The Impact of Airline Differentiation on Marginal Cost Pricing at UK Airports

AUTHOR QUERY FORM

ELSEVIER	**Journal: TRA** **Article Number: 1237**	**Please e-mail or fax your responses and any corrections to:** **E-mail: corrections.esch@elsevier.sps.co.in** **Fax: +31 2048 52799**

Dear Author,

Please check your proof carefully and mark all corrections at the appropriate place in the proof (e.g., by using on-screen annotation in the PDF file) or compile them in a separate list. Note: if you opt to annotate the file with software other than Adobe Reader then please also highlight the appropriate place in the PDF file. To ensure fast publication of your paper please return your corrections within 48 hours.

For correction or revision of any artwork, please consult http://www.elsevier.com/artworkinstructions.

Any queries or remarks that have arisen during the processing of your manuscript are listed below and highlighted by flags in the proof. Click on the 'Q' link to go to the location in the proof.

Location in article	**Query / Remark: click on the Q link to go** **Please insert your reply or correction at the corresponding line in the proof**
Q1	Please confirm that given name(s) and surname(s) have been identified correctly.
Q2	Please check whether the designated corresponding author and the details are okay as typeset.
Q3	Please check whether the typeset of affiliation is okay.
Q4	Please note that the 'italic' variables (e.g. VC, TC, IC, AIC and MC) have been changed to 'roman' to maintain consistency throughout the text. Please check and amend if necessary.
Q5	Please note that the following reference 'Button (2011)' is cited in the text but not provided in the list. Kindly check.
Q6	This section comprises references that occur in the reference list but not in the body of the text. Please position each reference in the text or, alternatively, delete it. Any reference not dealt with will be retained in this section.
	Please check this box if you have no corrections to make to the PDF file ☐

Thank you for your assistance.

Highlights

• This paper aims to prove that marginal passenger costs are sensitive to airline type. • Low-cost passengers impose lower costs to the airport than full-service passengers. • Charter passengers impose higher costs to the airport than full-service passengers. • This result support airlines' claims for differentiated airport charges.

Transportation Research Part A xxx (2013) xxx–xxx

Contents lists available at ScienceDirect

Transportation Research Part A

journal homepage: www.elsevier.com/locate/tra

The impact of airline differentiation on marginal cost pricing at UK airports

Q1 Augusto Voltes-Dorta *, Zheng Lei

Q3 Universitat de Barcelona, Diagonal 690, 08034 Barcelona, Spain

ARTICLE INFO

Article history:
Received 12 July 2012
Received in revised form 4 March 2013
Accepted 6 August 2013
Available online xxxx

Keywords:
Airport cost function
Marginal costs
Hedonic outputs

ABSTRACT

Airport pricing is a central issue in international transport policies, which tend to support pricing schemes based on marginal operating costs. This paper aims to provide empirical evidence in support of increased differentiation in airport charges on the basis of marginal passenger costs being sensitive to the type of airline, i.e. full-service, low-cost, and charter. To that end, both long- and short-run multi-output cost functions are estimated over an unbalanced pool database of 29 UK airports observed between 1995 and 2009. The passenger output is hedonically-adjusted in order to introduce the desired level of disaggregation while also keeping a parsimonious specification. Results show that low-cost passengers impose significantly lower costs to airport infrastructure than those from either full-service or charter airlines. A full schedule of marginal and average incremental cost estimates for the combined passenger categories is provided for all sample airports. Taking into account the existence of returns to scale and economies of capacity, this provides a useful guide for optimal pricing of aeronautical infrastructure under either single- or dual-till regulations.

1. Introduction

Airport pricing is a central issue in international transport policies (e.g. EC, 2001), which tend to support first-best pricing schemes based on marginal costs (MC) where the user pays exactly for the resources employed. According to the economic theory, MC prices would lead to optimal usage of airport infrastructure as well as to valid investment signals in the long run. These benefits, however, while being sought after by governments and regulators on the grounds of public welfare, do not tend to find much support from other industry agents. Airlines, for example, typically ask for lower, subsidized charges (e.g. landing, security, handling, etc.) arguing that they indirectly generate business for the airport in terms of non-aeronautical revenues (e.g. parking, retail, catering, etc.). Airports, especially those privatized, are also wary of MC pricing, since it does not lead to cost recovery of aeronautical infrastructure under the likely existence of returns to scale. These opposing views have led to a highly regulated environment. Thus, it is not uncommon that aeronautical charges for major airports are subject to the oversight of a public regulator, who needs to balance the public interest with the need for profitability or self-sustainability of a (possibly) corporatized operator. This fact, in combination with the increased importance of non-aviation activities in the airport business, has led to the adoption of two main price regulation approaches: (i) single-till, where prices are set to cover total costs and cross-subsidization between aeronautical and non-aeronautical activities is possible, and (ii) dual-till, where prices are related to specific costs without cross-subsidization (Lu and Pagliari, 2004). An additional distinction can be made by considering the long- or short-run nature of the regulatory cost base, which, will roughly depend on the level of congestion and the need to generate income to fund a capacity expansion (CAA, 2001a).

Q2 * Corresponding author. Tel.: +34 6 18 326 107.
E-mail address: avoltes@becarios.ulpgc.es (A. Voltes-Dorta).

0965-8564/$ - see front matter
http://dx.doi.org/10.1016/j.tra.2013.08.002

If the airport's aeronautical cost structures do not allow for MC pricing without incurring in losses, the operator may seek to charge second-best break-even prices. Under such circumstances, economic theory suggests that Ramsey prices[1] are the preferred option in terms of social welfare (See e.g. Morrison, 1982). In practice, however, average cost pricing has been the preferred pricing method in the airport industry during the last decades (Rendeiro, 1997). In a multi-output environment, this translates into average incremental costs (AIC) being used as benchmarks for second-best "subsidy-free" prices (Graniere, 1996).

All these economic principles are observed, to a great degree, in the price regulation process of several major airports by the UK's Civil Aviation Authority (CAA). In these cases, airport-specific price caps per passenger are typically set for a five-year period and then reviewed after a public consultation (See, e.g. UK CAA, 2007). These single-till price caps, and more specifically, their annual rate of change (*RPI-X*),[2] are set to incentivize capital investment and increase productivity. To that end, CAA calculations are largely cost-related, implicitly drawing on familiar concepts such as MC or AIC (UK CAA, 2001a). Illustratively, British Airport Authority (BAA)'s stated policy for air traffic services in the Southeast of England is to set charges on the basis of long-run MCs (cited in Starkie (2008)). However, its own research showed that the charges were actually well below MCs and the loss was cross-subsidized by the profit generated from the commercial revenues where prices are raised well above costs (Starkie, 2008).

In spite of that, there has been a growing concern among certain airlines (e.g. Easyjet, Bmi) that CAA regulated prices do not accurately reflect the differences in service quality offered by different terminal buildings within the same airport (UK CAA, 2007: p. 188). Moreover, low-cost carriers (LCCs) frequently argue that they do not need complicated infrastructure such as baggage-handling system,[3] airbridges, or seat reservation IT programs at check-in desks,[4] and hence, they should not have to pay for facilities which they do not want to use (Competition Commission, 2002: p. 262). On top of that, LCCs also claim that they impose lower costs on airport operations than full service and charter airlines as they generally have faster turnaround times.

LCCs' aggressive pursuit of lower airport charges is explained by their particular business model, in which cost minimization is paramount. Having pushed all other costs to minimal levels, airport charges are targeted for further reduction (Doganis, 2002). These typically represent roughly 10% of the cost base under the traditional airline model, but it amounts to a much higher share for LCCs as a result of frequent landing and taking-offs (Competition Commission, 2002). Airport costs in some cases represent 70% of ticket prices and LCCs claim that their margins are tight and have to rely on volume to generate a return (UK CAA, 2003c). In Europe, LCCs are putting pressure on airports to reduce charges and/or to provide commercial incentives by threatening to fly elsewhere if these demands are not met (Lei and Papatheodorou, 2010). Given the fact that LCCs now account for approximately 50% of intra-European passengers (Starkie, 2012), their demands cannot be ignored by airport authorities and regulators.

Under the aforementioned MC principle, it is clear that airline operations that require lower infrastructure usage should also face reduced prices (Gillen and Forsyth, 2010). In that regard, for the charges to remain cost-related, cheaper (i.e. less-quality) infrastructure should be less expensive for the airlines; high utilization and effective use of airport facilities should also be rewarded. While under such circumstances LCCs may have a point in demanding lower airport charges, the fact is that in a recent report it was found that average charges vary according to airline type, and LCCs actually pay the lowest charges at UK airports (Competition Commission, 2009). The cost-basis of said price differentiation policies, however, remains to be empirically determined.

With this background, and using the UK airport industry as a case study, this paper aims to provide new empirical evidence in support of airline-based differentiation in airport charges. The working hypothesis is that marginal passenger costs are sensitive to the type of airline (i.e. full-service, charter, and low-cost) as they may significantly differ in their use of airport infrastructure. Results are expected to lead to relevant policy and managerial conclusions regarding price discrimination in the airport industry. In order to cover the basic regulatory approaches explained above, both long- and short-run multi-output cost functions are estimated over an unbalanced pool database of 29 UK airports observed between 1995 and 2009. The passenger output is hedonically-adjusted in order to introduce the desired level of disaggregation while keeping a parsimonious specification. A full schedule of MC and AIC estimates for the combined passenger categories will be provided for all sample airports.

The rest of this paper is organized as follows: Section 2 provides a literature survey on the estimation of airport marginal costs. Section 3 describes the UK airport sample and data sources while Section 4 introduces the cost frontier methodology. This is followed by Section 5 which analyzes the resulting marginal cost estimates and their impact on optimal airport pricing in the UK. Finally, Section 6 summarizes the main findings.

2. Literature review

Although many past studies have addressed the issue of airport pricing, only a few of them have focused on the monetary valuation of airport MCs, featuring a variety of estimation methods and databases that make difficult to compare their

[1] These allow for MC mark-ups that are inversely proportional to the different users' demand elasticities.
[2] Price caps are allowed to grow with inflation (Retail Price Index) less a productivity incentive (*X*).
[3] Note that LCCs do not generally operate connecting flights.
[4] Most LCCs do not allocate seats before passengers board the aircraft.

results. An early example was Carlin and Park (1970), who calculated marginal runway costs for LaGuardia Airport (LGA), focusing on delay costs and peak considerations. Their estimates range between $3 and $1090 for off-peak and peak arrivals, respectively. Using simulation, BAA (1982) estimated peak and off-peak passenger charges at Heathrow and Gatwick. Considering that BAA policy was to charge peak users the costs of terminal construction (CAA, 2001b), results can be roughly interpreted as an approximation to long- vs. short-run MCs. Peak passenger costs at Heathrow were estimated at £25.69–£29.52 and off-peak costs of £0.76–£0.92 (1982 pounds). Morrison (1983) estimated several cost functions including operation, capital and delay expenditures in order to compute optimal long-run toll costs. He finally estimated a MC of $12.34 (1976 dollars) per aircraft movement (ATM). More recently, Link et al. (2006) made use of time-series data on staff costs that led to an MC estimate for an extra ATM of €22.60 (2000 euros).

