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The econometric estimation of airports' cost function

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ABSTRACT

The econometric estimation of cost functions has been proposed in the literature as a suitable approach in order to obtain estimations of marginal costs, efficiency levels and scale elasticities for transport industries. However, regarding the airport industry, no significant attention has been paid in developing an airport-specific estimation methodology rather than adapting the procedures applied to other industries. The lack of comparable airport data is one of the causes which could explain the scarcity of this literature in the past, as well as the use of very limited approaches to explain airport technology. This paper tries to overcome these limitations by developing an airport-specific methodology to estimate a multi-output long-run cost function using an unbalanced pooled database on 161 airports worldwide. The specification of hedonically-adjusted aircraft operations, domestic and international passengers, cargo and commercial revenues in the output vector, as well as the calculation of input prices are discussed. Both technical and allocative inefficiencies are specified in the model using a Stochastic Frontier method that has been estimated through Bayesian Inference and Markov Chain Monte Carlo methods.

1. Introduction

Charging for the use of airport infrastructures is a central issue in international transport policies, which commonly support pricing schemes based on marginal costs. Additionally, the analysis of the industry structure, especially regarding the presence of scale economies, seems to be fundamental at this time, where demand forecasts are exerting much pressure on airport development. In such sense, the econometric estimation of airport cost functions is proposed as the suitable methodology as it allows a proper analysis of the aforementioned features. In addition, the estimation of the industry's technology can be used to analyze the global efficiency of the industry as well as the individual performance of each airport.

There is a well established literature on the estimation of multi-output cost functions for transportation industries (Caves et al., 1980). However, the lack of financial data on airports imposes some restrictions on the choice of a model specification and the estimation methodology. Consequently, no significant efforts have been done in the literature to develop an airport-specific methodology to estimate a cost function, rather than adapting the procedures applied to other industries. This ultimately explains the relative scarcity of cost function studies in the airport industry.

Hence, the aim of this paper is to propose an airport-specific estimation procedure for the airport industry's cost function. In addition, the use of a broader database than the previous studies allows us to overcome many limitations that affect the generalization of results. The multi-ouput nature of airports will be considered in the cost function through the specification of hedonically-adjusted aircraft operations, domestic and international passengers, cargo, and commercial revenues as out-

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Table 1
Cost function studies in the airport industry.

Author/s	Functional form	Data (P = Panel, CS = Cross Section)	Output
Keeler (1970)	Cobb-Douglas	P 13 US 65–66	ATMs
Doganis and Thompson (1974)	Cobb-Douglas	CS 18 UK 1969	WLUs
Tolofari et al. (1990)	Translog	P 7 UK 79–87	WLUs
Martín-Cejas (2002)	Translog	P 40 Spain 96–97	WLUs
Main et al. (2003)	Cobb-Douglas	CS 27 UK 1988 P 44 worldwide, 98–00	PAX or WLUs
Jeong (2005)	Translog	CS 94 US 2003	PAX or WLUs or Output index
Low and Tang (2006)	Translog	P 9 Asia 1999–2003	WLUs
Martín and Voltes-Dorta (2008)	Translog	Unbalanced P 41 worldwide 1991–2005	WLUs and ATMs
Oum et al. (2008)	Translog (short-run)	Unbalanced P 109 worldwide 2001–2004	PAX, ATMs and REV.
Martín and Voltes-Dorta (present study)	Translog (long-run)	Unbalanced P 161 worldwide 1991–2008	Domestic and international PAX, ATM_{MTOW}, CGO and REV.

Source: Jeong (2005), own elaboration.

puts. The calculation of input prices is also discussed, and a new method is proposed, which is based on the estimation of quantity indexes. A long-run cost function is estimated using a Stochastic Frontier method featuring both technical and allocative inefficiencies. Bayesian Inference and Markov Chain Monte Carlo methods (MCMC) are used to deal with the non-linear complexity of the model.

2. Literature review

Only a few studies have dealt with the costs of airport infrastructure services, and the use of very different data and methodologies provides inconsistent findings, mainly related to: (1) a partial view of the airport activity, especially while dealing with the output definition; and (2) the difficulty in collecting comparable data across different airports size and location.

As a first approach, Keeler (1970) reported constant returns to scale from two Cobb–Douglas cost functions for capital and operating costs, using air transport movements (ATMs) as the output. He used pooled data from 13 US airports between 1965/1966. However, the results are limited by the small database and a partial approach. Doganis and Thompson (1974) estimated a Cobb–Douglas cost function, and also parameterized models for capital and operating costs separately, using work load units (WLUs)[2] as the output. They used data from 18 British Airports for 1969. However, this work presents the same limitations as Keeler's.[3]

Tolofari et al. (1990) used pooled data of seven British Airports for 1979–87 to model a short-run translog cost function with fixed capital stock. The variables were WLUs as the output, the input prices of labour, equipment, and residual factors; capital stock, passengers per ATM, share of international passengers, percentage of terminal capacity used and a time trend. They found economies of scale up to 20.3 million WLUs.

Martín-Cejas (2002) estimated a translog total cost function, using WLUs as the output and considering capital and labor costs, using data from 40 Spanish airports between 1996/97. The results show that middle size airports (1–3 million WLUs) presented higher levels of efficiency than small or large airports. Main et al. (2003) estimated four Cobb–Douglas cost functions with alternative specifications, including two different outputs (WLUs or passengers) and two different time dimensions (short run vs. long run in which the costs of depreciations were included or not). Other variables were the price of staff, price of factors other than staff, passengers per ATM, share of international passengers and total assets. The price of staff was estimated by dividing staff costs by the number of employees. Price of other factors was estimated by dividing the relevant expenditures by the value of tangible assets. They used a data from 27 UK airports for 1988 and another set from 44 airports worldwide between 1998/2000. They found economies of scale up to 5 million WLUs or 4 million passengers.

Jeong (2005) estimated a translog total cost function with three different outputs: WLUs, passengers, or an output index. Additionally, he used an aggregate input index (excluding capital) and a cost-of-living index as a proxy for the capital price. This study used a cross-section of 94 US airports for the year 2003. He found that returns to scale were exhausted at 3 million WLUs. Low and Tang (2006) analysed factor substitutability using data from major hubs in the Asia Pacific region, using WLUs as the output. However, the authors imposed constant returns to scale in the cost function. Martín and Voltes-Dorta (2008) present a first approximation to a multi-output cost function, featuring ATMs and WLUs as outputs and showing that the monoproductive approach biases the estimated coefficients. They used an unbalanced pool of 41 airports worldwide between 1991/2005. They found that returns to scale are not exhausted at any output level. Finally, Oum et al. (2008) analyses the effect of ownership on airport cost efficiency. A pool of 109 airports worldwide between 2001/2004 was used. A short-

[2] 1 WLU is equivalent to 1 passenger or 100 kg of cargo (Doganis, 1992).

[3] Tolofari et al. (1990) argued that the separate estimation of operating and capital costs results in biased estimates because the error terms are likely to be correlated and the separate estimation fails to adequately model this.

run multi-output cost frontier was estimated using Bayesian inference. The specification features geographical dummies and includes commercial revenues as an output.

Table 1 condenses all past literature, helping to place this contribution within the field of the estimation of airport cost functions. Past literature agrees on the presence of returns to scale in airport operations but only up to 20 million WLUs. However, the world's busiest airports are currently expanding far beyond this "minimum efficient scale". Clearly the use of poor data leads to results that are not generalizable because of the lack of representativeness of the sample.[4] Baumol et al. (1982) shows that in order to determine whether costs are subadditive at a particular output level, observations of costs incurred by smaller firms are required. Hence, a broad database is required for a proper estimation of an industry's cost function.

3. The econometric estimation of cost functions

The estimation of a cost function $C(w, Y)$ requires observations on costs, outputs (Y) and input prices (w) of firms whose behavior is assumed to be cost-minimizing. A functional form has to be postulated in the specification of the cost function. The transcendental logarithmic "translog" (Christensen et al., 1973) provides a local approximation to any cost structure allowing a wide variety of substitution patterns. Linear homogeneity and concavity can be imposed through parametric restrictions. It presents this general structure:

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

The translog cost function is commonly estimated with its cost minimizing input share equations in a seemingly unrelated equations (SURE) regression (Zellner, 1962) and using maximum likelihood estimators. Input shares (s_i) are obtained by applying Shephard's lemma (2). This method allows us to introduce additional equations into the system without increasing the number of parameters. Hence, the estimation becomes more efficient.

$$s_i = \frac{w_i X_i}{C} = \frac{\partial C}{\partial w_i} \frac{w_i}{C} = \frac{\partial \ln C}{\partial \ln w_i} = \beta_i + \sum_{j=1}^{m} \delta_{ij} \ln w_j + \sum_{j=1}^{s} \gamma_{ij} \ln y_j \tag{2}$$

Typically, the explanatory variables are deviated with respect to an approximation point. In a translog specification, the mean of the logged variable is usually the approximation point. This transformation allows a direct interpretation of the first-order coefficients in terms of cost elasticities or factor shares. The partial derivative of the translog cost function with respect to a certain output gives the same output's cost elasticity. The inverse of the sum of all output's cost elasticities gives the firm's scale elasticity (S), which is used as an indicator of the degree of economies of scale in multi-production.

$$S = \left(\sum_{i=1}^{n} \partial \ln C / \partial \ln y_i\right)^{-1} \tag{3}$$

