,04	1,10	1,54	1469,77	-0,21[28]	330,18	0,43	0,76	979,89	-0,18
SYDNEY	26,43	1,21	1,93	2266,07	-0,86	91,83	0,17	0,83	1842,93	-1,03
GRAZ	0,90	1,02	18,60	635,34	9,20	435,77	9,09	0,87	545,32	10,72
LINZ	0,75	1,01	19,53	1115,68	7,97	720,38	9,51	0,77	778,47	8,78
SALZBURGO	1,42	1,04	23,05	1199,82	11,37	1032,34	11,87	0,75	815,14	11,77
VIENNA INTL	14,88	1,18	13,70	459,29	10,60	38,62	8,87	0,57	286,63	6,66
LIEGE	0,21	1,09	5,22	275,59	3,98	324,40	3,64	0,80	209,97	3,76
NATIONAL	15,63	1,19	8,74	447,94	5,83	118,06	4,16	0,91	434,72	5,80
TORONTO	28,62	1,21	15,56	676,76	10,36	56,71	5,67	0,92	630,44	10,44
BEIJING	34,90	1,17	18,38	1092,98	14,12	207,32	11,02	0,85	543,36	13,54
ZAGREB	1,41	1,02	28,95	655,61	19,14	157,85	20,00	0,61	351,87	14,63
PRAHA	9,59	1,12	13,49	355,70	10,87	-	9,25	0,81	253,84	10,00
BILLUND	1,85	1,07	14,48	407,62	8,49	227,57	8,63	0,64	291,30	6,49
COPENHAGEN	19,03	1,19	6,29	376,22	3,42	15,14	2,91	0,73	321,42	2,48
TALLIN	1,00	1,02	24,06	541,62	13,32	228,63	11,64	0,85	454,34	14,57
BREMEN	1,67	1,07	16,30	511,15	8,18	262,82	7,21	0,85	475,04	8,74
KÖLN	8,41	1,14	12,00	620,44	8,26	232,82	7,47	0,70	405,11	6,56
DRESDEN	1,63	1,04	21,00	568,58	12,85	397,52	10,88	0,98	533,49	16,40
DUSSELDORF	15,34	1,15	16,12	711,71	10,64	208,98	8,72	0,73	490,09	8,68
HAMBURG	9,90	1,14	13,01	367,34	10,21	155,63	8,63	0,68	263,70	7,83
HANOVER	5,17	1,10	19,35	625,15	12,90	308,30	11,30	0,77	452,84	11,84
MUNICH	26,84	1,20	17,58	329,44	16,27	59,15	11,79	0,72	213,66	12,90
NUREMBERG	3,65	1,09	15,00	538,92	9,21	60,29	8,71	0,71	391,11	7,71
PADERBORN	0,94	1,08	26,42	135,77	22,86	126,70	16,95	0,90	180,32	24,65
STUTTGART	8,83	1,13	19,00	403,94	15,17	157,07	11,32	0,89	338,21	15,65
HONG KONG	27,75	1,18	7,56	2253,81	2,39	853,72	2,72	0,85	1611,95	2,35
OSLO	14,87	1,16	10,38	539,52	5,96	96,01	3,90	0,98	542,80	6,47
LJUBLJANA	1,05	1,06	25,30	516,28	13,92	235,47	12,67	0,72	423,10	12,68
ZURICH	17,25	1,17	12,19	605,34	7,20	53,63	4,87	0,84	535,41	6,58
BIRMINGHAM	8,80	1,13	10,47	449,07	6,66	142,84	5,54	0,86	398,87	6,56
LUTON	7,52	1,11	9,87	458,44	6,49	138,16	5,51	0,99	417,34	7,48
MANCHESTER	20,97	1,15	10,10	673,88	5,91	77,51	4,95	0,77	496,06	4,94
BALTIMORE	20,34	1,21	4,09	158,65	3,13	26,86	2,25	0,92	186,10	2,95
DALLAS-FW	59,45	1,30	2,87	168,14	1,82	-	1,25	0,71	171,96	1,06
DENVER	42,28	1,24	8,34	483,31	4,48	13,73	2,38	0,83	477,67	3,52
HARTSFIELD	83,27	1,33	1,45	140,11	0,58	-	0,40	0,80	162,76	0,21
O'HARE INTL	75,53	1,32	4,11	248,14	2,65	-	1,36	0,84	288,53	1,94
S. FRANCISCO	32,74	1,21	10,54	1053,86	3,81	145,18	2,84	0,79	902,89	2,91
SEATTLE INTL	28,80	1,22	4,46	372,79	1,75	32,55	1,43	0.79	366.20	1,16
Mean (USD)	**15,9**	**1.14**	**12.57**	**582.04**	**8.02**	**170.78**	**6.83**	**0.82**	**460.25**	**7.48**

[28] These results are due to a very high cargo activity in both airports, which generate negative elasticities and should be treated as outliers.