Additional references on second-best pricing for airports include Morrison (1982), Rendeiro (1997), and Rendeiro (2010). These papers focus on Ramsey pricing and to date, there has been no attempt to estimate airport AICs in the literature.

2.1. Airport cost functions and economies of scale

According to the economic theory, the econometric estimation of parametric cost functions is the suitable methodology to calculate MCs.[5] An additional advantage of this approach is that it also allows for returns to scale to be calculated from the cost function parameters. A cost function is a formal construction that links total or variable costs to outputs, input prices, and capital stock of firms whose behavior is assumed to be cost minimizing. Early examples of airport cost functions include Keeler (1970) and Doganis and Thompson (1974), all of them limited for MC analysis by their use of Cobb–Douglas specifications. Tolofari et al. (1990) used pooled data for seven BAA Airports between 1979 and 1987 to estimate both long- and short-run cost functions. To allow for a flexible functional form, they adopted the translogarithmic specification (see Section 4). They found economies of scale up to 20 million work-load units (WLUs).[6] Also using UK data, Main et al. (2003) found scale economies up to a minimum efficient scale of 5 million WLUs.

A more recent approximation to the cost structure of UK airports is found in Bottasso and Conti (2012), who estimated a variable short-run cost function using a panel of 25 UK airports between 1994 and 2005. Results support previous studies as scale economies are found to be exhausted at around 5 million annual passengers, remaining at constant returns to scale until approximately 14 million annual passengers. Finally, in order to complete the survey of returns to scale, it is also worth noting the non-parametric approach[7] by Assaf (2010a), who obtained bootstrapped estimates of scale elasticities using Data Envelopment Analysis (DEA). Results show that most large airports (including Manchester and all airports serving the London area) present constant or decreasing returns to scale while small airports tend to enjoy increasing returns. In summary, while the existing literature on airport cost functions for the UK has not focused on MC estimations, a general agreement appears to exist about the existence of returns to scale for small airports, in which case MC pricing would not lead to cost recovery unless some sort of cross-subsidization is implemented.

2.2. Stochastic frontiers and output disaggregation

The calculation of social MCs of airports was one of the main objectives of project GRACE,[8] funded by the European Commission. Within that project's framework, Martín et al. (2006) introduced the use of stochastic cost frontiers (as opposed to the deterministic cost functions from the previous section) in order to eliminate any biases in MC estimates linked to a possible inefficiency component. The stochastic frontier methodology has been applied in a large number of airport efficiency studies including Pels et al. (2003),[9] Oum et al. (2008), Barros (2008a,b, 2011), Martín et al. (2009), Assaf (2010b), Martín and Voltes-Dorta (2011a), and Assaf et al. (2012). Due to the nonlinear complexities of these models, Bayesian inference is the most common estimation method.

Martín et al. (2006) features the first multi-output (ATM and WLU) cost frontier specifications, which allows for disaggregated MCs to be calculated. Using an unbalanced database of 56 airports worldwide between 1991 and 2005, they estimated two specifications (single- and multi-output) in order to show that MCs are biased in the single-output case. Long-run MC estimates for the year 2005, at the average airport, were about $406.03 and $5.97 for ATM and WLU, respectively. Introducing terminal surface as a fixed production factor, average short-run MC are $119.02 and $4.89 for ATM and WLU, respectively. Using the same methodology over a sample of 37 Spanish airports, Martín et al. (2009) obtained long-run MC estimates ranging between €80 up to €413 per ATM, and from €0.98 to €13.66 per WLU (1997 euros).

More recent academic contributions focus on increasing output disaggregation, expanding airport samples, and more sophisticated cost function specifications. Oum et al. (2008) introduced a non-aeronautical output (commercial revenues-REV) in the cost frontier specification to avoid estimation biases. This is related to the impossibility of separating aeronautical and non-aeronautical costs in the financial data provided by the airports (annual reports and financial statements). Building on that contribution, Martín et al. (2011) estimated both long- and short-run cost functions for Spanish Airports,

[5] As opposed to non-parametric methodologies such as Data Envelopment Analysis (DEA).
[6] A work-load unit aggregates a passenger and 100 kg of cargo.
[7] Non-parametric studies on UK airport efficiency include Parker (1999) and Barros and Weber (2009).
[8] Generalisation of Research on Accounts and Cost Estimation. http://www.grace-eu.org/project.htm.
[9] They estimated a production frontier.

Table 1
UK-specific airport cost frontier studies.

Author(s)	Data sample (UK)	Method	Output vector
Doganis and Thompson (1974)	CS 18 airports, 1969	Cobb–Douglas CF	WLU
Tolofari et al. (1990)	P 7 airports, 1979–1987	Translog CF	WLU
Main et al. (2003)	CS 27 airports 1988	Cobb–Douglas CF	PAX or WLU (alternative models)
Barros (2008a)	P 27 airports 2000–2005	Translog SCF	PAX, ATM
Assaf (2009)	P 27 airports 2002–2007	Cobb–Douglas CF	Operating income
Assaf et al. (2012)	P 26 airports 1998–2008	Translog SCF	Operating revenue
Bottasso and Conti (2012)	P 25 airports 1994–2005	Translog CF	ATM, WLU, REV or ATM, PAX, CGO, REV

Note: CS: cross-section, P: panel, CF: cost function, SCF: stochastic cost frontier, WLU: workload units, PAX: passengers, ATM: aircraft movements, REV: commercial revenues, CGO: cargo traffic.

now featuring ATM, WLU, and REV. The introduction of the new output, as expected, led to a significant reduction of the aeronautical MCs, which now averaged €273 and €1.08 for ATMs and WLUs in the long run (€15.44 and €0.79 in the short run).

Martín and Voltes-Dorta (2011a) further disaggregated the output vector in order to approximate the complexity of airport operations. Thus, WLUs were split in cargo, domestic passengers and international/transborder passengers. In addition, ATMs were hedonically-adjusted (Spady and Friedlaender, 1978) using the airport's average maximum take-off weight (MTOW) as a quality variable. The output vector was completed with the non-aeronautical output (REV). In order to support such level of disaggregation a much larger airport sample was employed, featuring 161 all-size airports worldwide observed between 1991 and 2008. Note that, besides a concern for the available degrees of freedom, a large database is required to mitigate the potential impact of multicollinearity[10] arising from high linear correlation among the specified outputs (e.g. passengers, ATM, and REV). Results found evidence of unexhausted economies of scale in airport operations (beyond 80 million annual passengers), as well as evidence supporting the WLU disaggregation: international passengers imposed higher MC than domestic ones, and both were significantly costlier for the airports than cargo operations, which remains mostly an airline activity. Using the hedonic ATM equation, MCs estimates featuring increasing unit rates per ton MTOW were obtained.[11]

Taking into account that this paper employs a smaller airport sample (27 UK airports), it is difficult to include as many outputs and interactions as the international studies. While this appears to contradict our stated objective of providing a new approach for output disaggregation, it is important to understand the restrictions imposed by the dataset in terms of degrees of freedom. In order to illustrate that, Table 1 shows the output choices for all previous cost frontier studies using only UK airport data.

From this table, it is clear that single-output specifications have been the preferred approach to formalize UK airport technology, featuring in both early and recent contributions regardless of sample size. This is discussed in Assaf et al. (2012), who developed a state-of-the-art dynamic SCF model to estimate UK airport efficiency and its determinants. They argued that operating revenue is an appropriate indicator of the airports' overall output level, in substitution of the physical units, for the purposes of performance assessment. This approach, however, is not suitable for our research objectives since it does not allow for output-specific MCs to be obtained.

Barros (2008a) estimated the first multi-output SCF specification for UK airports including both PAX and ATMs as outputs. While a very strong correlation between both variables is certain, this issue is of little relevance for the purposes of that paper since multicollinearity does not affect the predictive capacity of the model, and, in turn, the reliability of the efficiency estimates obtained from the SCF. On the other hand, Bottasso and Conti (2012) included up to four outputs in their cost function (ATM, PAX, CGO and REV) with the objective to calculate economies of scale for UK airports. This study, however, did not estimate MCs and linear correlations among the outputs are not discussed. Since our study shares a very similar dataset, we are able to address this issue in Section 4, while also proposing a novel strategy to increase output disaggregation for estimating airport MCs, i.e. hedonically-adjusting the passenger output. This aspect, rather than improving the estimation method,[12] becomes the technical contribution of our paper that supports the policy discussion about airline-based price discrimination at UK airports.

3. Database and data sources

The short- and long-run cost frontiers were estimated over an unbalanced pool of financial, traffic, and infrastructure data on 27 UK commercial airports between 1995 and 2009, for a grand total of 381 observations. It is worth noting that using a single-country sample allows for better homogeneity and comparability, especially in regard to external factors that can

[10] Since the calculation of MCs requires making structural analysis on the cost function coefficients, estimation biases, such as those related to multicollinearity, need to be avoided.

[11] The same method was used in Voltes-Dorta and Pagliari (2012) but they did not provide MC estimates.

[12] More advanced estimation methods such as the above-mentioned dynamic SCF model developed by Assaf et al. (2012) are not implemented in this paper since the improvements with respect to our method are related to estimation of efficiency, which is not the main focus of this paper.

affect airport costs and their operating performance such as e.g. accounting practices, regulatory framework, labor regulations, or weather conditions.

Data collection was completed for the following variables: (a) total costs: capital (cap), labor (lab), and materials (mat); (b) outputs: Full-service (fsc), low-cost (lcc), and charter (cha) passengers, aircraft movements (atms), commercial (non-aviation) revenues (rev); (c) fixed factors: terminal surface (ter), runway length (run), runway capacity (runcap), boarding gates (gat), check-in desks (chk), (d) other: time (t), full-time equivalent employees of the Airport Authority (fte). For homogeneity purposes, all monetary variables were adjusted for inflation using UK's Retail Price Index (RPI).

Total costs (TC) will be the dependent variable in the long-run model. In the short run, only labor and materials, the variable costs (VC), are considered. Labor costs include all types of employee compensation, such as salaries and wages, retirement and health benefits. Only the employees of the reporting authority, typically the airport operator, are considered as they are the decision-making units in this study. We define "Material costs" as a very broad category that covers any airport expenditure not directly attributable to in-house labor or capital costs.[13] Hence, it includes maintenance, utilities, external services and other administrative costs. Capital costs aggregate amortization of fixed assets and interest paid, following the definition by Doganis (1992). Note that these costs include all activities performed in-house,[14] which are not heterogeneous across airports. In addition, amortization charges are sensitive to each airport's investment cycle. It is also worth pointing out that commercial revenue activities may have significant impact on operating cost as airports have to incur additional costs such as marketing, product promotion, retail operations staff to the generation of commercial revenue (BAA, 2001). Section 4 discusses how the proposed methodology for calculating input prices brings this heterogeneity into the cost function estimation. Table 2 provides the mean, range, and standard deviation of the most important variables for the cost frontier estimation. The scale of production ranges between 497 annual passengers at Southend Airport in 1995 and slightly over 69 million annual passengers (mppa) at London Heathrow in 2007. The average sample airport serves about 7 mppa (thereof 17% low-cost and 33% charter) and it is able to obtain almost £60 million in non-aviation revenues. However, given the logarithmic transformation, the translog approximation point will be located at the vector of geometric means (slightly under 2 million passengers). The largest cost element is "materials" with an average 50% cost share. Capital inputs only account for 18% of annual operating costs at the average airport, which would bring long- and short-run MC estimates closer.