Many technologies are characterized by multiple outputs with variable qualities or attributes. Therefore, the "effective output" does not only depend upon the physical units produced, but also upon their qualities or attributes. This output heterogeneity is usually dealt with by specifying the quality variable in the output vector. However, this is not satisfactory for goods characterized by a continuum of qualities (Spady and Friedlaender, 1978). In these cases, it is more convenient to treat effective outputs as hedonic functions (ψ_i) of a generic measure of physical output (y_i) and its qualities (q_i), i.e.[5]

$$C = C(\psi_i(y_i, q_i), w) \tag{4}$$

For panel data, it may be interesting to measure technological change and technological bias (Stevenson, 1980). Using the time variable (t) as a proxy, the level of technological development (T_d) can be measured as (5). The existence of input bias can be tested by (6), where s_i is the cost share of the ith input. Technical change may also bias the scale elasticity (S), thus providing very important policy conclusions. The scale bias is given by (7).[6]

$$T_d = \partial \ln C / \partial t|_{y,w} \tag{5}$$

$$I_b = \partial s_i / \partial t|_{y,w} \tag{6}$$

$$S_{bi} = \partial S / \partial t|_{y,w} \tag{7}$$

The present methodology is complemented with the consideration of cost inefficiencies. In the real world, some firms deviate from cost minimisation for different reasons. Given the input quantities, a producer is said to be technically inefficient if it fails to produce the maximum possible output. Similarly, allocative inefficiency (AI) is related to a non-optimal input allocation given input prices. There are different methods to deal with these topics, such as Total Factor

[4] Note that only one airport in Tolofari's sample (London Heathrow) operated more than 20 million WLUs.

[5] Note that the effect of quality variations on costs and outputs should be independent of input prices.

[6] A positive value implies that the minimum efficient scale can be attained at a higher level of output.

Productivity (TFP), Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA).[7] This paper uses SFA as the natural extension of the cost function methodology. SFA is an econometric method that estimates a cost frontier as follows:

$$C = f(y, w) + u_i + v_i \tag{8}$$

where v is the white noise, and u is a disturbance term, which is interpreted as an indicator of the technical inefficiency of each airport.[8] Note that u should follow a one-sided distribution, since inefficiency can only take positive values within the cost approach. However, in this case u captures not just the technical inefficiencies but also the AI and the potential influence of other variables that have not been specified in the model (e.g. the type of ownership or the geographic location). Kumbhakar and Wang (2006) show that failure to include AI explicitly in the cost function biases the parameter estimates. However, the joint estimation of both inefficiencies in a translog system presents a complexity that is known as the "Greene problem" (Greene, 1980). Kumbhakar and Tsionas (2005) showed that the problem is complex because the deviations from optimal factor shares are complicated functions of AI. Kumbhakar (1997) solved this issue using a "shadow price" approach in order to assess an exact relationship between AI and cost share equations, introducing a theoretically consistent dependence between AI and output and price levels using a translog specification. Thus, the relevant prices to the firm are:

$$w^* = [w_1, w_2 \exp(\xi_2), \ldots, w_j \exp(\xi_j)] \tag{9}$$

where $\xi_j \neq 0$ represents the allocative inefficiency for the input pair (j, 1). Following the notation of Kumbhakar (1997), the translog cost system can be rewritten as follows:

$$\begin{aligned} \ln C^a(w, y) &= \ln C^o(w, y) + \ln C^{al}(\xi, w, y) + u + v \\ S_i^a &= S_i^o + \lambda_i \end{aligned} \tag{10}$$

where u now accounts only for technical inefficiency; v is the usual white noise; and lnC^{al} represents the percentage increase in costs due to allocative distortions, which depends on the estimation of the allocative inefficiency parameters (ξ). The empirical estimation of this kind of models is restricted to panel data in which both technical and allocative inefficiency are either assumed to be fixed parameters or functions of the data and unknown parameters. Kumbhakar and Tsionas (2005) provide a Bayesian approach to estimate this econometric model, using Markov Chain Monte Carlo (MCMC) methods. AI is modelled via price distortions from which firm-specific inferences are drawn on input over- or underutilization.

4. Methodological issues

4.1. Output vector

The estimation of a cost frontier requires the specification of an output vector. However, the multi-output nature of transport firms has been typically neglected in empirical studies due to the lack of data, which led to the use of output aggregates (Jara-Díaz, 2007). The specification of disaggregated outputs allows output-specific marginal costs to be estimated, upon which the analysis of optimal pricing and investments is based. Besides, in the event that airport activities (*airside, landside*, *retail*) were regulated and managed independently, the calculation of the output-specific scale economies would be essential in order to assess the optimal airport size, which could be totally different than in an environment in which all the activities are under the umbrella of the Airport Authority. For these reasons, this paper proposes a multi-output specification of the cost function.

Airports do not provide transportation directly, but provide all the necessary infrastructures for air traffic. Their multi-product nature is related to the very different use that aircraft, passengers/baggage and freight make of airport facilities. Hence, this three-dimensional output vector can be considered the starting point to the study of airport cost functions.

4.1.1. Aircraft operations

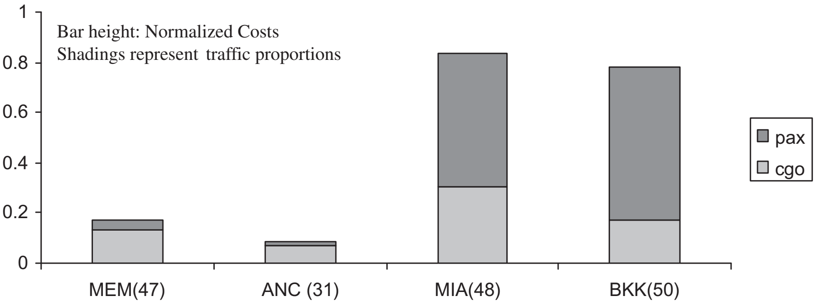
The specification of aircraft operations as an output of the airport is a contentious issue. Reviewing past literature, it does not seem a popular output measure. Because of the strong correlation between passenger and aircraft traffic, a first approach is to drop the latter of the specification. In fact, many authors consider that passengers are the only output of an airport. This would be acceptable if the subject under study was the air transport industry, i.e. the joint operation of the carriers and the airport. However, this paper deals only with airports, and these do not provide transportation but just the infrastructure, including those facilities needed to serve aircraft, such as runways and taxiways. These infrastructures, and hence the costs imposed to the airport, are not related to the passengers as they are completely separated.[9] Consequently, in spite of the single-output approach can make sense econometrically, it is not supported by neither economic nor technological grounds.

Air traffic movements (ATMs) are defined as either a landing or a take-off. From the airport's perspective, the output is defined as the provision of infrastructure to the carrier in order to perform such movements. However, landings and

[7] A comprehensive survey of airport productivity and efficiency studies can be found in Oum and Yu (2004).

[8] The estimation of technical efficiency using SFA was introduced by Aigner et al. (1977) and Meeusen and van der Broeck (1977).

[9] Airports are divided in airside and landside, which are defined according to the different outputs they serve.



Source: Own elaboration.

Fig. 1. Comparison between cargo and passenger airports.

take-offs may not be comparable in terms of infrastructure usage and since they are usually produced in sequence and jointly charged, this study will only consider the number of landings, redefining the ATM variable to represent a landing-take-off (LTO) cycle. Only commercial aviation is considered.

The specification of ATMs leads to a problem of output separation, as different aircraft impose different costs on the airport's infrastructure. Heavier aircraft require longer, wider and stronger runways and take up more space on the aprons. Therefore, one would expect that two airports with the same number of ATMs have very different airside costs if one airport serves mainly to the short-haul – small aircraft of regional markets and the other is concentrated on long-haul – wide-body aircraft of international markets. Hence, the "effective output" is not properly described by the physical units produced because they are not homogenous across the industry. Furthermore, the existence of a wide range of aircraft models operating at each sample airport generates a continuum of qualitative dimensions for the output ATM, whose impact on costs are completely independent of input prices. These are the conditions, described by Spady and Friedlaender (1978), which make the specification of ATMs as hedonically-adjusted output as one of the preferred solutions. The only question that remains is to choose a proper attribute to characterize the difference in infrastructure costs imposed by different aircraft models.

Littlechild and Thompson (1977) estimate a Runway User Index for different aircraft types, suggesting that the most important cost drivers related to the maintenance of runways were takeoff distance, runway pressure and manoeuvrability. These and many other factors were summarised by an ICAO rating known as the Aircraft Classification Number (ACN). Hogan and Starkie (2003) show that, if the damage inflicted on the runway by a "base aircraft" can be measured by its ACN, then the relative damage imposed by another aircraft can be expressed as the ratio between its ACN and the base aircraft's raised to the fourth power.[10] This indicates that damage costs increase more than proportionally with the ACN and hence a non-linear increasing relationship between aircraft categories should be defined.

However, the calculation of the airport-specific "average ACN" requires comprehensive data, but in most cases, only the information on the total or average landed aircraft weight will be available. Hence, the aircraft's maximum take-off weight (MTOW) is used as a proxy for the ACN. Hogan and Starkie (2003) show that the relationship between damage costs and the MTOW presents a similar increasing and non-linear shape as the ACN. For that reason, the airport-specific "average MTOW" will be used as a quality variable, to capture differentials in the provision of infrastructure for aircraft operations. The hedonically-adjusted output will be renamed ATM_{MTOW}. Using a translog specification, we can write:

$$\ln \text{ATM}_i^{\text{MTOW}} = \ln \text{ATM}_i + \psi(\ln \text{MTOW}_i) \tag{11}$$

The estimated value of ψ will provide important conclusions in terms of runway pricing. If the estimated value ψ is equal to 1, then all metric tons impose the same costs to the infrastructure and hence the optimal landing charges should be based on constant unit rates per weight. However, the position of the airports that are nowadays charging increasing unit rates per metric ton will be justified if the estimated value ψ is greater than 1. This scheme is the most widely applied system (e.g., the US, Australia, Italy and Spain). If the estimated value ψ is less than 1[11] then the airports should charge decreasing unit rates.