6.SUMMARY AND CONCLUSIONS

We propose a very first approximation to an empirical model to evaluate economies of scale, economic inefficiency and marginal costs in airports industry. Fisrtly we estimated a translog model, formed by a cost function and two input cost share equations that allow us to estimate the airport parameters under study. Estimations presents important economies of scale which are not exhausted at any output level, as well as very significant technological progress. We estimate two different specifications (monoproduction and multiproduction cost functions) showing that elasticities of scale and marginal costs are overestimated in the case of the monoproduction estimation. Regarding long-run marginal cost estimations, some reasonable values are obtained for ATMs and WLUs in the average airport, which are about 582,04 and 8.02 $ respectively. We also estimate a short-run cost function using the total surface of terminal building as a fixed production factor. It can be seen that the marginal costs of one additional ATM and WLU for the average airport are 170.78 and 6.83 $, respectively, showing the great importance of capital costs in the calculus of optimal pricing policies.

Nevertheless, the strong variability of these results indicate the existence of a high level of inefficiency in airport operations. Therefore, we also estimated a stochastic frontier model by imposing an (truncated) normally distributed inefficiency component in the structure of the error term. Results indicate that economic inefficiencies are about 18% for the mean airport, and taking this inefficiency costs into account, marginal cost estimates present lower variance. The average values obtained for the representative airport of the sample regarding marginal costs for ATMs and WLUs are 460.25 and 7.48 US dollars, respectively.

In our opinion, some major improvements should be made to the database and the method of estimation, as long as the stochastic frontier specification does not completely eliminate variability. The main explanation could be based on the heterogeneity of the airports included in the sample. In this area, some additional field work should help identifying all those outliers which still exist. The second major improvement is related to the way in which capital prices are obtained. We think that the calculation should be more related to a capital measure than to an output factor. Thirdly, in order to properly account for systematic cost differences, and due to the extreme complexity of the airport activities, some hedonic approach could be carried out by enriching the specification with indicators such as type of property, slot coordination, percentage of long haul traffic, etc[29]. Finally, stochastic frontier estimation should also be improved by estimating separately the effects of both technical and allocative inefficiency. However this kind of models require a more complex specification, and are commonly solved using Bayesian Inference and MCMC. This type of models could be an area of promising future research.

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Figure 2. Stochastic Frontier WLU marginal cost estimation

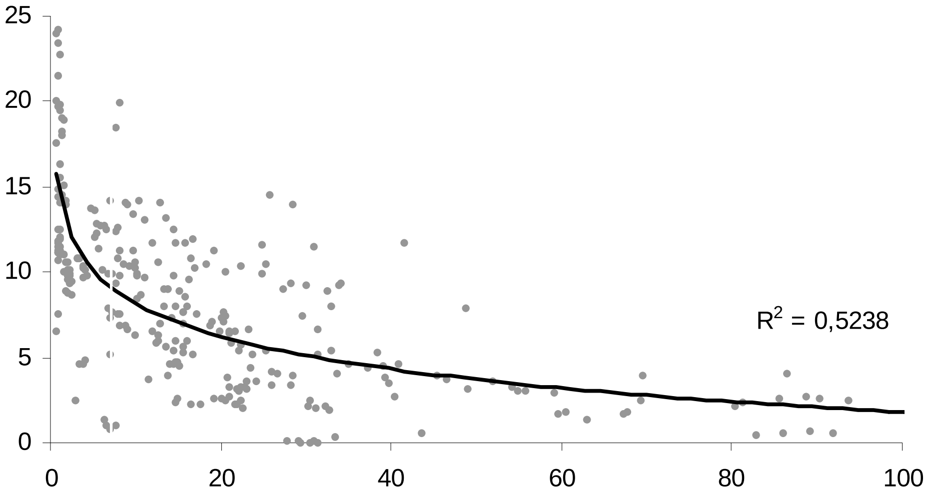

Figure 3. Marginal costs estimations. Kernel Densities