Financial data was collected from the UK Airport Statistics compiled by the Centre for Regulated Industries at the University of Bath (e.g. Sharp et al., 2010). Since this publication was recently discontinued, the year 2009 was completed using the 2009/2010 issue prepared by Leigh-Fisher (2011). Airports with reporting periods different than 12 months (typically 9 or 15 months) were proportionally adjusted for homogeneity purposes. Since traffic data was easier to adapt to each airport's reporting period, calendar vs. financial year figures were mixed in the database, with the small differences accounted for by the time variable (t). Furthermore, cost and revenues were adjusted for inflation using UK's Retail Price Index (RPI). UK CAA statistics were the main source for passenger data (CAA, 2011). Scheduled passengers were separated in full-service and low-cost using a database also provided by the UK CAA. Infrastructure data, including runway capacity was compiled from a variety of sources, including annual reports, public consultation documents, press releases, and by direct request.

4. Cost frontier estimation

A cost function is a formal construction that links operating costs with outputs (y) and input prices (w) of firms whose behavior is assumed to be cost-minimizing. If that assumption cannot be made, some degree of (positively-truncated) cost inefficiency can be added to the disturbance term (u), thus separating this effect from the statistical noise (v). This is a stochastic long-run cost frontier (Eq. (1)). If some inputs, however, are to be considered fixed in the short-run, then their price is substituted by the fixed factor demand (K), in that case, only variable costs (VC) are modeled (Eq. (2)). A time trend (t) can be added in both models to account for technical change.

$$C = C(w, y, t) + u + v \tag{1}$$

$$\mathrm{VC} = \mathrm{VC}(w, y, K, t) + u + v \tag{2}$$

Q4 The preferred functional form for $C(w, y, t)$ and $\mathrm{VC}(w, y, K, t)$ is the translog (Christensen et al., 1973) as it does not impose restrictions to the underlying technology.

4.1. Output vector

The cost function features passengers (hedonically-adjusted by airline type) and commercial revenues as outputs.

In order to meet our research objectives, the level of disaggregation in the output vector must allow for airline-specific MCs to be calculated and compared to the established price caps. Also, results should allow us to discuss the single- or dual-till nature of the regulated prices. From a methodological perspective, this requires: (i) the separation of aeronautical and

[13] Other studies simply define this category as "other costs".
[14] The same applies to commercial revenues.

Please cite this article in press as: Voltes-Dorta, A., Lei, Z. The impact of airline differentiation on marginal cost pricing at UK airports. Transport. Res. Part A (2013), http://dx.doi.org/10.1016/j.tra.2013.08.002

Table 2
Database summary.

	Total costs (GBP'000)	Variable costs (GBP'000)	Total passengers	Share low-cost	Share charter	Commercial revenues (GBP'000)	Terminal surface (m^2)	Runway length (m)	Share capital cost	Share material cost	Share labor cost
Max	1,844,900	970,800	69,334,563	0.77	1.00	740,300	691,665	7561	0.56	0.88	0.69
Min	3410	3247	497	0.00	0.00	170	1000	1508	0.02	0.07	0.03
Mean	86,794	64,120	7,117,190	0.17	0.33	59,335	46,524	2822	0.18	0.49	0.33
Std	191,679	129,287	13,248,067	0.21	0.24	140,845	81,004	1.470	0.10	0.12	0.10
Geom	–	–	1,931,794	–	–	16,621	–	–	–	–	–

Note: Monetary variables expressed in 2009 prices.

non-aeronautical outputs in the cost function, and (ii) the specification of airline-specific aeronautical outputs. Due to the small sample, this must be achieved while keeping a parsimonious specification and also avoiding multicollinearity.

Previous literature has employed aircraft movements (ATMs), passengers (PAX), and cargo (CGO) as the traditional aeronautical outputs in airport efficiency and productivity studies (Assaf et al., 2012). Introducing ATMs has the advantage of producing more detailed MCs but only for larger samples that provide enough airport variability. In our case, ATMs were discarded given their extremely high level of linear correlation with passenger traffic (92.7%). This will allow, however, for a direct comparison between the estimated passenger MCs (now accounting for airside and landside costs) and the published price caps at Heathrow or Gatwick, typically set as "maximum revenue per passenger". Cargo traffic, measured in tonnes, was also discarded to save degrees of freedom, due to lack of significance in the estimated cost function. This is not surprising as cargo operation is a much an airline activity and a less important dimension of output than passenger numbers for UK airports (NERA, 2001).

This leaves passenger traffic as the sole aeronautical output, upon which the airline disaggregation needs to be implemented. Splitting the passenger output in airline categories (i.e. full-service, low-cost, and charter) has the enormous advantage of allowing for airport-specific airline-disaggregated MCs to be calculated. However, this also leads to a dramatic increase in the cost function parameters that makes this option only suitable for large samples. An alternative strategy is to use the hedonic approach (Spady and Friedlaender, 1978), in which output differentiation is introduced with only few added coefficients[15] (linked to the airline categories). Thus, hedonically-adjusted passengers (*paxh*) are defined as the aeronautical output with the following expression:

$$paxh = pax e^{\psi_1 slcc} e^{\psi_2 scha} \tag{3}$$

$$\ln paxh = \ln pax + \psi_1 slcc + \psi_2 scha \tag{4}$$

where *slcc* and *scha* represent low-cost and charter traffic shares, respctively. In order to avoid zero values in the translog specification, these shares are not logged (Eq. (4)). A value of ψ higher or lower than zero indicates that the relevant passenger category imposes, on average, higher or lower costs to the airport than full-service carriers (*fsc*) in proportion e^{ψ}. Also note that the significance of these hedonic parameters provides a test for MC differentiation based on airline type, which is our main working hypothesis.

The only candidate for non-aeronautical output is commercial revenue (REV). This variable was regressed against the remaining exogenous covariates for an approximate estimate of the Variance Inflation Factor (VIF). A VIF marginally under 5 was obtained ($R^2 = 0.799$), which is the commonly accepted threshold for severe mutlicollinearity. Thus, the variable was included, helping to introduce dual-till considerations in the interpretation of results.

4.2. Input prices

The long-run cost system features three input prices, capital (w_c), materials (w_m), and labor/personnel (w_p). Labor prices are obtained by dividing labor costs by the number of full-time equivalent employees of the airport authority (*fte*).[16] Since the other cost categories encompass a heterogeneous set of inputs, quantity indexes for capital (*iqc*) and materials (*iqm*) were constructed.[17] Assuming that competitive tendering for airport service contracts is successful in bringing prices close to com-

[15] This advantage was noted by Oum and Threteway (1989).

[16] This approach is the most commonly used in the literature. One may argue that different outsourcing practices across the airport sample lead to inconsistent unit labor costs. Bottasso and Conti (2012) compared this traditional method against an alternative approach of using average wages in the respective local authorities as labor prices. They did not find significant differences in the estimated models.

[17] Recent papers on UK airport cost functions provide alternative methods for estimating the price of materials. Bottasso and Conti (2012) construct a price index for "other costs" by combining construction, utilities, and retail price indexes. The aggregation weights are based on the breakdown of "other costs" in BAA's accounts. This information, however, is not available at an airport level for the entire sample and there is no reason to assume that BAA's cost breakdown is representative of the UK airport industry. A simpler method is proposed by Assaf et al. (2012), who used regional price indexes as proxy for the price of materials. These indexes however, have only been released in 2000, 2004, and 2010 by the Office for National Statistics (ONS), which, furthermore, indicates that the indexes are not fully comparable due to methodological differences (ONS, 2010).

Please cite this article in press as: Voltes-Dorta, A., Lei, Z. The impact of airline differentiation on marginal cost pricing at UK airports. Transport. Res. Part A (2013), http://dx.doi.org/10.1016/j.tra.2013.08.002

petitive levels, input quantity indexes can be constructed using the individual marginal productivities (MPs) as aggregation weights (Martín and Voltes-Dorta, 2011a). Thus, *iqc* combines terminal surface (*ter*) and runway length (*run*). In the case of materials costs, *iqm* combines boarding gates (*gat*) and check-in desks (*chk*). Even though these variables are mostly fixed, in combination with the MPs they are assumed to be good indicators for the airports' annual demand for utilities, maintenance, etc.

$$iqc = ter + run\frac{MPrun}{MPter}, \quad w_c = \frac{capitalcosts}{iqc} \tag{5}$$

$$iqm = gat + chk\frac{MPchk}{MPgat}, \quad w_m = \frac{materialscosts}{iqm} \tag{6}$$

Airport-specific MPs are estimated from the only available multi-output ray production frontier for the airport industry (Martín and Voltes-Dorta, 2011a). Finally, w_c and w_m are calculated by dividing the respective costs by the quantity indexes.[18] As these prices are directly related to the observed costs, they reflect each airport's specific circumstances (i.e., scope of outsourcing, investment cycles, etc.). In order to illustrate this, Figs. 1 and 2 show the evolution of estimated factor prices at selected airports.

The sharp increase in factor prices at Heathrow in recent years is related to the new Terminal 5. This price effect, with the subsequent frontier shift, helps offsetting the increased technical inefficiency commonly associated with airport expansions and temporary excess capacity. The same applies to Manchester Airport with the inauguration of the *skylink* back in 1997 and to Luton after the ownership change in 1998. It is also worth noting the apparent convergence in capital prices between East Midlands and its "parent" airport, after the first was acquired by Manchester Airport Group. However, the similarity does not extend to the price of materials, given the significantly higher degree of outsourcing at East Midlands, which translates into reduced in-house expenditures. A similar effect is found at Cardiff, where only the "core activities" and estate management (see Sharp et al., 2010) are performed by the airport company. Finally, the lack of significant infrastructure developments at London Southend during the sample period clearly accounts for the reduced cost of capital. All this heterogeneity is brought into the model as an exogenous component, thus allowing for fair efficiency comparisons between different airports as the technological frontier adapts to the different levels of expenditure.

Furthermore, since delayed passengers spend more time in the terminals and congested runways increase stand occupation, the estimated prices can also be expected to react to capacity constraints if increased congestion has a significant impact on infrastructure usage. In order to support that assumption, a simple runway congestion indicator was constructed by dividing observed aircraft movements by annual runway capacity (ranging between 0.01 at Southend and 1.00 at Gatwick). A positive and significant Pearson correlation coefficient was found between the congestion indicator and the estimated capital and materials prices.[19]

4.3. Model specification

The cost frontier is completed with the time variable (t) in order to account for technical change. Both models are estimated as systems of equations featuring the input cost shares (s_j) that are regressed against their theoretical expressions.[20] A set of parametric restrictions were included in order to impose linear homogeneity in w. Concavity is checked *a posteriori* by calculating the elasticities of substitution in the sample average. Full specifications are shown in Appendix A.