4.1.2. WLUs, passengers, cargo and commercial revenues

To date, work load units (WLUs) have been the most popular output measure in the past literature. This aggregate assumes that a passenger (with the luggage) imposes the same costs to the airport infrastructure than 100 kg of cargo. However, according to Doganis (1992), while such a weight relationship seems logical for airlines as it affects aircraft payloads, its relevance to airports is questionable since the same weight of passenger and freight does not require the use of similar resources in physical or financial terms. To give some evidence on this issue, let us compare the operational costs of two major cargo airports against other commercial airports producing the same level of WLUs but more focused on passenger transport (Fig. 1).

[10] According to the generalized 4th power law for pavements.

[11] This result is not expected by what has been previously explained by other authors like Hogan and Starkie (2003); however there are airports that charge decreasing unit rates per weight.

Fig. 1 shows four comparable airports in terms of millions of WLUs serviced (indicated in parentheses). Bar height indicates the cost index, and the different shadings indicate the proportion of each output that has been serviced in each of the airports. It can be seen that the busiest airport in the world for cargo traffic (Memphis) produced about 47 million WLUs in 2005 (of which 76% were cargo units). Miami presents a similar level of WLU activity, but the importance of cargo is lower (only 36%). This significant difference in costs provides the economic justification to disaggregate WLUs into cargo and passenger variables. These two outputs do not usually share the same infrastructures and workforce. In addition, the processing of cargo parcels is much an airline activity, especially in those airports that have dedicated cargo terminals in the hands of the big cargo operators. On the contrary, the processing of passengers occurs completely in the passenger terminal and using the infrastructures provided by the airport operator. Therefore, the costs imposed by the two outputs are not comparable and a separate specification of passengers and cargo is needed.

Now when we focus in the provision of infrastructure for passengers and baggage (PAX), it becomes evident that the problem of output heterogeneity is again present. It is well known that international passengers (INT) usually impose higher costs to the airport than domestic ones (DOM). These higher costs are related to the provision of exclusive terminal areas dedicated to customs and immigration procedures. For that reason, most airports charge a higher terminal fee to international passengers. However, it is worth noting that not all international passengers are subject to these controls, since many international agreements (most notably the Schengen Agreement in the EU) have come into force in the last decades. Hence, all intra-EU (or similar) traffic will be labeled as domestic. Thus, international passengers (INT) and domestic passengers (DOM) will be specified as separate outputs.

Freight and mail operations (CGO) are the fourth output considered, the unit of observation being the metric ton (1000 kg). Cargo operations are performed exclusively in the airport's landside, and comprise the processing of both air and ground freight. However, this last item is only considered when the airport provides its own infrastructure for ground freight operations, hence serving as a logistic platform, and therefore assuming part of the processing costs. In cargo airports, major freight carriers operate their own on-site facilities. In these cases, ground transport tonnage is not counted as an airport's output.

Finally, the fifth output included in the specification of the cost function is the provision of infrastructure for commercial activities such as retail, food and beverage, parking, real estate and many others. The unit of observation is defined as thousands of 2008 Purchasing Power Parity (PPP) USD of non-aviation revenues. The importance of this variable cannot be neglected because major airports are currently obtaining up to 70% of their total revenues from commercial activities (ATRS, 2007). In addition, the estimated parameters will help in identifying the presence of scope economies between aviation and non-aviation activities. This speciation could be used to explain why airports may have incentives to expand themselves beyond the level that would be expected from profit-maximization behavior obtained only from aeronautical services (Beesley, 1999).

It may seem inappropriate to specify a monetary variable as an output instead of using any other indicator of service. Price distortions are partially reduced by the conversion to PPP, but the existence of a wide variety of retail regulations may introduce some noise in the results. In spite of that, as Oum et al. (2008) suggest it is necessary to include this variable if one wants to analyze airports' cost functions.

4.2. Input prices

The calculation of input prices is a delicate issue. Airport operations require a huge amount of different inputs, which first need to be categorized in order to serve as explanatory variables in a reasonable cost specification. This work follows the categorisation presented in Doganis (1992) which identifies three major input/cost categories: namely, labor; materials and outsourcing (OS); and capital. As each item is defined to represent a heterogeneous set of inputs, the prices are obtained by dividing the respective costs by quantity indexes, which will be constructed with the intention of correlating them with the aggregated input demands.

Labor is the most important cost element, mainly because handling activities are particularly labor intensive. However, these activities are commonly OS, and, hence, a great amount of labor costs is typically recorded by the operator under materials/OS. As there is no practical way of determining either the number of OS employees or their payroll, the best estimation of an airport's labor price (wp) is obtained by dividing the recorded labor costs by the number of full-time equivalent employees (FTEE) of the Airport Authorities (AA).

The category "materials/OS" includes utilities, maintenance, and administration costs. Capital costs encompass interest paid and the economic depreciation of the airport's fixed capital assets, such as landside buildings or the airside movement areas. In the airport industry it is a common practice that the constructions projects and supply contracts are usually awarded through competitive tendering to the most economically advantageous bid. This practice is common not only in the case of public but also at the privatized airports (e.g. BAA). In addition, the new technologies provide larger coverage of the market on a global scale, giving the airports access to information on potential suppliers on a worldwide basis.

Because of the scarcity of information, the calculation of both capital and materials prices has been considered a delicate issue in the past literature, and no satisfactory solution has been proposed to date. In this paper, a new approach is carried out. Assuming that the airport input markets may have the characteristics of a monopsony, the contract prices are expected to be less than marginal revenue product [MRP/1 + e] of the purchased input, where e represents monopsony power. Since there is no practical way of obtaining contract-specific values of e with the available data, a representative average for each

Table 2
Posterior statistics of MPs, quantity indexes and input prices at Zurich/2008.

Node	Mean	sd	2.5%	Median	97.5%
MPgat	118,400	11,250	96,220	118,400	140,300
MPchk	37,470	5373	26,940	37,450	37,450
MPwar	197.5	14.79	168.6	197.5	226.4
Iqm	232.1	17.18	201.8	231.0	269.4
wm	591.7	43.12	507.1	591.5	676.9
MPter	154.1	14.79	125.3	154.1	183.1
MPrun	1364.0	216.5	938.1	1364.0	1790.0
Iqc	24,560.0	2778.0	20,220.0	24,180.0	31,020.0
wc	7.06	0.75	5.53	7.09	8.48

factor is used, i.e. $e_{capital}\ e_{materials}$. In addition, as these projects are usually very complex, there is need to define a set of proxy factors (x) whose demand should directly explain the aggregated expenditure. Then all proxy factors' marginal products (MPs) are derived from a ray production frontier (Löthgren, 1997). The N-dimensional output vector is represented by the Euclidean norm (Q) of the quantities and the $N-1$ polar coordinate angles (θ).[12] Using the Bayesian methodology explained in Section 6.1, Q is assumed to be normally distributed around a log-linear specification, i.e.

$$\ln Q \sim N(a + b\ln x + c\theta + dt - u, \sigma_v^2); \quad Q = \sqrt{\sum_{j=1}^{N} y_j^2}; \quad \theta_j = \cos^{-1}\left(y_j/Q\prod_{h=0}^{j-1}\sin\theta_h\right) \tag{12}$$

where t is the time variable, v is white noise and u is an exponentially distributed disturbance that represents technical inefficiency. Non-informative prior distributions were assigned to all the remaining coefficients. After the estimation, the MPs of the relevant proxy factors, the MP ratio-α and the quantity index-I are defined as stochastic nodes in order to reflect the variability of the estimated parameters into the fitted input prices (Eq. (14)), which will be incorporated into the cost model as normally-distributed stochastic variables, featuring an empirically determined variance ($\sigma^2{}_w$). The calculations are:

$$\begin{aligned} &\mathrm{MP}^j = (\partial\ln Q/\partial\ln x^j)\cdot(Q/x^j) \\ &\mathrm{MP}^k/\mathrm{MP}^j = \alpha \\ &C^j = (p\cdot \mathrm{MP}^j/1+e^j)\cdot(x^j+\alpha\cdot x^k) = w^j(I^j) \end{aligned} \tag{13}$$

Finally, the distribution of the input price (w^j) is easily obtained by dividing the relevant costs (capitals or materials) by the quantity index:

$$w^j \sim N(C^j/I^j, \sigma_{wj}^2) \tag{14}$$

The proxy inputs considered in the calculation of the price of materials (wm) were the number of boarding gates (GAT), which served as the base input, the number of check-in desks (CHK) and the total warehouse area (WAR). These variables were chosen because they are correlated with the airport's demand for utilities and maintenance. The proxy inputs considered in the calculation of the capital price (wc) were the total terminal floor area (TER) and the total runway length (RUN), which served as the base capital input. The full specification of the production frontier and the estimation results are shown in Appendix B.

The MPs are then calculated and combined with the actual data in order to obtain the quantity indexes and the prices. Note that each airport has its own mean price and variability. Table 2 shows the posterior statistics of a random observation, Zurich/2008. Fig. 2 shows that even though a flat prior density was specified, the fitted prices follow a normal distribution.

It is worthwhile noting here that the proposed methodology provides price estimates that are implicit of the actual value of e, which can be calculated afterwards. Also note that the role these prices play in the estimation process of a cost function depends heavily on the existence of monopsony power. Factor price endogeneity exists in the case of monopsony power, so researchers need to add the input supply functions $w = w(I)$ to the system (Morrison, 1999). In view of these methodological implications, the markets for labor and materials are assumed to be competitive ($e = 0$) and the existence of significant monopsony power in the capital market will be checked at the average airport. Using a simple test of competition, it can be seen that the hypothesis of the existence of monopsony power in capital markets is rejected (see Appendix C). Therefore, all input markets are assumed to be competitive and thus prices are exogenous to the airport decision makers.

5. Database and sources

The database is mostly composed of financial data collected from the accounts published by the Airport Authorities (AAs). It is an unbalanced pool of 161 airports wordwide between 1991 and 2008 (1294 observations). The sample contains many

[12] Angles are obtained recursively, starting from $\sin(\theta_0) = 1$ (Löthgren, 2000).

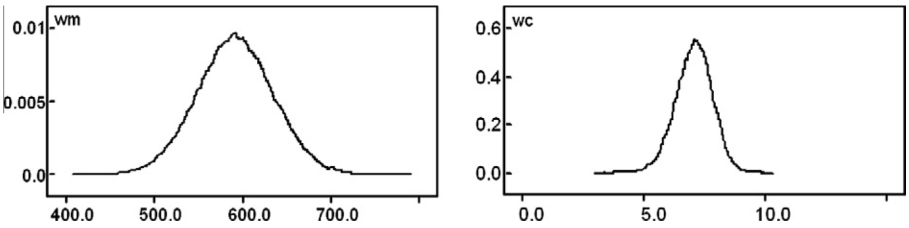


Fig. 2. Posterior densities of the capital and material prices at Zurich/2008.

Table 3
Sample airports.

Country	Airport	Time span	Country	Airport	Time span	Country	Airport	Time span
Austria	Graz	00-08	Italy	Bologna	05-08	Spain	Madrid	91-97
	Klagenfurt	02-07		Brescia	05-08		Málaga	91-97
	Linz	99-08		Florence	99-08		Melilla	91-97
	Salzburg	02-08		Orio al Serio	01-08		Menorca	91-97
	Vienna	99-08		Palermo	03-08		Murcia	91-97
Belgium	Brussels	00-08		Pisa	02-08		Palma de Mallorca	91-97
	Liege	01-05		Turin	99-08		Pamplona	91-97
	Ostend	02-08		Venice	03-08		Reus	91-97
Croatia	Zagreb	98-04		Verona	05-08		San Sebastián	91-97
Czech Rep.	Prague	00-08	Latvia	Riga	01-08		Santander	91-97
Denkmark	Aarhus	00-08	Malta	Malta	03-08		Santiago	91-97
	Billund	97-08	Netherlands	Amsterdam	96-08		Sevilla	91-97
	Copenhagen	91-08		Eindhoven	01-08		Tenerife Norte	91-97
Estonia	Tallinn	02-08	Norway	Oslo	99-08		Tenerife Sur	91-97
France	BSL/MLH/FRE	02-08	Slovenia	Ljubljana	98-08		Valencia	91-97
	Nantes	04-05	Spain	Alicante	91-97		Valladolid	91-97
Germany	Bremen	01-08		Almería	91-97		Vigo	91-97
	Dortmund	04-08		Asturias	91-97		Vitoria	91-97
	Dresden	04-08		Badajoz	91-97		Zaragoza	91-97
	Dusseldorf	90-08		Barcelona	91-97	Switzerland	Geneva	90-08
	Frankfurt	03-08		Bilbao	91-97		Zurich	96-08
	Hahn	05-08		Cordoba	91-97	UK	Birmingham	01-08
	Hamburg	99-08		Fuerteventura	91-97		Bournemotuh	03-08
	Hannover	99-08		Girona	91-97		Bristol	03-04
	Cologne/Bonn	02-08		Gran Canaria	91-97		Cardiff	01-04
	Munich	92-08		Granada	91-97		East Midlands	03-08
	Munster	03-06		El Hierro	91-97		Humberside	03-08
	Nuremberg	97-06		Ibiza	91-97		London Luton	00-06
	Paderborn	02-04		Jerez	91-97		Manchester	90-08
	Rostock	03-04		La Coruña	91-97		Newcastle	01-04
	Stuttgart	94-08		La Palma	91-97			
Greece	Athens	04-08		Lanzarote	91-97			
Canada	Calgary	93-08	US	Denver	00-08	US	Chicago O'Hare	00-08
	Halifax	02-08		Detroit	00-08		Orlando	00-08
	Ottawa	98-08		Dulles	00-08		Phoenix	00-08
	Toronto	99-08		Fort Lauderdale	00-08		Pittsburgh	00-08
	Vancouver	99-08		Honolulu	00-08		Portland	00-08
	Victoria	99-08		Indianapolis	00-08		Pt. Columbus	00-08
	Winnipeg	99-08		Jacksonville	00-08		Reagan	00-08
Mexico	Mexico City	03-08		Kansas City	00-08		Reno	00-08
Panama	Panama City	04-07		Knoxville	00-08		Salt Lake City	00-08
US	Anchorage	00-08		Las Vegas	00-08		San Francisco	00-08
	Atlanta	00-08		Los Ángeles	00-08		Seattle	00-08
	BWI	00-08		Louisville	01-08		SW Florida	00-08
	Charlotte	00-08		Memphis	00-08		Tampa	00-08
	Cincinnati	00-08		Miami	00-08		Tucson	00-08
	Dallas–FW	00-08		Chicago Midway	00-08			
	Dayton	00-08		Minneapolis-S.P.	00-08			
Australia	Adelaide	99-08	New Zealand	Christchurch	99-08	Japan	Tokio Narita	01-08
	Alice Springs	02-08		Wellington	99-08	South Korea	Incheon	04-08
	Brisbane	98-08	South Africa	Johannesburg	05-08	Thailand	Bangkok	05-08
	Darwin	02-08	China	Beijing	00-08		Chiang Mai	05-08
	Perth	99-08		Haikou	03-08		Chiang Rai	05-08
Australia	Sydney	01-08		Hong Kong	99-08		Hat Yai	05-08
New Zealand	Auckland	96-08	Japan	Osaka kansai	99-08		Phuket	05-08

Table 4
Database overview (monetary variables expressed in 000's PPP USD).

	Cost	dom	int	atm	mtow	cgo	rev	wc*	wm*	wp
Max.	2024,278	80,858,789	48,900,000	981,402	287	3840,941	988,544	63.69	7561.10	201.43
Min.	692	1	1	205	16	1	2	0.01	2.92	15.57
Mean	174,945	8414,092	3795,596	153,900	60	276,629	75,632	4.62	599.33	56.62

of the world busiest airports in terms of either passengers/aircraft operations or cargo tonnage. The geographical breakdown is as follows: 94 airports from Europe, 45 from North America, 11 from Asia–Pacific and 9 from Oceania. Besides, Johannesburg and Panama City are also included (Table 3). The European sample features 36 Spanish airports between 1991 and 1997, which were included in order to increase the number of observations and reduce the variability of the estimations.

It is worth noting that, in spite of being frequently used in the literature, regional dummies are not specified in the cost function because no systematic technological differences could be identified a priori among the sample airports in connection to their geographic location. Such difference would exist if, for example, the database featured a significant number of high-altitude airports in Bolivia or Peru. In this case, it is well known that the reduced air pressure increases the runway requirements, thus shifting the transformation elasticities.

Data collection was completed for the following variables: (a) Total costs: labor, materials and capital expenditures (amortization and interest); (b) Output: Domestic and international passengers, commercial ATMs, metric tons of cargo (CGO) and commercial (non-aviation) revenues (REV); (c) Fixed factors: terminal floor area in m^2 (TER), runway length in m (RUN), number of gates (GAT), check-in desks (CHK) and warehouse area in m^2 (WAR); (d) Other: time (t), full-time equivalent employees (FTEE), and total landed MTOW in metric tons. The monetary variables were converted to 2008 PPP USD using the OECD published indicators. Table 4 provides the mean and range of each variable.[13] The mean airport serves about 153,900 ATMs, 8.4 million domestic and 3.8 million international PAX, and 276,329 metric tons of cargo, being relatively small in comparison with the world busiest airports.

Regarding general data sources, for other than US airports, financial data comes directly from the AA's published financial statements. In most cases, airports' web sites include enough detailed information of traffic activity, such as ATMs, passenger enplanements, landed MTOW, and cargo. Regarding this last variable, foreign trade records were also consulted. Regarding the figures for the US airports, the main source is the CATS financial database provided online by the Federal Aviation Administration (FAA, 2008). The traffic figures were mainly collected from the ICAO/ATI Airport Traffic Summary reports (ICAO, 2004), which provide data for airports around the world between 1992 and 2004. Operational data was also obtained from the FAA Airport Master Records, and further details were available in the 2003 edition of the Airport Capacity and Demand profiles (IATA, 2003).