Given the non-linear complexity of the proposed hedonic model, Bayesian inference and numerical models are the preferred method for estimation (Van der Broeck et al., 1994). We adapt the stochastic frontier codification provided in Griffin and Steel (2007). This assumes that the dependent variable (i.e. the logarithm of the total or variable costs) is normally distributed, with the aforementioned translog specification as the mean and σ_v^2 as the white noise variance (Eqs. (7) and (8)). The parameter of technical inefficiency u_{it} is allowed to vary systematically over time with airport-specific effects η_i, following Cuesta (2000). Note that a negative η_i indicates that the airport increases efficiency over time (T is the baseline year 2009). The firm's average inefficiency u_i is assumed to be exponentially distributed with mean λ^{-1} (Eq. (9)).

$$\ln \mathrm{TC}_{it} \sim N(\ln \mathrm{TC}_{it}(w, Y, \psi, t) + u_{it}, \sigma_v^{-2}) \tag{7}$$

$$\ln \mathrm{VC}_{it} \sim N(\ln \mathrm{VC}_{it}(w, Y, K, \psi, t) + u_{it}, \sigma_v^{-2}) \tag{8}$$

$$u_{it} \sim \exp\{\eta_i(t - T)\}u_i, \text{ where } u_i \sim \exp(\lambda) \tag{9}$$

[18] Note that the short-run model features the capital quantity index (*iqc*) as fixed factor, in place of w_c.
[19] The estimated correlation coefficients, with their respective 95% CIs are: 0.235 [0.138–0.328] and 0.274 [0.179–0.365] for capital and materials, respectively.
[20] Input cost shares are obtained by differentiating logged costs with respect to logged prices. All share equations are included because no singularity problems may arise in this type of Bayesian estimation.

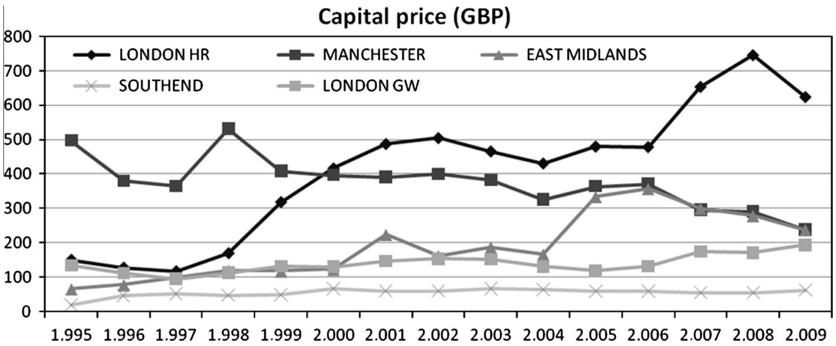

Fig. 1. Evolution of estimated capital prices at selected airports (base year 2009).

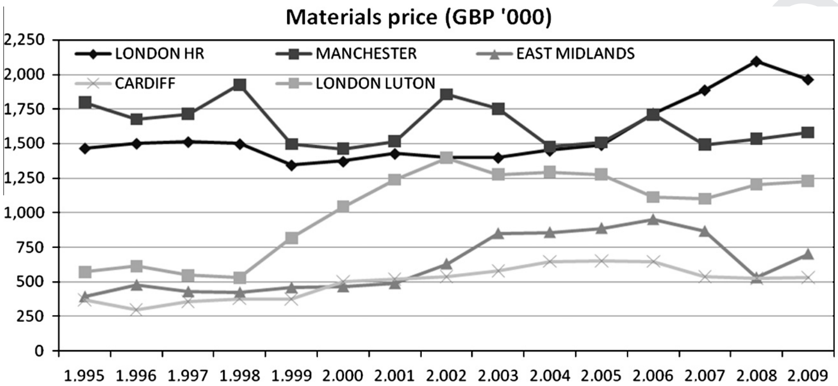

Fig. 2. Evolution of estimated materials prices at selected airports (base year 2009).

Prior distributions must be assigned to the parameters. Cost frontier coefficients (β) follow a non-informative normal distribution with mean zero and infinite variance. In the same spirit, a gamma distribution (0.01, 0.01) is assigned to the white noise inverse-variance. The distributional structure of technical inefficiency, via the λ parameter, allows us to impose prior ideas about mean efficiency (r^*) in the airport industry. This is set at 0.85 in accordance with the previous literature. The prior distributions of η_i and the hedonic coefficients ψ was chosen to be a zero-mean normal distribution with an inverse-variance of 10 that allows for a reasonable spread.

$$\beta \sim N(0,0),\ \sigma_v^{-2} \sim G(0.01, 0.01),\ \lambda \sim \exp(-\log r^*),\ \eta_i \sim N(0,10),\ \psi \sim N(0,10) \tag{10}$$

Input share equations are modeled using a similar codification than that of the cost frontier (i.e. normally distributed) with correlated error terms.

4.4. Technological indicators

Once the cost function parameters have been estimated, airport-specific MCs for the hedonic passenger output (*paxh*) are calculated by evaluating the expressions below at sample levels (see Jara-Díaz, 2007):

$$\text{Long-run}:\ \mathrm{MC}_{paxh} = \frac{\partial \ln C}{\partial \ln paxh}\frac{\widehat{C}}{paxh};\quad \text{Short-run}:\ \mathrm{MC}_{paxh} = \frac{\partial \ln \mathrm{VC}}{\partial \ln paxh}\frac{\widehat{\mathrm{VC}}}{paxh} \tag{11}$$

where $\widehat{C}$ and $\mathrm{V}\widehat{C}$ indicate predicted (i.e. efficient) total or variable costs, respectively.

Long-run economies of scale (S) and short-run economies of capacity utilization (ECU) are calculated as well:

$$\text{Long-run}:\ S = \left(\sum_j \frac{\partial \ln C}{\partial \ln y_j}\right)^{-1};\quad \text{Short-run}:\ \mathrm{ECU} = \left(\sum_j \frac{\partial \ln \mathrm{VC}}{\partial \ln y_j}\right)^{-1} \tag{12}$$

where j = (*paxh*, *rev*).

Average incremental costs (AIC) are presented as second-best pricing references. The incremental cost (IC) of output j is defined as the cost of adding the jth output's production to the vector of outputs produced by the airport. The AIC of output j is then obtained as the ratio between the IC and the same output's level of production (y_j). For the relevant *paxh* output, the expressions are as follows:

$$IC_{paxh} = C(paxh, rev) - C(0, rev)\quad AIC_{paxh} = \frac{IC_{paxh}}{y_{paxh}} \tag{13}$$

Since the translog specification does not allow us to estimate ICs,[21] AICs are approximated using an alternative formula provided by Jara-Díaz (2007):

$$AIC_{paxh} = MC_{paxh} S_{paxh}\quad AIC_{paxh} = MC_{paxh} ECU_{paxh} \tag{14}$$

where the output-specific scale elasticities (S_{paxh} or ECU_{paxh} – also not available for calculation) are assumed equal to the airport's global level (S or ECU).[22]

Finally, note that *paxh* refers to the reference airline type, i.e. full-service. The estimated hedonic proportions are used to derive the MCs and AICs of the others,[23] i.e. $MC_{lcc} = MC_{fsc} e^{\psi 1}$.

5. Results and discussion

Both models were run on WinBUGS (Lunn et al., 2000) and convergence was achieved after 100,000 random draws.[24] Table 3 shows the long-run cost system estimation results. It is clearly seen that most relevant parameters are significant and show the expected signs. The scale elasticity at the average airport in 2009 (the reference year) can easily be obtained as the inverse of the sum of the first-order output coefficients (*rev* and *paxh*). It yields 1.99 (std. deviation: 0.29), indicating the existence of significant returns to scale at the approximation point (slightly under 2 million passengers). As seen in Fig. 3, the hypothesis of constant returns to scale at that level of output can be rejected.

The estimated parameters also indicate the presence of non-neutral technological progress, both in inputs and in scale. In particular, the negative sign of the $t * rev$ parameter shows that the maximum output size that allows UK airports to enjoy scale economies (i.e. the industry's minimum efficient scale-MES) has been expanded by the increasing importance of non-aviation activities on airport operations. The last decade has also seen increase the importance of capital costs on airport operations, to the detriment of materials and labor costs. Average long-run inefficiency in 2009 is calculated as $\lambda^{-1} = 21.44\%$. No conclusions regarding increasing or decreasing efficiency in the sample period can be drawn since the average *eta* parameter is not significantly different from zero.

Regarding the hedonic coefficients, both are significant[25] and support the main working hypothesis of this paper. The negative sign of ψ_{lcc} indicates that low-cost passengers can be served at a reduced marginal cost (69.6%) in comparison with those traveling on full-service airlines. This is clearly related to the significantly lower infrastructure demands of low-cost carriers, which are typically assigned low-quality piers or, in a few cases, may even have no-frills terminals built for them. In addition, it is widely acknowledged in the industry that the low-cost business model is based on higher aircraft utilization rates that rest upon shorter turnaround times, short-haul routes and smaller, homogeneous, aircraft types. Reduced runway damage costs (related to tire pressure and aircraft weight) can also be present since low-cost carriers usually carry less or no belly cargo (Button, 2011). All these factors reduce their capital usage and hence the long-run marginal costs. From a financial perspective, our results would support low-cost airlines' claims for lower airport charges. Charter passengers, on the contrary, are found to cost 33% more than full service. This is likely related to the fact that the charter business is very seasonal and their flights tend to be at fixed intervals such as 7 or 14 days, which leads to low weekly and annual utilization of airport facilities. In addition, charter operations normally concentrate at peak times, also having aircraft parked for longer periods making charter carriers more expensive to serve (Competition Commission, 2009). Moreover, charter passengers tend to spend more time in the terminals, carry heavier baggage and often travel on aircraft with very high load factors (normally over 90%), that take longer to board. Furthermore, almost 100% of charter passengers are international, as opposed to 60–70% for full service or LCC passengers, hence the former make more use of immigration and custom facilities, further imposing higher operating costs to airports. If terminal use charges ignore these cost differences, airports would be implicitly allowing cross-subsidization from low-cost and full-service to charter passengers, thus defeating the purpose of MC pricing and limiting its potential benefits.

Table 4 shows the short-run cost system estimation results. Note that the first-order fixed factor coefficient is clearly significant, indicating some degree of short-run disequilibrium in the UK airport industry. Using the same method as before, significant economies of capacity utilization-ECU at the average airport in 2009 are found (from Fig. 3, average: 1.69, std deviation: 0.21). Technological progress is also present but only the output interaction is significant. Average short-run cost inefficiency in 2009 is calculated as $\lambda^{-1} = 26.80\%$. The hedonic coefficients are both significant and lead to the same conclusions as before, yet price discrimination would now be justified on the basis of different non-capital usage. Note that the MC difference in comparison with full-service passengers is accentuated in this second model.