The database does not feature many of the busiest airports in Europe (e.g. London, Paris) because the AAs did not publish disaggregated information at a single-airport level. Though most financial reports consulted follow the International Financial Reporting Standards (IFRS), many airports were dropped from the database because of heterogeneity. For example, at the three New York metro airports, policemen are considered airport staff, thus resulting in a much higher labor price than the rest of the sample. On the contrary, the quality of the financial reports in certain cases (e.g. Amsterdam, Frankfurt) allowed us to locate the airport-related figures within a broad scope of activities, thus improving the comparability of the observations. The same applies to the few cases in which the airports charge depreciation on the land (e.g. man-made islands) or they pay a rent for the land (Canada). These costs are usually detailed in the financial statements and have been removed in order to homogenize the data. Finally, another source of heterogeneity is the presence of dedicated terminals (typical of the US airports). Most capital expenditures are not directly recorded by the AA but by the concessionaire. Hence, the capital costs collected from the AAs' financial statements were proportionally adjusted to meet the declared airport capacity (Voltes-Dorta, 2008).

6. Model specification and estimation

The decision on whether a long- or short-run specification should be estimated will be now briefly discussed. The previous literature does not provide any further help on this issue, except for Tolofari et al. (1990) and Oum et al. (2008) which decided for short-run – all other studies simply estimated both equations, having in mind that the issue of capital costs has usually been circumvented. On the one hand, most airports' capital assets are planned and built to accommodate the forecasted traffic demand well into the future. Airport capacity remains clearly fixed for long periods of time. Hence the cost function analysis should, at first sight, be more appropriately based on a short-run specification featuring the capital stock as a fixed factor. On the other hand, the capital costs as defined by Doganis (1992) mainly consist of the economic depreciation of the fixed assets as they enter into use. Therefore, taking into account that the airports' output is highly dependent on the provision of infrastructure, then capital costs are sharply related to the level of production and hence cannot be considered as fixed costs. It is true that accounting practices allow that some structures could be written off in fixed amounts at the

[13] The translog is not analytic in zero. All zeros in the database were turned into ones.

end of each financial year but this fact does not intrinsically mean that economic depreciation is truly represented by these figures. Thus the specification of a capital stock variable in a short-run model may lead to significant parameters, but a wrong interpretation could be induced by the poor quality of the data.

Besides, a little investigation on our database shows that the short-run assumption does not hold for all sample airports because 60 out of the featured 161 airports have already expanded either their runway system or the terminal buildings (or both) during the time span considered. In addition, most of these expansions are justified by a significant development in both aircraft and passenger operations. With a few exceptions, the remaining airports tend to show moderate traffic increases. The weighted average annual growth rate for the expanded airports is 6.8% compared with a 3.8% for the non-expanded.

Finally, Oum et al. (2000) state that a good knowledge of the data is the best guide to assess the nature of the estimated elasticities. The use of time-series leads to short-run estimates if the observed capital costs are most likely linked to the existing capital stock. On the contrary, if the data features a cross-section on a wide range of traffic levels and infrastructures, the estimated elasticities should be interpreted as long-run. This is because the wide variation across firms allows the consideration of all factors as variable, and hence, even the most fixed capital expenditures can be assumed to be fairly adjusted to their optimal scale of production. In our case, the pooled panel data is comprised of a wide range of airport sizes and for this reason we propose the long-run model as the chosen approach.

6.1. Bayesian estimation

Due to the complexity of the cost model, Bayesian inference and simulation (MCMC) are used for the estimation (Van der Broeck et al., 1994). For its simplicity, the WinBUGS software (Lunn et al., 2000) will be used to derive the posterior densities of all coefficients. This work uses the codification proposed in Griffin and Steel (2007), which is adapted to the specification of Kumbhakar (1997). The dependent variable (the log of the total costs) is normally distributed, with a standard translog specification as the mean and σ_v^2 as the variance representing the white noise. Apart from specifying the time variable in order to measure technological development, the parameter of technical inefficiency is also allowed to vary systematically over time (Battese and Coelli, 1992), allowing firm-specific parameters η_i (Cuesta, 2000). Hence u_{it} represents the technical inefficiency of firm *i* at time *t*. The firm's average inefficiency u_i is exponentially distributed[14] with mean λ^{-1}, and a negative η_i indicates that the airport increases its efficiency over time.

$$\ln C_{it}^a \sim N(\ln C_{it}^o(w,y,\psi,t) + \ln C_{it}^{al}(\xi,w,y,\psi,t) + u_{it}, \sigma_v^2) \tag{15}$$

$$u_{it} \sim \exp\{\eta_i(t-T)\}u_i, \quad \text{where } u_i \sim \exp(\lambda) \tag{16}$$

Prior distributions are assigned to the parameters, such as the multivariate normal with mean zero to the vector of regressors β, a gamma distribution ($a0, a1$) for the white noise precision (σ_v^{-2}), and another exponential for the λ parameter which allows us to impose our prior ideas about mean efficiency (r^*) in the airport industry. Allocative distortions ξ are specified as normal variables with zero mean representing the prior notion that average allocative inefficiency is likely to be small (Kumbhakar and Tsionas, 2005). The prior distribution of η_i was also chosen to be a zero mean normal distribution representing the prior indifference between the increasing or decreasing efficiency at each individual airport. Finally, the ψ coefficient of the hedonic ATM function (Eq. (11)) is specified as a uniform distribution.

$$\beta \sim N(0,\Sigma) \quad \sigma_v^{-2} \sim G(a0,a1) \quad \lambda \sim \exp(-\log r^*) \quad \xi_j \sim N(0,\sigma_\xi^2) \quad \eta_i \sim N(0,\sigma_\eta^2) \quad \psi \sim U(a,b) \tag{17}$$

Once the specification has been chosen, the system is formulated taking into account primarily the allocative effects defined across the input price vector. Following Kumbhakar's shadow price approach, one input category is chosen as the reference, and the allocative effects are defined with respect to it. In this work, the capital is chosen as the base input,[15] hence the relevant input price vector for the allocatively inefficient cost minimizing airport is:

$$W^* = [w_c, w_m \exp(\xi_m), w_p \exp(\xi_p)], \quad w_c, w_m \sim N(C_i/I_i, \sigma_{wi}^2)|i = c, m \tag{18}$$

where ξ_j indicates the allocative inefficiency for the input pair (*j*, capital). In addition, remember that the fitted input prices w_c and w_m are defined as normally-distributed stochastic variables as explained in Section 4.2. Factor share equations are specified in a similar fashion as the cost frontier, being normally distributed and assuming that their errors are likely to be highly correlated. Note that technical efficiency does not affect factor shares as all inputs are used inefficiently in the same proportion. The input share equations are directly derived from the cost frontier (Eq. (15)), using the Shephard's Lemma, resulting in this expression:

$$S_i^a = [S_i^o(w,y,\psi,t) + S_i^{al}(\xi,w,y,\psi,t)]/G_i \exp(\xi_i) \tag{19}$$

[14] Other distributions, such as Gamma and Truncated Normal were also checked. The choice of an exponential distribution for *u* was based on the Deviance Information Criterion (DIC) test (Spiegelhalter et al., 2002).

[15] The selection of capital as the reference input is appropriate since "labor" and "materials/OS" input categories may overlap at some airports (see Section 4.2). Allocative distortions between labor and materials cannot be properly estimated using the present data. We thank an anonymous referee for this observation.

As noted, the system will benefit from any additional information the data can provide. Hence, as no singularity problems arise when Bayesian methods are used, the three factor share equations are included in the system. Finally, the regularity restrictions to the parameters are imposed to comply with the linear homogeneity in *w*. The symmetry of the Hessian matrices is also imposed to liberate degrees of freedom. Concavity is not imposed but it will be checked at the average airport. The complete model specification is shown in Appendix A. Note that all explanatory variables are divided by their sample means and logged.

The precision of the *eta* parameter (σ_η^{-2}) was set at 10 because changes in technical efficiency are not expected to present a high variability in the database. The same applies to both allocative effects (σ_ξ^{-2}) where prior precisions were set at 18 allowing for a narrow variability. This value was calculated in order to prevent allocative distortions in excess than $2^{\pm 1}$. This is considered to be a reasonable spread for the airport industry, as labor and materials will rarely be demanded more (less)

Table 5
Long-run cost system parameter estimates.

Node	Mean	sd	2.5%	Median	97.5%
Constant	10.76696	0.01591	10.73573	10.76953	10.79805
ATMmtow	0.12228	0.02060	0.08167	0.12236	0.16323
dom	0.13116	0.01095	0.10970	0.13121	0.15269
int	0.04314	0.00680	0.02986	0.04314	0.05660
cgo	0.06838	0.00787	0.05304	0.06834	0.08377
rev	0.13475	0.01479	0.10600	0.13481	0.16333
wc	0.37069	0.00288	0.36510	0.37070	0.37641
wm	0.31785	0.00214	0.31367	0.31779	0.32204
wp	0.31072	0.00319	0.30458	0.31077	0.31692
ATMmtow ∗ wc	−0.00999	0.00512	−0.01988	−0.00998	0.00020
ATM ∗ wm	0.02457	0.00362	0.01739	0.02459	0.03165
ATMmtow ∗ wp	−0.00913	0.00469	−0.01827	−0.00913	0.00009
dom ∗ wc	0.00034	0.00108	−0.00178	0.00033	0.00243
dom ∗ wm	0.00398	0.00074	0.00256	0.00398	0.00543
dom ∗ wp	−0.00312	0.00101	−0.00510	−0.00313	−0.00115
int ∗ wc	−0.00773	0.00120	−0.01008	−0.00772	−0.00538
int ∗ wm	0.00478	0.00086	0.00307	0.00478	0.00646
int ∗ wp	0.00330	0.00118	0.00102	0.00330	0.00562
cgo ∗ wc	−0.00053	0.00213	−0.00474	−0.00055	0.00365
cgo ∗ wm	−0.00830	0.00164	−0.01149	−0.00831	−0.00505
cgo ∗ wp	0.00763	0.00220	0.00325	0.00762	0.01196
rev ∗ wc	0.00442	0.00443	−0.00434	0.00442	0.01319
rev ∗ wm	0.01676	0.00297	0.01093	0.01675	0.02262
rev ∗ wp	−0.02363	0.00397	−0.03146	−0.02364	−0.01586
0.5 ∗ wc^2	0.10550	0.00446	0.09664	0.10546	0.11430
wc ∗ wm	−0.09310	0.00248	−0.09792	−0.09309	−0.08822
wc ∗ wp	−0.02381	0.00359	−0.03081	−0.02381	−0.01679
0.5 ∗ wm^2	0.09293	0.00291	0.08721	0.09289	0.09860
wm ∗ wp	−0.00667	0.00305	−0.01258	−0.00669	−0.00070
0.5 ∗ wp^2	0.02983	0.00454	0.02102	0.02979	0.03860
0.5 ∗ ATMmtow^2	0.01050	0.00923	−0.00748	0.01053	0.02862
0.5 ∗ dom^2	0.01653	0.00149	0.01357	0.01652	0.01948
0.5 ∗ int^2	0.00520	0.00114	0.00295	0.00519	0.00745
dom ∗ int	−0.00945	0.00206	−0.01345	−0.00945	−0.00542
0.5 ∗ cgo ∗ cgo	0.00754	0.00223	0.00323	0.00753	0.01196
0.5 ∗ rev ∗ rev	0.03715	0.00513	0.02697	0.03713	0.04733
t	−0.02639	0.00220	−0.03068	−0.02636	−0.02208
t ∗ ATMmtow	0.01211	0.00363	0.00505	0.01210	0.01918
t ∗ dom	0.00146	0.00092	−0.00033	0.00147	0.00324
t ∗ int	−0.00143	0.00094	−0.00328	−0.00144	0.00039
t ∗ cgo	0.00343	0.00172	0.00008	0.00343	0.00676
t ∗ rev	−0.00920	0.00304	−0.01523	−0.00918	−0.00331
t ∗ wc	−0.00588	0.00073	−0.00731	−0.00588	−0.00446
t ∗ wm	0.01061	0.00052	0.00957	0.01062	0.01164
t ∗ wp	−0.00403	0.00071	−0.00544	−0.00402	−0.00260
psi (hedonic)	1.11147	0.11219	0.94271	1.10876	1.36997
lambda	6.83276	6.84570	0.18509	4.74198	25.31179
eta	0.02829	0.05659	−0.05453	0.03011	0.11742
Cal	1.06321	0.04445	1.00522	1.06040	1.16312
Elasticity capital	−0.93020	0.03213	−0.99370	−0.93000	−0.86780
Elasticity material	−1.22700	0.04250	−1.31100	−1.22600	−1.14500
Elasticity labor	−1.90900	0.08899	−2.08500	−1.90900	−1.73600
Elasticity cap/mat	0.21040	0.03890	0.13330	0.21060	0.28580
Elasticity cap/lab	0.79320	0.03313	0.72880	0.79320	0.85810
Elasticity mat/lab	0.93250	0.04104	0.85220	0.93260	1.01300

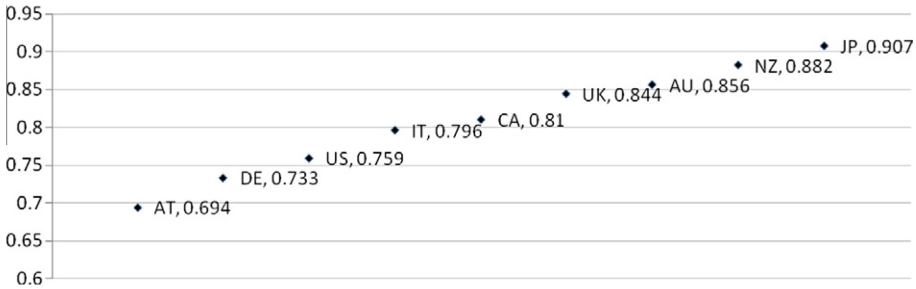


Fig. 3. Traffic-weighted average economic efficiency at major geographical clusters (2008).

than twice (a half) as optimal with respect to the capital. The hedonic coefficient ψ will be uniformly distributed between 0 and 2, also allowing for a reasonable spread, given the results from Hogan and Starkie (2003).

The white noise for both cost frontier and factor share equations (σ_v^{-2}) was given a Gamma distribution with shape parameter a_0 and mean a_0/a_1. They were set ($a_0 = a_1 = 0.001$), as shown in Griffin and Steel (2007), this ensures very diffuse prior information. Technical inefficiency was assumed to be exponentially distributed with parameter λ. Prior ideas on the industry's median efficiency can be added to the system by means of the r^* parameter in the distribution of *lambda*. This was set at 0.82, as obtained in a previous study (Martín and Voltes-Dorta, 2008) using a very similar but smaller database. Finally, as the most important outcome of the estimation process, the prior distribution for the *beta* parameter vector was intended to remain absolutely non-informative, and hence its precision was set at 0.01.

Because of the non-linear complexities of the proposed system, the sampling may crash even after imposing such tight prior distributions. Hence, it is advisable that variables such as *eta* or the allocative effects are initialized at zero. In this particular estimation, the specification of initial values for the *beta* parameter vector was not necessary.[16] A burn-in of 30,000 iterations was made, and the chain was successfully run with 300,000 retained draws. The results are shown in Table 5, which reports the posterior mean, standard deviation, and a 95% confidence interval. Note that most parameters are significant and show correct signs. The ψ coefficient of the hedonic function of ATMs is significant, thus validating the chosen model.

Regarding the cost function regularity conditions, the positive signs of the first-order coefficients indicate that monotonicity is satisfied in the average airport. Concavity in w has also been checked in the average airport and we report in the Table 5 the factor price elasticities for the average airport. It can be seen that all the own-price elasticities present the expected negative signs, and demand for labor is the most elastic one. The results also suggest limited possibilities for substitution between the inputs.

7. Results

The estimation of the cost function is a proper methodology for the analysis of the most relevant technological features of airport operations, such as efficiency, scale economies, technical change, and marginal costs. In addition, the results also provide interesting conclusions regarding the specification of the output vector.

Average technical efficiency (TE) is calculated from the posterior mean of λ (Table 5), yielding 85.4%. The average time-varying TE parameter (η) is 0.03. This indicates that the overall TE has decreased during the time span considered. The main explanation for that result is the huge financial effort made by the airports in order to carry out capacity expansions combined with several traffic shocks. Regarding allocative inefficiency (AI), the model provides airport-specific estimations of the allocative effects, whose averages are $\xi_m = -0.03$ and $\xi_p = -0.01$. This indicates that, at the mean airport, the demands of both labor and materials are above the optimal proportion with respect to capital. However, more interesting is the quantification of AI as a fraction of the observed costs. This is given by the lnC^{al} component of the cost function. Airport-specific estimations for C^{al} vary between 1 and 1.16, indicating that AI may increase costs up to 16% from C^o. The mean C^{al} is 6.9%.

The analysis of the differences in efficiency among the featured geographical clusters is very interesting.[17] Under the assumption that all airports share the same technology, the influence of some external variables is suggested by the results. In order to do that, each country's traffic-weighted average economic efficiency (EE) was calculated. The ranking is shown in Fig. 3. Austrian and German airports are the least efficient. Average EE varies between 69% and 74%. They are publicly owned and face the strong competition of the rail mode as well as of airports in bordering countries. In spite of that, German and Austrian airports show increasing TE during the time span considered. Allocative distortions show overuse of labor, related to the lack of flexibility in labor markets that translates into a higher share of labor costs. US airports average 76% EE. The temporal evolution of the TE indicates a steady downward trend, clearly explained by the traffic shock of 9/11. The last clus-

[16] In case initial values become necessary, they can be obtained from a simplified version of the model, e.g., by keeping the inefficiency parameters equal to a prior value from past literature, or simply equal to zero.

[17] Note that some clusters may not be representative of their country's airport industry.

ter featuring a majority of public airports is Italy, which shows an average EE of 80%. Regarding AI, the variability in the estimations does not allow us to draw any general conclusions.

The next clusters feature mostly privatised airports, i.e. Canada (81%), UK (84%), and Australia (86%). Besides ownership, geographical clusters also differ in price regulation. US airports operate under a rate-of-return mechanism, where no incentive for cost minimization is given. To overcome this, price caps were introduced in the UK and it has been the most popular approach adopted for privatised airports. Nevertheless, none of the three New Zealand sample airports (88%) is subject to price regulation. Alternatively, other differentiating characteristic is the territorial isolation that increases aircraft size. An example of that is Japan whose EE achieves a notorious 91%. The Asia–Pacific sample serves an average aircraft of 158 metric tons MTOW which is much bigger than the industry average. This is related to the service of long-haul aircraft at these airports. The hypothesis of large aircraft increasing the airports' efficiency has been addressed before in the literature.[18]

The analysis of the economies of scale is based on the output-related parameters. The scale elasticity at the average airport is directly obtained as the inverse of the sum of the first-order output parameters. It yields 1.99, a very significant value. However, this result is of little interest as it is clearly related to the small size of the average airport. Hence, there is need to assess the evolution of the output cost elasticity as the scale of production departs from the sample mean. The positive signs of the squared output coefficients indicate that IRS will become inevitably exhausted at a certain, yet unknown, level of production. On the contrary, the negative sign of the interaction $dom * int$ indicates that the range within airport enjoy IRS will be expanded by the cost complementarity between domestic and international passengers as they are capable of sharing many landside facilities. In order to establish whether IRS are exhausted at any observed level of production, the individual scale elasticities of all sample airports over 40 million annual passengers were calculated. The estimations range between 1.52 and 1.28 for an average value of 1.46. Therefore, it is clear that even the world biggest airports are enjoying IRS in the joint production of aviation and commercial outputs, providing economic justification for the current expansive trend.