Table 5 provides airport-specific MCs, scale elasticities, ECUs, and AIC estimates for the year 2009 (full confidence intervals are provided in Appendix B). The reduced cost share of capital in the UK airport industry, combined with the increased cost

[21] Note that the translog is not analytic in zero.
[22] The airport's global scale elasticity is a weighted average of the output-specific ones (Jara-Díaz, 2007).
[23] This method assumes that the MC proportion between different passenger categories is constant throughout the UK airport industry and across the sample period. Lack of degrees of freedom precluded us from using a more sophisticated hedonic specification.
[24] Convergence was checked using the Gelman-Rubin statistic implemented in WinBUGS.
[25] psi[cha] is significant at a 90% confidence level.

Table 3
Long-run cost system parameter estimates.

Node	Mean	Std. dev.	MC error	2.50%	Median	97.50%	Sample
Constant	9.8050	0.0598	0.0029	9.6780	9.8080	9.9140	100,000
rev	0.1047	0.0504	0.0016	0.0056	0.1050	0.2023	100,000
wc	0.2132	0.0062	0.0001	0.2010	0.2132	0.2254	100,000
wm	0.4702	0.0062	0.0001	0.4580	0.4703	0.4824	100,000
wp	0.3166	0.0062	0.0000	0.3043	0.3165	0.3289	100,000
rev * wc	−0.0034	0.0045	0.0000	−0.0122	−0.0034	0.0054	100,000
rev * wm	0.0115	0.0046	0.0000	0.0027	0.0116	0.0204	100,000
rev * wp	−0.0081	0.0048	0.0000	−0.0176	−0.0081	0.0013	100,000
0.5 * wc2	0.0872	0.0059	0.0000	0.0756	0.0872	0.0988	100,000
wc * wm	−0.0545	0.0046	0.0000	−0.0635	−0.0545	−0.0455	100,000
wc * wp	−0.0256	0.0060	0.0000	−0.0373	−0.0256	−0.0139	100,000
0.5 * wm2	0.1089	0.0073	0.0000	0.0946	0.1089	0.1232	100,000
wm * wp	−0.0529	0.0072	0.0000	−0.0669	−0.0530	−0.0389	100,000
0.5 * wp2	0.0243	0.0232	0.0002	−0.0207	0.0242	0.0700	100,000
0.5 * rev2	0.0142	0.0302	0.0006	−0.0457	0.0145	0.0728	100,000
time	−0.0047	0.0057	0.0003	−0.0157	−0.0045	0.0058	100,000
time * rev	−0.0081	0.0037	0.0001	−0.0154	−0.0081	−0.0009	100,000
time * wc	0.0039	0.0008	0.0000	0.0024	0.0039	0.0055	100,000
time * wm	−0.0012	0.0008	0.0000	−0.0028	−0.0012	0.0004	100,000
time * wp	−0.0020	0.0008	0.0000	−0.0036	−0.0020	−0.0004	100,000
paxh	0.3961	0.0433	0.0017	0.3080	0.3972	0.4782	100,000
paxh * wc	−0.0231	0.0044	0.0000	−0.0317	−0.0231	−0.0146	100,000
paxh * wm	0.0173	0.0042	0.0000	0.0090	0.0173	0.0256	100,000
paxh * wp	0.0039	0.0046	0.0000	−0.0052	0.0039	0.0130	100,000
0.5 * paxh2	0.0816	0.0155	0.0006	0.0504	0.0820	0.1110	100,000
paxh * rev	0.0189	0.0274	0.0009	−0.0339	0.0186	0.0734	100,000
time * paxh	0.0004	0.0026	0.0001	−0.0047	0.0004	0.0054	100,000
psi[lcc]	−0.3615	0.1410	0.0048	−0.6395	−0.3623	−0.0797	100,000
psi[cha]	0.2860	0.1656	0.0064	−0.0499	0.2923	0.5952	100,000
lambda	4.6630	1.2820	0.0481	2.5910	4.5150	7.5710	100,000

Note: rev: commercial revenues, wc: capital price, wm: material price, wp: labor price, paxh: hedonically-adjusted passengers.

elasticity of the passenger output under a short-run specification, lead to similar long- and short-run MC estimates in most small and medium-size airports. Larger differences, however, are found at London Heathrow, due to the recent opening of Terminal 5. With much higher long-run MCs than all other airports,[26] the results also confirm the pervasive view that Heathrow is an expensive airport to use due to its capital intensive, complex facilities as a hub airport and severe capacity constraints. As expected, returns to scale and economies of capacity tend to decrease with airport size. In particular, note that London Heathrow is very close to reaching its efficient scale in the long run while operating slightly over capacity in the short run.[27] This proximity to constant returns would make either long- or short-run MCs the ideal price benchmarks at UK's main gateway. In the case of London Gatwick, a slight departure from short-run MC would be acceptable, while AIC is arguably the preferred *dual-till* alternative in the long run. The same applies to Stansted or Manchester, where higher scale elasticities are found.

These results, as well as any hypothetical cross-subsidies between passenger categories, are shown in Fig. 4. The four charts present the evolution of established price caps at these (currently or historically) designated airports against the estimated price benchmarks between 2000 and 2009 (thus partially covering three regulatory periods, from the end of Q3 to the beginning of Q5). Historical data on price regulation at UK airports can be obtained from the CAA website. Price caps are expressed in terms of "maximum revenue per passenger" in current prices. Note that all our MC and AIC estimates were also converted to current prices. Table 6 provides complementary information on traffic distribution at these airports in order to facilitate the analysis.

Results, as expected, agree with CAA's declared long-run approach to airport pricing in all cases. In addition, there is need to consider the *single-till* nature of all price caps (see, e.g. CAA, 2003a and CAA, 2003b). This clearly applies to the case of Heathrow Airport (that serves only full-service passenger traffic), where a slight level of cross-subsidization from commercial activities is present. Note that price caps are systematically set below aeronautical cost recovery, in a trend that has accentuated in recent years, probably due to the capacity expansions. In that regard, and taking into account the estimated MCs and AICs represent the technological "efficient" minimum, it can be assumed that the actual *single-till* subsidization is much more significant.

For the purposes of this paper, however, the case of Gatwick Airport is much more interesting. In the last decade, Gatwick has seen a significant shift from charter to low-cost operations, while the full-service traffic share has remained fairly con-

[26] With the exception of Coventry whose MCs were mainly due to its small scale of operation.
[27] As seen in Appendix B, both long- and short-run scale elasticities at Heathrow (and also Gatwick) are not significantly above constant returns. In spite of that, the overall density of probability clearly favors the hypothesis of increasing returns in both cases.

Please cite this article in press as: Voltes-Dorta, A., Lei, Z. The impact of airline differentiation on marginal cost pricing at UK airports. Transport. Res. Part A (2013), http://dx.doi.org/10.1016/j.tra.2013.08.002

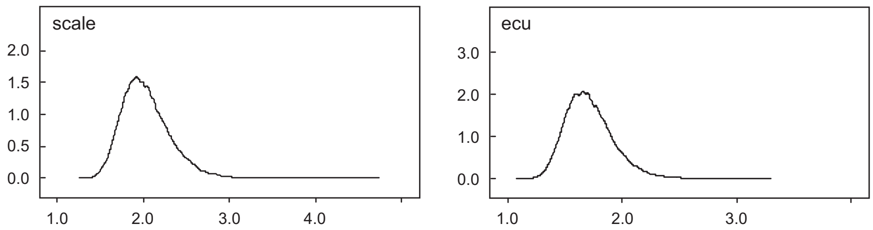

Fig. 3. Kernel density graphs for economies of scale (*scale*) and economies of capacity utilization (*ecu*) at the average airport.

Table 4
Short-run Cost System parameter estimates.

Node	Mean	Std. dev.	MC error	2.50%	Median	97.50%	Sample
Constant	9.5550	0.0679	0.0026	9.4130	9.5580	9.6820	100,000
rev	0.1091	0.0544	0.0012	0.0003	0.1098	0.2138	100,000
iqc	0.1071	0.0499	0.0010	0.0107	0.1064	0.2064	100,000
wm	0.5927	0.0068	0.0000	0.5794	0.5927	0.6060	100,000
wp	0.4073	0.0068	0.0000	0.3940	0.4073	0.4206	100,000
rev * wm	0.0118	0.0055	0.0000	0.0011	0.0118	0.0225	100,000
rev * wp	−0.0118	0.0055	0.0000	−0.0225	−0.0118	−0.0011	100,000
iqc * wm	0.0138	0.0135	0.0000	−0.0126	0.0137	0.0402	100,000
iqc * wp	−0.0048	0.0137	0.0000	−0.0316	−0.0048	0.0222	100,000
0.5 * wm2	0.1049	0.0092	0.0000	0.0869	0.1049	0.1228	100,000
wm * wp	−0.0914	0.0091	0.0000	−0.1091	−0.0914	−0.0736	100,000
0.5 * wp2	−0.0497	0.0309	0.0001	−0.1099	−0.0497	0.0108	100,000
0.5 * rev2	0.0252	0.0341	0.0005	−0.0420	0.0253	0.0916	100,000
rev * iqc	−0.0111	0.0536	0.0007	−0.1157	−0.0113	0.0948	100,000
0.5 * iqc2	0.0382	0.1186	0.0017	−0.1957	0.0388	0.2687	100,000
time	−0.0145	0.0053	0.0002	−0.0240	−0.0149	−0.0031	100,000
t * rev	−0.0118	0.0041	0.0001	−0.0200	−0.0118	−0.0038	100,000
t * iqc	0.0134	0.0072	0.0001	−0.0009	0.0135	0.0271	100,000
t * wm	0.0014	0.0009	0.0000	−0.0005	0.0014	0.0032	100,000
t * wp	0.0001	0.0010	0.0000	−0.0017	0.0001	0.0020	100,000
paxh	0.4812	0.0433	0.0013	0.3910	0.4829	0.5614	100,000
0.5 * paxh2	0.0836	0.0158	0.0004	0.0503	0.0843	0.1126	100,000
paxh * rev	0.0074	0.0308	0.0007	−0.0521	0.0070	0.0688	100,000
paxh * iqc	−0.0252	0.0286	0.0004	−0.0814	−0.0252	0.0308	100,000
paxh * wm	0.0021	0.0044	0.0000	−0.0066	0.0021	0.0108	100,000
paxh * wp	0.0049	0.0045	0.0000	−0.0040	0.0049	0.0138	100,000
t * paxh	0.0040	0.0031	0.0000	−0.0022	0.0040	0.0102	100,000
psi[lcc]	−0.4474	0.1374	0.0037	−0.7073	−0.4495	−0.1669	100,000
psi[cha]	0.3900	0.1640	0.0050	0.0715	0.3883	0.7124	100,000
lambda	3.7230	0.9285	0.0243	2.1570	3.6360	5.7750	100,000

Note: rev: commercial revenues, iqc: capital index, wm: material price, wp: labor price, paxh: hedonically-adjusted passengers.

stant at around 60%. Fig. 4 shows that, during the regulatory period 2003–2008 (Q4), price caps converge to the long-run marginal costs imposed by full service passengers, catching up with aeronautical cost recovery at the beginning of Q5. This situation would be very close to optimal *dual-till* pricing without passenger differentiation, but our estimates reveal the existence of strong cross-subsidies from low-cost to charter. From a theoretical perspective, this departure from MC pricing would distort airline demands for airport capacity. Thus, the existing regulatory regime will not lead to optimal usage and valid investment signals, properties that would be highly desirable to price such a congested airport as Gatwick. Stansted airport has been historically priced above cost recovery levels, which brings into question the *single-till* nature of CAA pricing approach. In addition, at price-cap levels low-cost airlines, which are predominant at the airport, would again be severely overcharged. Thus, our results definitely call for a more differentiated approach to price regulation in the UK.