The analysis of technological change is based on the time-related parameters.[19] The negative sign of τ_{37} indicates that airports have experienced some degree of technical progress, which, in addition, has increased the share of materials/outsourcing and reduced the share of labor and capital. Finally, there is also some degree of scale bias. The airports' scale elasticities are shown to decrease with the production of ATMs, domestic passengers and cargo, whereas the growing international traffic and the increasing importance of commercial revenues are shown to have increased IRS during the last decades.

The analysis of optimal pricing is based on the calculation of the marginal operating costs (MC). At the average airport, the MCs are (all values in PPP) USD 5.33 per domestic passenger, USD 6.19 per international passenger, USD 134.07 per metric ton of cargo and USD 436.33 per thousand dollars of commercial revenues. First, note that the average MCs of either type of passenger are significantly different from the MC imposed by 100 kg of cargo (USD 13.36). This clearly shows the convenience of disaggregating WLUs in the specification of the airports' cost function. Finally, the MC of an additional "effective" metric ton MTOW serviced at the average airport is USD 2.85. Optimal runway pricing should feature increasing unit rates per "actual" metric ton MTOW by converting them to "effective" tons using a calculation method based on the estimated cost relationship. The determination of the actual method lies beyond the scope of the present work.

8. Summary

This paper aims to provide an airport-specific methodology to estimate the cost function in this industry, filling the existing literature gap by estimating the first long-run multi-product cost frontier to describe airport technology. The specification of five different outputs is discussed. ATMs are hedonically-adjusted using the average aircraft MTOW. Domestic, international passengers and cargo outputs are specified separately instead of aggregating them in WLUs. The appropriateness of these methodological contributions was empirically proven. Finally, the commercial revenues are also included. A new method is proposed for estimating input prices that are implicit of the input market structure. The existence of monopsony power in the capital market is rejected at the average airport. A translog cost frontier is specified including both technical and allocative inefficiencies. The non-linear system was estimated using Bayesian inference and numerical methods.

The results show that TE has decreased during the last decades, having an average of 85% and AI is around 6.3%. Differences in efficiency were found among some geographical clusters featured in the database, suggesting the influence of external variables such as ownership or regulation, as well as the positive impact of aircraft size on TE. Airports are shown to have experienced some degree of technical progress that has altered the input proportions. Airport technology is also shown to exhibit unexhausted IRS.

Finally, note that the database is mostly composed by financial information directly collected from the Airport Authorities. No external effects derived from airport operations have been included in the database and hence the effect of the service quality is not addressed by the present methodology. Therefore, policy implications can only be interpreted from a financial point of view, but they can hardly be taken in terms of social benefits. Nevertheless, the proposed methodology can be easily adapted to the analysis of external costs, such as noise or congestion, if adequate data are provided to researchers. Anyway, the conclusions derived from the structural analysis of the estimated parameters are of major interest for private or public airport operators, airlines, air transport regulators and even policy makers.

[18] Givoni and Rietveld (2006) discussed the inefficiencies related to the use of small aircraft in short-haul routes.

[19] Many studies address the issue of technical change in airport technology; see e.g. Barros (2008).

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Appendix A. Long-run specification (explanatory variables are logged and deviated, time is not logged)

$$\begin{aligned}\ln C^a_{it} = {} & \alpha_1 + \alpha_2 \mathrm{atm_{mtow}} + \alpha_3 \mathrm{dom} + \alpha_4 \mathrm{int} + \alpha_5 \mathrm{cgo} + \alpha_6 \mathrm{rev} + \beta_7 \mathrm{wc} + \beta_8 \mathrm{wm} + \beta_9 \mathrm{wp} + \gamma_{10} \mathrm{atm_{mtow}} \cdot \mathrm{wc} \\ & + \gamma_{11} \mathrm{atm_{mtow}} \cdot \mathrm{wm} + \gamma_{12} \mathrm{atm_{mtow}} \cdot \mathrm{wp} + \gamma_{13} \mathrm{dom} \cdot \mathrm{wc} + \gamma_{14} \mathrm{dom} \cdot \mathrm{wm} + \gamma_{15} \mathrm{dom} \cdot \mathrm{wp} + \gamma_{16} \mathrm{int} \cdot \mathrm{wc} \\ & + \gamma_{17} \mathrm{int} \cdot \mathrm{wm} + \gamma_{18} \mathrm{int} \cdot \mathrm{wp} + \gamma_{19} \mathrm{cgo} \cdot \mathrm{wc} + \gamma_{20} \mathrm{cgo} \cdot \mathrm{wm} + \gamma_{21} \mathrm{cgo} \cdot \mathrm{wp} + \gamma_{22} \mathrm{rev} \cdot \mathrm{wc} + \gamma_{23} \mathrm{rev} \cdot \mathrm{wm} \\ & + \gamma_{24} \mathrm{rev} \cdot \mathrm{wp} + \delta_{25} 0.5\mathrm{wc}^2 + \delta_{26} \mathrm{wc} \cdot \mathrm{wm} + \delta_{27} \mathrm{wc} \cdot \mathrm{wp} + \delta_{28} 0.5\mathrm{wm}^2 + \delta_{29} \mathrm{wm} \cdot \mathrm{wp} + \delta_{30} 0.5\mathrm{wp}^2 \\ & + \rho_{31} 0.5\mathrm{atm}^2_{\mathrm{mtow}} + \rho_{32} 0.5\mathrm{dom}^2 + \rho_{33} 0.5\mathrm{int}^2 + \rho_{34} 0.5\mathrm{dom} \cdot \mathrm{int} + \rho_{35} 0.5\mathrm{cgo}^2 + \rho_{36} 0.5\mathrm{rev}^2 \\ & + \tau_{37} t + \tau_{38} t \cdot \mathrm{atm_{mtow}} + \tau_{39} t \cdot \mathrm{dom} + \tau_{40} t \cdot \mathrm{int} + \tau_{41} t \cdot \mathrm{cgo} + \tau_{42} t \cdot \mathrm{rev} + \tau_{43} t \cdot \mathrm{wc} + \tau_{44} t \cdot \mathrm{wm} \\ & + \tau_{45} t \cdot \mathrm{wp} + \beta_8 \xi m + \beta_9 \xi p + \gamma_{11} \mathrm{atm_{mtow}} \cdot \xi m + \gamma_{12} \mathrm{atm_{mtow}} \cdot \xi p + \gamma_{14} \mathrm{dom} \cdot \xi m + \gamma_{15} \mathrm{dom} \cdot \xi p \\ & + \gamma_{17} \mathrm{int} \cdot \xi m + \gamma_{18} \mathrm{int} \cdot \xi p + \gamma_{20} \mathrm{cgo} \cdot \xi m + \gamma_{21} \mathrm{cgo} \cdot \xi p + \gamma_{23} \mathrm{rev} \cdot \xi m + \gamma_{24} \mathrm{rev} \cdot \xi p + \delta_{26} \mathrm{wc} \cdot \xi m \\ & + \delta_{27} \mathrm{wc} \cdot \xi p + \delta_{28} \mathrm{wm} \cdot \xi m + \delta_{28} 0.5\xi_m^2 + \delta_{29} \xi m \cdot \mathrm{wp} + \delta_{29} \mathrm{wm} \cdot \xi p + \delta_{29} \xi m \cdot \xi p + \delta_{30} \mathrm{wp} \cdot \xi p \\ & + \delta_{30} 0.5\xi_p^2 + \tau_{44} t \cdot \xi m + \tau_{45} t \cdot \xi p + \ln(G_{it}) + u_{it} + v_{it}\end{aligned}$$

$$\mathrm{atm_{mtow}} = \mathrm{atm} + \psi(\mathrm{mtow})$$

$$S^a_C = \frac{\beta_7 + \gamma_{10} \mathrm{atm_{mtow}} + \gamma_{13} \mathrm{dom} + \gamma_{16} \mathrm{int} + \gamma_{19} \mathrm{cgo} + \gamma_{22} \mathrm{rev} + \delta_{25} \mathrm{wc} + \delta_{26} \mathrm{wm} + \delta_{27} \mathrm{wp} + \delta_{26} \xi m + \delta_{27} \xi p + \tau_{43} t}{G_{it}}$$

$$S^a_M = \frac{\beta_8 + \gamma_{11} \mathrm{atm_{mtow}} + \gamma_{14} \mathrm{dom} + \gamma_{17} \mathrm{int} + \gamma_{20} \mathrm{cgo} + \gamma_{23} \mathrm{rev} + \delta_{26} \mathrm{wc} + \delta_{28} \mathrm{wm} + \delta_{29} \mathrm{wp} + \delta_{28} \xi m + \delta_{29} \xi p + \tau_{44} t}{G_{it} \cdot e^{\xi m}}$$