Manchester airport was de-designated in 2009. A very strong efficiency incentive (5% below RPI) was set during Q4 that allowed for a near perfect convergence to long-run MCs by the end of the period. While again the price-cap level would generate cross-subsidization between airline types, the regulatory discussion is not as relevant in this case due to the existence of data confirming that price discrimination has already been applied at the airport. While the actual charges paid by the airlines are usually confidential, some details were revealed in a Competition Commission's investigation of Manchester Airport in 2002 (Competition Commission, 2002). It was estimated that British Airways (largest airline), would have paid £6.08 per passenger. The level of charges paid by four large charter carriers (MyTravel, JMC, Air2000 and Britannia), ranged from £6.55 to £6.71. By contrast, Ryanair only paid £4.29 per passenger in the same period. Given the fact that Ryanair carried only 326,200 passengers at Manchester Airport in 2001/02, the substantially lower charge can be assumed to reflect

Please cite this article in press as: Voltes-Dorta, A., Lei, Z. The impact of airline differentiation on marginal cost pricing at UK airports. Transport. Res. Part A (2013), http://dx.doi.org/10.1016/j.tra.2013.08.002

Table 5
Estimated marginal costs and average incremental costs at UK airports (2009).

Airport		Scale/ECU	Efficiency	Marginal Cost (GBP)			Average incremental cost (GBP)		
				Full-service	Low-cost	Charter	Full-service	Low-cost	Charter
Aberdeen	Long-run	1.80	0.91	3.18	2.22	4.24	5.74	4.00	7.64
	Short-run	1.51	0.87	3.26	2.08	4.82	4.92	3.15	7.27
Belfast	Long-run	1.66	0.79	2.66	1.85	3.53	4.42	3.08	5.88
	Short-run	1.56	0.86	2.77	1.77	4.09	4.31	2.76	6.37
Birmingham	Long-run	1.52	0.86	4.24	2.95	5.64	6.46	4.50	8.60
	Short-run	1.28	0.72	3.10	1.98	4.58	3.97	2.54	5.87
Blackpool	Long-run	3.22	0.55	5.24	3.65	6.97	16.83	11.73	22.41
	Short-run	2.53	0.44	5.47	3.50	8.08	13.87	8.87	20.48
Bournemouth	Long-run	2.05	0.98	5.52	3.85	7.35	11.30	7.87	15.04
	Short-run	1.92	0.99	5.79	3.70	8.54	11.10	7.10	16.39
Bristol	Long-run	1.67	0.90	2.59	1.80	3.44	4.32	3.01	5.75
	Short-run	1.41	0.84	2.24	1.44	3.32	3.18	2.03	4.69
Cardiff	Long-run	2.05	0.81	2.70	1.88	3.59	5.53	3.86	7.37
	Short-run	1.74	0.82	2.76	1.76	4.07	4.81	3.07	7.10
Coventry	Long-run	2.89	0.82	15.58	10.85	20.73	44.94	31.30	59.82
	Short-run	2.30	0.74	15.91	10.17	23.50	36.62	23.41	54.09
East Midlands	Long-run	1.68	0.90	3.85	2.68	5.12	6.48	4.51	8.63
	Short-run	1.44	0.91	3.71	2.37	5.48	5.36	3.43	7.92
Edinburgh	Long-run	1.53	0.76	3.05	2.12	4.06	4.65	3.24	6.19
	Short-run	1.41	0.87	2.93	1.87	4.32	4.12	2.63	6.08
Exeter	Long-run	2.19	0.77	7.00	4.87	9.31	15.35	10.70	20.44
	Short-run	1.86	0.74	7.36	4.71	10.88	13.70	8.76	20.24
Glasgow	Long-run	1.61	0.78	3.01	2.09	4.00	4.84	3.37	6.45
	Short-run	1.37	0.69	2.32	1.49	3.43	3.18	2.03	4.69
Humberside	Long-run	2.59	0.96	7.92	5.52	10.54	20.54	14.31	27.34
	Short-run	2.09	0.96	8.05	5.15	11.89	16.80	10.74	24.81
Leeds	Long-run	2.08	0.80	3.68	2.56	4.89	7.65	5.33	10.18
	Short-run	1.67	0.79	2.81	1.79	4.14	4.70	3.00	6.94
Liverpool	Long-run	1.81	0.67	2.58	1.80	3.43	4.68	3.26	6.23
	Short-run	1.50	0.57	1.98	1.27	2.93	2.98	1.90	4.40
London City	Long-run	1.68	0.79	4.18	2.91	5.56	7.03	4.90	9.36
	Short-run	1.51	0.73	4.27	2.73	6.31	6.43	4.11	9.50
London GW	Long-run	1.21	0.73	5.49	3.82	7.30	6.62	4.61	8.81
	Short-run	1.09	0.65	4.12	2.64	6.09	4.52	2.89	6.67
London HR	Long-run	1.11	0.82	15.49	10.79	20.62	17.12	11.93	22.79
	Short-run	0.99	0.70	7.97	5.09	11.76	7.92	5.06	11.70
London Luton	Long-run	1.48	0.93	4.77	3.33	6.35	7.05	4.91	9.39
	Short-run	1.28	0.87	4.65	2.97	6.87	5.98	3.82	8.83
London STN	Long-run	1.37	0.82	4.81	3.35	6.40	6.59	4.59	8.77
	Short-run	1.18	0.62	3.41	2.18	5.03	4.00	2.56	5.91
Manchester	Long-run	1.28	0.85	5.87	4.09	7.81	7.48	5.21	9.96
	Short-run	1.15	0.85	4.77	3.05	7.05	5.50	3.52	8.12
Newcastle	Long-run	1.71	0.80	4.31	3.00	5.73	7.37	5.14	9.82
	Short-run	1.54	0.80	2.19	1.40	3.23	3.36	2.15	4.96
Sheffield	Long-run	2.68	0.67	4.69	3.27	6.24	12.54	8.74	16.69
	Short-run	2.10	0.85	3.98	2.55	5.88	8.38	5.36	12.38
Southampton	Long-run	2.14	0.79	4.07	2.84	5.42	8.71	6.07	11.60
	Short-run	1.75	0.69	4.17	2.67	6.16	7.31	4.68	10.80
Southend	Long-run	6.45	0.63	12.79	8.91	17.03	82.52	57.49	109.85
	Short-run	4.42	0.57	13.53	8.65	19.98	59.71	38.17	88.20
Teesside	Long-run	2.68	0.87	6.07	4.23	8.09	16.25	11.32	21.63
	Short-run	2.26	0.90	7.01	4.48	10.35	15.85	10.13	23.41

Manchester's recognition that Ryanair imposed lower costs on airport operations. If inflation is taken into account, the airport charges that Manchester levied to different airline types are consistent with our estimates, thus providing economic justification for the Airport's price discrimination strategy.

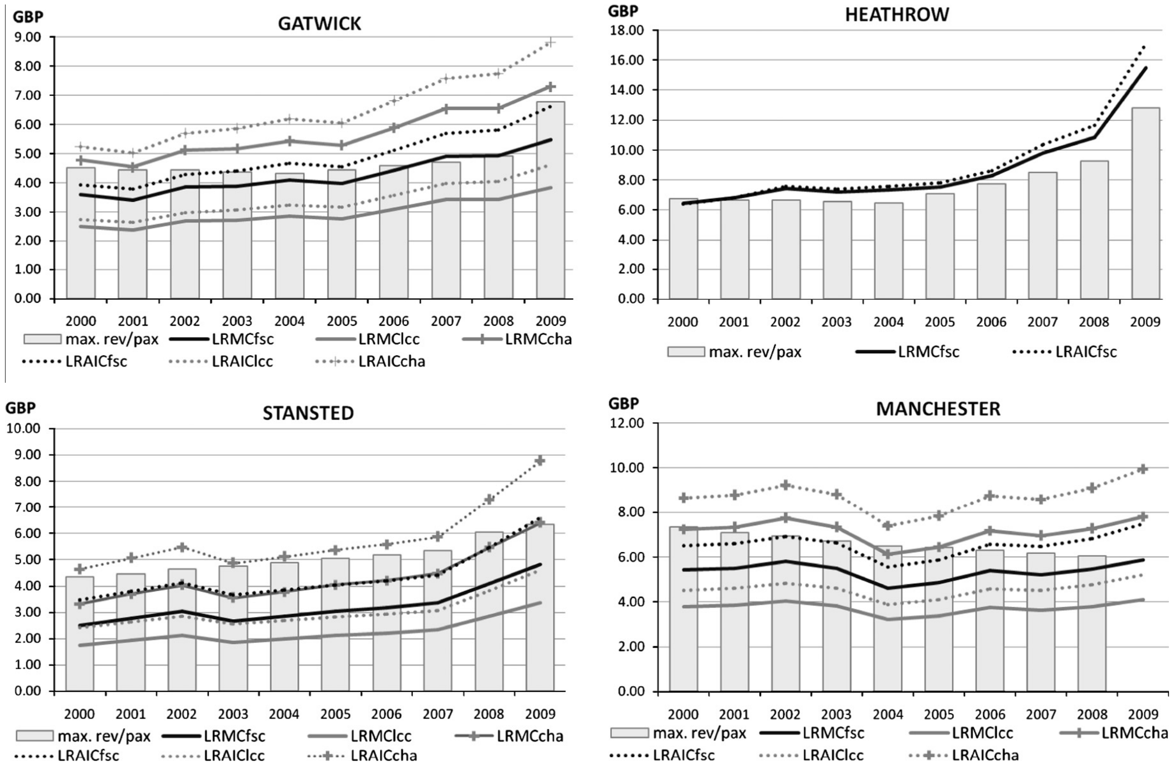

Fig. 4. Evolution of price caps and estimated long-run marginal and incremental costs at designated airports 2000–2009 (current prices). *Note*: LR: long-run, MC: marginal cost, AIC: average incremental cost, fsc: full-service, lcc: low-cost, cha: charter. *Source*: CAA statistics.

Table 6
Traffic distribution at designated airports 2000–2009. *Source*: CAA statistics.

	2000 (%)	2001 (%)	2002 (%)	2003 (%)	2004 (%)	2005 (%)	2006 (%)	2007 (%)	2008 (%)	2009 (%)
Gatwick										
slcc	0.5	0.6	1.6	5.1	9.3	10.9	14.1	15.8	17.7	22.5
scha	35.8	34.3	36.2	37.3	34.6	31.6	28.4	27.1	24.0	22.8
Stansted										
slcc	29.0	40.3	46.7	49.9	52.1	52.2	48.3	51.8	51.9	51.9
scha	13.1	10.5	8.5	7.4	6.0	5.2	4.3	4.2	3.9	3.4
Manchester										
slcc	0.6	1.0	1.0	0.8	2.8	5.4	9.3	15.6	16.0	19.2
scha	53.6	49.6	50.8	50.7	46.7	43.0	40.2	38.2	36.3	33.9

Note: Heathrow shares of low-cost (*slcc*) and charter traffic (*scha*) are negligible (<0.2%).

6. Summary

This paper aims to provide empirical evidence in support of increased differentiation in airport charges on the basis of marginal passenger costs being sensitive to the type of airline. To that end, both long- and short-run multi-output cost functions are estimated over an unbalanced pool database of 29 UK airports observed between 1995 and 2009. The passenger output is hedonically-adjusted in order to introduce the desired level of disaggregation while keeping a parsimonious specification.

Results show that low-cost passengers impose significantly lower costs to the airport than those from either full-service or charter flights. This is clearly related to the lower infrastructure demands of low-cost operations in terms of aircraft turnarounds and terminal amenities. From a financial perspective, this result would support airlines' claims for lower airport charges that reflect the quality of the available infrastructure. In case no terminal differentiation exists, price discrimination on the basis of usage will equally be justified. At congested airports, this would lead to optimal usage and valid investment

Please cite this article in press as: Voltes-Dorta, A., Lei, Z. The impact of airline differentiation on marginal cost pricing at UK airports. Transport. Res. Part A (2013), http://dx.doi.org/10.1016/j.tra.2013.08.002

signals. Besides the UK, these policy conclusions can be very relevant for other countries, e.g. Spain, where the envisaged privatization process will generate a great need for price regulation. On non-designated airports, our results provide economic justification for the price discrimination strategies already implemented in the UK, in which low-cost carriers pay reduced charges for the use of the infrastructure.

Further research should implement the proposed methodology on a much broader database that is able to provide enough degrees of freedom to support the specification of e.g. airport-specific hedonic estimates. This would allow for a much deeper investigation of the differences in infrastructure usage of different airline categories. Finally, note that service quality has not been taken into account in this research due to lack of reliable data. Also, our cost function does not take into account externalities or other undesirable outputs of airport operations. Hence, all policy conclusions should be interpreted in purely financial terms, which, in any case, will be of major interest for the airport operators, regulators and other stakeholders.

7. Uncited references

Q6 Zhang et al. (2011), Martín and Voltes-Dorta (2011b) and Morrison and Winston (1989).

Acknowledgements

The authors wish to thank Charles Ng from the UK CAA, Xiaowen Fu from Hong Kong Polytechnic University, and Héctor Rodríguez-Déniz from the University of Las Palmas de Gran Canaria for their valuable comments and support in the early stages of this research.

Appendix A. Model specifications

All variables are logged, except time, and deviated from their sample averages.

A.1. Long-run model

$$\begin{aligned}\ln \mathrm{TC}_{it} = {} & \alpha_1 + \alpha_2 paxh + \alpha_3 rev + \beta_4\omega_c + \beta_5\omega_m + \beta_6\omega_p + \gamma_7 paxh\omega_c + \gamma_8 paxh\omega_m + \gamma_9 paxh\omega_p + \gamma_{10} rev\omega_c + \gamma_{11} rev\omega_m \\ & + \gamma_{12} rev\omega_p + \delta_{13}0.5\omega_c\omega_c + \delta_{14}\omega_c\omega_m + \delta_{15}\omega_c\omega_p + \delta_{16}0.5\omega_m\omega_m + \delta_{17}\omega_m\omega_p + \delta_{18}0.5\omega_p\omega_p + \rho_{19}0.5paxhpaxh \\ & + \rho_{20} paxhrev + \rho_{21}0.5revrev + \tau_{22}t + \tau_{23}tpaxh + \tau_{24}trev + \tau_{25}t\omega_c + \tau_{26}t\omega_m + \tau_{27}t\omega_p + u_{it} + v_{it}\end{aligned}$$

$$S_m = \beta_4 + \gamma_7 paxh + \gamma_{10} rev + \delta_{13}\omega_c + \delta_{14}\omega_m + \delta_{15}\omega_p + \tau_{25}t$$

$$S_m = \beta_5 + \gamma_8 paxh + \gamma_{11} rev + \delta_{14}\omega_c + \delta_{16}\omega_m + \delta_{17}\omega_p + \tau_{26}t$$

$$S_p = \beta_6 + \gamma_9 paxh + \gamma_{12} rev + \delta_{15}\omega_c + \delta_{17}\omega_m + \delta_{18}\omega_p + \tau_{27}t$$

$$\begin{aligned}&\beta_4 + \beta_5 + \beta_6 = 1;\ \gamma_7 + \gamma_8 + \gamma_9 = 0;\ \gamma_{10} + \gamma_{11} + \gamma_{12} = 0;\ \delta_{13} + \delta_{14} + \delta_{15} = 0;\ \delta_{14} + \delta_{16} + \delta_{17} = 0; \\ &\delta_{15} + \delta_{17} + \delta_{18} = 0;\ \tau_{25} + \tau_{26} + \tau_{27}\end{aligned}$$

$$paxh = pax + \psi_1 slcc + \psi_2 scha$$

A.2. Short-run model

$$\begin{aligned}\ln \mathrm{VC}_{it} = {} & \alpha_1 + \alpha_2 paxh + \alpha_3 rev + \varphi_4 iqc + \beta_5\omega_m + \beta_6\omega_p + \gamma_7 paxh\omega_m + \gamma_8 paxh\omega_p + \gamma_9 rev\omega_m + \gamma_{10} rev\omega_p + \gamma_{11} iqc\omega_m \\ & + \gamma_{12} iqc\omega_p + \delta_{13}0.5\omega_m\omega_m + \delta_{14}\omega_m\omega_p + \delta_{15}0.5\omega_p\omega_p + \rho_{16}0.5paxhpaxh + \rho_{17} paxhrev + \rho_{18} paxhiqc \\ & + \rho_{19}0.5revrev + \rho_{20} reviqc + \rho_{21}0.5iqciqc + \tau_{22}t + \tau_{23}tpaxh + \tau_{24}trev + \tau_{25}tiqc + \tau_{26}t\omega_m + \tau_{27}t\omega_p + u_{it} \\ & + v_{it}\end{aligned}$$

$$S_m = \beta_5 + \gamma_7 paxh + \gamma_9 rev + \gamma_{11} iqc + \delta_{13}\omega_m + \delta_{14}\omega_p + \tau_{26}t$$

$$S_p = \beta_6 + \gamma_8 paxh + \gamma_{10} rev + \gamma_{12} iqc + \delta_{14}\omega_m + \delta_{15}\omega_p + \tau_{27}t$$

Appendix B. Confidence intervals for scale economies, MC and AIC estimates

Airport		Scale/ECU			MC (GBP)									AIC (GBP)								
					Full-service			Low-cost			Charter			Full-service			Low-cost			Charter		
		2.5%	Median	95%	2.5%	Median	95%	2.5%	Median	95%	2.5%	Median	95%	2.5%	Median	95%	2.5%	Median	95%	2.5%	Median	95%
Aberdeen	Long-run	1.44	1.81	2.40	2.53	3.17	3.85	1.60	2.20	3.00	2.98	4.20	5.84	4.69	5.74	7.20	2.95	4.00	5.47	5.60	7.64	10.63
	Short-run	1.22	1.51	2.00	2.67	3.25	3.86	1.54	2.07	2.77	3.47	4.79	6.52	4.03	4.93	6.21	2.34	3.16	4.33	5.35	7.28	10.12
Belfast	Long-run	1.34	1.67	2.18	2.05	2.64	3.32	1.44	1.84	2.29	2.42	3.50	5.10	3.44	4.42	5.80	2.50	3.08	3.85	4.07	5.88	8.69
	Short-run	1.24	1.56	2.09	2.16	2.76	3.45	1.40	1.76	2.18	2.81	4.06	5.87	3.32	4.32	5.75	2.20	2.76	3.55	4.38	6.37	9.52
Birmingham	Long-run	1.15	1.53	2.29	3.21	4.22	5.27	2.07	2.93	4.07	3.88	5.60	7.86	5.17	6.48	8.57	3.32	4.52	6.40	6.27	8.62	12.38
	Short-run	0.99	1.29	1.85	2.46	3.09	3.75	1.44	1.97	2.65	3.27	4.55	6.25	3.24	3.98	5.15	1.90	2.55	3.57	4.32	5.87	8.30
Blackpool	Long-run	1.53	3.15	17.91	2.07	5.20	8.58	1.40	3.63	6.05	2.63	6.84	12.60	9.01	16.59	56.84	6.27	11.63	38.98	10.75	22.26	79.30
	Short-run	1.33	2.51	10.75	2.71	5.45	8.42	1.67	3.49	5.43	3.77	7.97	13.87	8.47	13.79	39.33	5.38	8.84	25.15	11.16	20.51	61.40
Bournemouth	Long-run	1.57	2.05	2.97	4.13	5.49	7.08	2.78	3.82	5.00	4.92	7.28	10.61	8.72	11.28	15.24	6.06	7.90	10.54	10.46	15.04	22.47
	Short-run	1.48	1.92	2.77	4.43	5.75	7.33	2.73	3.68	4.75	5.86	8.47	12.19	8.58	11.10	14.97	5.47	7.12	9.50	11.45	16.40	24.49
Bristol	Long-run	1.30	1.68	2.36	1.99	2.58	3.22	1.33	1.79	2.34	2.36	3.42	4.87	3.43	4.33	5.70	2.34	3.02	3.99	4.10	5.75	8.36
	Short-run	1.12	1.42	1.94	1.78	2.23	2.73	1.10	1.43	1.81	2.34	3.29	4.62	2.55	3.19	4.12	1.60	2.03	2.65	3.38	4.69	6.71
Cardiff	Long-run	1.59	2.06	2.89	2.02	2.68	3.47	1.31	1.87	2.57	2.53	3.56	4.90	4.26	5.54	7.43	2.81	3.87	5.38	5.48	7.37	10.17
	Short-run	1.39	1.75	2.37	2.15	2.74	3.44	1.29	1.75	2.34	2.99	4.05	5.40	3.77	4.81	6.33	2.28	3.08	4.21	5.37	7.11	9.64
Coventry	Long-run	1.91	2.90	5.99	9.41	15.47	22.12	6.39	10.81	15.53	11.57	20.43	33.48	29.06	44.73	80.68	19.91	31.43	54.91	34.59	59.76	116.32
	Short-run	1.59	2.31	4.19	10.50	15.84	21.67	6.58	10.17	13.93	13.99	23.16	36.58	24.62	36.50	60.93	15.64	23.50	38.29	32.51	53.97	98.78
East Midlands	Long-run	1.33	1.69	2.31	2.96	3.83	4.80	1.99	2.66	3.48	3.58	5.09	7.10	5.12	6.50	8.50	3.50	4.52	5.96	6.27	8.62	12.21
	Short-run	1.16	1.45	1.93	2.95	3.70	4.53	1.82	2.36	3.01	3.94	5.45	7.48	4.29	5.38	6.93	2.69	3.44	4.47	5.82	7.93	11.07
Edinburgh	Long-run	1.18	1.53	2.17	2.36	3.03	3.76	1.58	2.11	2.73	2.70	4.02	5.94	3.73	4.66	6.08	2.55	3.25	4.26	4.26	6.21	9.31
	Short-run	1.07	1.41	2.08	2.27	2.91	3.61	1.41	1.86	2.40	2.88	4.29	6.30	3.22	4.12	5.57	2.02	2.64	3.60	4.15	6.10	9.43
Exeter	Long-run	1.67	2.20	3.25	5.10	6.95	9.17	3.44	4.85	6.43	6.23	9.23	13.36	11.52	15.35	21.31	8.07	10.73	14.49	14.27	20.43	30.37
	Short-run	1.44	1.87	2.65	5.56	7.32	9.44	3.48	4.69	6.05	7.52	10.81	15.30	10.43	13.69	18.90	6.69	8.79	11.86	14.22	20.25	29.79
Glasgow	Long-run	1.23	1.62	2.35	2.29	2.99	3.74	1.52	2.08	2.77	2.74	3.97	5.64	3.85	4.85	6.42	2.57	3.38	4.60	4.62	6.45	9.36
	Short-run	1.07	1.37	1.92	1.85	2.32	2.82	1.12	1.48	1.92	2.43	3.41	4.75	2.56	3.18	4.13	1.57	2.04	2.72	3.41	4.70	6.72
Humberside	Long-run	1.78	2.59	4.75	5.24	7.88	11.02	3.34	5.46	8.49	6.78	10.48	14.73	14.45	20.56	32.55	9.11	14.36	24.25	19.61	27.41	41.86
	Short-run	1.49	2.09	3.47	5.74	8.01	10.78	3.35	5.10	7.61	8.31	11.85	15.91	12.19	16.83	25.35	7.03	10.78	17.49	18.35	24.85	36.39