$$S^a_P = \frac{\beta_9 + \gamma_{12} \mathrm{atm_{mtow}} + \gamma_{15} \mathrm{dom} + \gamma_{18} \mathrm{int} + \gamma_{21} \mathrm{cgo} + \gamma_{24} \mathrm{rev} + \delta_{27} \mathrm{wc} + \delta_{29} \mathrm{wm} + \delta_{30} \mathrm{wp} + \delta_{29} \xi m + \delta_{30} \xi p + \tau_{45} t}{G_{it} \cdot e^{\xi p}}$$

$$\begin{aligned}G_{it} = {} & [\beta_7 + \gamma_{10} \mathrm{atm_{mtow}} + \gamma_{13} \mathrm{dom} + \gamma_{16} \mathrm{int} + \gamma_{19} \mathrm{cgo} + \gamma_{22} \mathrm{rev} + \delta_{25} \mathrm{wc} + \delta_{26} \mathrm{wm} + \delta_{27} \mathrm{wp} + \delta_{26} \xi m + \delta_{27} \xi p + \tau_{43} t] \\ & + [\beta_8 + \gamma_{11} \mathrm{atm_{mtow}} + \gamma_{14} \mathrm{dom} + \gamma_{17} \mathrm{int} + \gamma_{20} \mathrm{cgo} + \gamma_{23} \mathrm{rev} + \delta_{26} \mathrm{wc} + \delta_{28} \mathrm{wm} + \delta_{29} \mathrm{wp} + \delta_{28} \xi m + \delta_{29} \xi p + \tau_{44} t] e^{-\xi m} \\ & + [\beta_9 + \gamma_{12} \mathrm{atm_{mtow}} + \gamma_{15} \mathrm{dom} + \gamma_{18} \mathrm{int} + \gamma_{21} \mathrm{cgo} + \gamma_{24} \mathrm{rev} + \delta_{27} \mathrm{wc} + \delta_{29} \mathrm{wm} + \delta_{30} \mathrm{wp} + \delta_{29} \xi m + \delta_{30} \xi p + \tau_{45} t] e^{-\xi p}\end{aligned}$$

$$\begin{aligned}&\beta_7 + \beta_8 + \beta_9 = 1 \\ &\gamma_{10} + \gamma_{11} + \gamma_{12} = 0 \\ &\gamma_{13} + \gamma_{14} + \gamma_{15} = 0 \\ &\gamma_{16} + \gamma_{17} + \gamma_{18} = 0 \\ &\gamma_{19} + \gamma_{20} + \gamma_{21} = 0 \\ &\gamma_{22} + \gamma_{23} + \gamma_{24} = 0 \\ &\delta_{25} + \delta_{26} + \delta_{27} = 0 \\ &\delta_{26} + \delta_{28} + \delta_{29} = 0 \\ &\delta_{27} + \delta_{29} + \delta_{30} = 0 \\ &\tau_{43} + \tau_{44} + \tau_{45} = 0\end{aligned}$$

Appendix B. Translog specification of the airport industry's stochastic production frontier

$$\begin{aligned}\ln Q_{it} = {} & \alpha_1 + \alpha_2 \mathrm{run} + \alpha_3 \mathrm{ter} + \alpha_4 \mathrm{chk} + \alpha_5 \mathrm{gat} + \alpha_6 \mathrm{war} + \alpha_7 \mathrm{fte} + \beta_8 \theta_1 + \beta_9 \theta_2 + \beta_{10} \theta_3 + \beta_{11} \theta_4 + \gamma_{12} \mathrm{ter} \cdot \theta_1 + \gamma_{13} \mathrm{ter} \cdot \theta_2 \\ & + \gamma_{14} \mathrm{ter} \cdot \theta_3 + \gamma_{15} \mathrm{ter} \cdot \theta_4 + \gamma_{16} \mathrm{chk} \cdot \theta_2 + \gamma_{17} \mathrm{gat} \cdot \theta_2 + \gamma_{18} \mathrm{war} \cdot \theta_3 + \gamma_{19} \mathrm{fte} \cdot \theta_4 + \rho_{20} 0.5\mathrm{ter}^2 + \rho_{21} \mathrm{ter} \cdot \mathrm{run} \\ & + \rho_{22} 0.5\mathrm{war}^2 + \rho_{23} 0.5\mathrm{fte}^2 + \rho_{24} \mathrm{fte} \cdot \mathrm{run} + \rho_{25} \mathrm{fte} \cdot \mathrm{chk} + \delta_{26} 0.5\theta_1^2 + \delta_{27} \theta_1 \theta_2 + \delta_{28} \theta_1 \theta_3 + \delta_{29} \theta_1 \theta_4 + \delta_{30} 0.5\theta_2^2 \\ & + \delta_{31} \theta_2 \theta_3 + \delta_{32} \theta_2 \theta_4 + \delta_{33} 0.5\theta_3^2 + \delta_{34} \theta_3 \theta_4 + \delta_{35} 0.5\theta_4^2 + \tau_{36} t + \tau_{37} t \cdot \mathrm{war} - u_{it} + v_{it}\end{aligned}$$

The polar coordinates and the time variable are deviated from their averages. Inputs are logged and deviated. The MTOW is the reference output at the time of calculating the polar coordinates, which represent the proportion of domestic (θ_1), international passengers (θ_2), cargo (θ_3), and commercial revenues (θ_4). The initial model featured all feasible second-order interactions. In order to minimize the variability of the resulting MPs, only significant interactions (5%) remain. Lambda is the parameter of technical inefficiency $u = exp(\lambda)$.

Coefficient	Mean	sd	Coefficient	Mean	sd	Coefficient	Mean	sd
Constant	15.38117	0.03002	ter θ_3	1.86219	0.63413	θ_1 θ_2	1.58071	0.24068
run	0.13404	0.03408	ter θ_1	0.30044	0.08985	θ_1 θ_3	0.22093	1.36575
ter	0.20945	0.02242	chk θ_2	−0.50530	0.08882	θ_1 θ_4	1.07796	0.37286
chk	0.18624	0.02872	gat θ_2	0.32672	0.10450	0.5 θ_2 θ_2	4.04596	0.40990
gat	0.26537	0.03341	war θ_3	−1.02448	0.32991	θ_2 θ_3	0.79157	1.91044
war	0.19720	0.01308	fte θ_4	−1.26902	0.13682	θ_2 θ_4	0.91822	0.35035
fte	0.30895	0.01947	0.5terter	0.11330	0.02621	0.5 θ_3 θ_3	65.46996	13.85770
θ_1	0.34539	0.07876	terrun	−0.14322	0.03643	θ_3 θ_4	−19.17414	9.88216
θ_2	0.52580	0.07878	0.5warwar	0.02012	0.00266	0.5 θ_4 θ_4	0.96071	0.70313
θ_3	14.93041	1.28242	0.5ftefte	−0.14802	0.02532	t	0.01382	0.00327
θ_4	0.78488	0.21215	fterun	0.34321	0.04117	twar	−0.00317	0.00117
ter θ_1	0.36956	0.04968	ftechk	−0.09391	0.02021	lambda	7.13283	7.11386
ter θ_2	0.47719	0.08810	0.5 θ_1 θ_1	0.10833	0.36441	(R^2 = 0.958)		

The scale elasticity at the average airport is the sum of the first-order input parameters, it yields 1.3. Average technical inefficiency is 0.13. The sign of the time parameter indicates some degree of technological development. Weak-separability and homotheticity are clearly rejected.

Appendix C. Testing the existence of monopsony power in the airport capital market

Airports employ three inputs, capital (K), over which they may exercise monopsony power, materials (M) and labor (L), with prices $r(K)$, m, and w, respectively. Airports minimize costs: $C = r(K)K + \mathrm{mM} + \mathrm{wL}$ subject to the output restriction: $y = y(K, M, L)$. The first-order conditions result in the following equilibrium:

(1) $(r + (\partial r/\partial K)K)/\mathrm{MPK} = m/\mathrm{MPM} = w/\mathrm{MPL}$

An expression of the rate of exploitation e (or monopsony power) of the capital input can be obtained from (1):

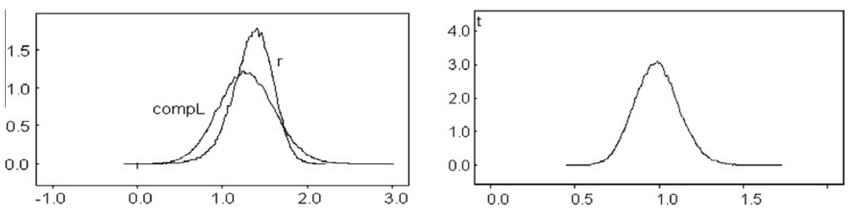
(2) $e = \dfrac{\partial r}{\partial K}\dfrac{K}{r} = \dfrac{\mathrm{wMPK/MPL} - r}{r}$

The following test statistic t is constructed, its distribution of probability is not known:

(3) $t = 1 + e = \dfrac{\mathrm{wMPK}}{\mathrm{rMPL}}$

This expression is then evaluated from the outcome of the previously estimated production frontier. The alternative hypothesis is that the capital market is as competitive as the labor market ($t = 1$). The null hypothesis is that capital is not as competitive as labor ($t \neq 1$). Results are shown for the average airport. It is clearly seen that the test statistic is not significantly (5%) different from 1, and thus the null hypothesis is clearly rejected. The posterior densities of t and the stochastic nodes r and compL = wMPK/MPL are shown below.

Node	Mean	sd	2.5%	Median	97.5%
r	1.3532	0.2374	0.8366	1.3660	1.7700
wMPK/MPL	1.3337	0.3491	0.6622	1.3272	2.032
t	0.9893	0.1319	0.7427	0.9858	1.255



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