(*continued on next page*)

Appendix B (*continued*)

Airport		Scale/ECU			MC (GBP)									AIC (GBP)									
					Full-service			Low-cost			Charter			Full-service			Low-cost			Charter			
		2.5%	Median	95%	2.5%	Median	95%	2.5%	Median	95%	2.5%	Median	95%	2.5%	Median	95%	2.5%	Median	95%	2.5%	Median	95%	
Leeds	Long-run	1.63	2.09	2.88	2.79	3.65	4.65	1.87	2.55	3.34	3.28	4.85	7.14	5.98	7.65	10.09	4.11	5.34	6.98	6.99	10.20	15.13	
	Short-run	1.36	1.68	2.19	2.25	2.79	3.41	1.39	1.79	2.24	2.89	4.11	5.89	3.77	4.70	6.00	2.38	3.01	3.84	4.86	6.94	10.06	
Liverpool	Long-run	1.43	1.82	2.46	1.98	2.57	3.24	1.37	1.79	2.26	2.27	3.40	5.09	3.64	4.68	6.17	2.61	3.26	4.15	4.18	6.23	9.48	
	Short-run	1.22	1.51	1.95	1.58	1.98	2.43	1.01	1.26	1.55	1.99	2.91	4.27	2.37	2.98	3.85	1.56	1.91	2.38	3.00	4.40	6.60	
London City	Long-run	1.37	1.69	2.18	3.39	4.16	4.95	2.07	2.89	4.02	3.78	5.53	8.01	5.93	7.04	8.49	3.55	4.90	6.82	6.50	9.36	13.56	
	Short-run	1.23	1.51	1.95	3.54	4.26	4.98	1.97	2.71	3.72	4.34	6.27	9.00	5.38	6.43	7.87	2.99	4.12	5.76	6.61	9.50	13.79	
London GW	Long-run	0.84	1.21	2.21	4.41	6.35	8.33	2.90	4.40	6.29	5.46	8.40	12.29	5.94	7.69	11.32	3.87	5.39	8.28	7.23	10.26	16.01	
	Short-run	0.75	1.10	2.05	3.70	5.23	6.84	2.24	3.33	4.71	5.05	7.70	11.15	4.40	5.75	8.73	2.63	3.70	5.83	5.99	8.53	13.60	
London HR	Long-run	0.72	1.11	2.44	9.76	15.47	21.00	6.34	10.69	16.35	11.80	20.36	32.15	13.11	17.12	27.62	8.11	12.04	20.64	14.97	23.00	40.42	
	Short-run	0.64	1.00	2.25	5.11	7.95	10.72	3.05	5.05	7.64	6.84	11.63	18.19	5.97	7.91	13.53	3.40	5.11	9.08	7.64	11.81	21.41	
London Luton	Long-run	1.12	1.48	2.19	3.58	4.75	6.03	2.45	3.31	4.28	4.17	6.30	9.43	5.54	7.07	9.44	3.88	4.92	6.53	6.41	9.41	14.32	
	Short-run	0.99	1.29	1.86	3.60	4.63	5.78	2.26	2.96	3.75	4.61	6.81	10.01	4.75	5.99	7.91	3.05	3.83	5.04	6.09	8.87	13.32	
London STN	Long-run	0.98	1.37	2.32	3.44	4.79	6.27	2.34	3.33	4.46	4.02	6.34	9.74	5.06	6.62	9.38	3.55	4.60	6.54	5.88	8.81	13.99	
	Short-run	0.86	1.18	1.91	2.53	3.39	4.33	1.59	2.17	2.81	3.28	4.98	7.52	3.12	4.02	5.58	2.01	2.57	3.58	3.99	5.95	9.25	
Manchester	Long-run	0.91	1.28	2.15	4.19	5.84	7.60	2.73	4.06	5.78	5.25	7.76	10.90	5.81	7.50	10.54	3.76	5.25	7.84	7.32	10.00	14.65	
	Short-run	0.82	1.15	1.97	3.46	4.76	6.13	2.08	3.03	4.27	4.81	7.01	9.75	4.24	5.52	7.96	2.53	3.54	5.35	5.95	8.16	12.19	
Newcastle	Long-run	1.35	1.72	2.36	3.33	4.29	5.32	2.18	2.98	3.98	4.03	5.69	7.90	5.88	7.39	9.58	3.89	5.15	6.92	7.22	9.82	13.73	
	Short-run	1.17	1.54	2.26	1.68	2.18	2.72	1.02	1.39	1.85	2.27	3.21	4.43	2.56	3.36	4.64	1.57	2.16	3.08	3.53	4.97	7.30	
Sheffield	Long-run	1.80	2.67	5.15	3.02	4.66	6.52	2.01	3.24	4.74	3.81	6.18	9.32	9.01	12.55	20.10	5.99	8.80	13.86	11.32	16.71	27.45	
	Short-run	1.48	2.10	3.61	2.84	3.96	5.27	1.73	2.53	3.50	3.95	5.84	8.38	6.25	8.39	12.60	3.84	5.39	7.99	8.70	12.41	19.33	
South ampton	Long-run	1.66	2.15	3.07	3.02	4.05	5.32	2.09	2.83	3.60	3.50	5.37	8.20	6.54	8.69	12.06	4.81	6.08	7.84	7.60	11.60	18.38	
	Short-run	1.37	1.76	2.47	3.18	4.15	5.35	2.06	2.66	3.28	4.07	6.12	9.23	5.52	7.31	10.14	3.72	4.68	6.12	7.08	10.82	16.96	
Southend	Long-run	0.00	4.37	66.29	0.00	12.61	30.20	0.00	8.72	21.90	0.00	17.00	38.69	0.00	62.79	578.4	0.00	43.93	401.1	0.00	84.84	781.9	
	Short-run	0.00	3.66	43.45	0.33	13.33	27.98	0.21	8.47	18.60	0.44	19.94	39.51	0.00	51.87	358.3	0.00	33.41	225.9	0.00	77.61	531.7	
Teesside	Long-run	1.71	2.67	6.04	3.73	6.05	8.51	2.47	4.19	6.32	4.69	8.00	12.41	11.57	16.22	28.66	7.59	11.42	20.02	14.31	21.70	39.61	
	Short-run	1.48	2.26	4.68	4.69	6.98	9.43	2.85	4.44	6.44	6.50	10.26	15.31	11.60	15.84	26.42	6.99	10.22	17.17	15.83	23.51	40.82	

$$\beta_5 + \beta_6 = 1;\ \gamma_7 + \gamma_8 = 0;\ \gamma_9 + \gamma_{10} = 0;\ \gamma_{11} + \gamma_{12} = 0;\ \delta_{13} + \delta_{14} = 0;\ \delta_{14} + \delta_{15} = 0;\ \tau_{26} + \tau_{27} = 0$$

$$paxh = pax + \psi_1 slcc + \psi_2 scha$$

References

Assaf, A., 2009. Accounting for size in efficiency comparisons of airports. Journal of Air Transport Management 15 (5), 256–258.
Assaf, A., 2010a. Bootstrapped scale efficiency measures of UK airports. Journal of Air Transport Management 16 (1), 42–44.
Assaf, A., 2010b. The cost efficiency of Australian airports post privatisation: a Bayesian methodology. Tourism Management 31 (2), 267–273.
Assaf, A., Gillen, D., Barros, C., 2012. Performance assessment of UK airports: evidence from a Bayesian dynamic frontier model. Transportation Research Part E 48 (3), 603–615.
BAA, 1982. Cost and Charging Study, BAA 76/82, October 1982. British Airport Authority.
BAA, 2001. BAA Response: The Use of Benchmarking, British Airport Authority.
Barros, C., 2008a. Technical efficiency of UK airports. Journal of Air Transport Management 14, 175–178.
Barros, C., 2008b. Technical change and productivity growth in airports: a case study. Transportation Research Part A 42, 818–832.
Barros, C., 2011. Cost efficiency of African airports using a finite mixture model. Transport Policy 18 (6), 807–813.
Barros, C., Weber, W., 2009. Productivity growth and biased technological change in UK airports. Transportation Research Part E 45 (4), 642–653.
Bottasso, A., Conti, M., 2012. The cost structure of the UK airport industry. Journal of Transport Economics and Policy 46 (3), 313–332.
CAA, 2001a. Economic Regulation and Incremental Costs. UK Civil Aviation Authority (February 2001).
CAA, 2001b. Peak Pricing and Economic Regulation. UK Civil Aviation Authority (November 2001).
CAA, 2003a. Economic Regulation of BAA London Airports. CAA Decision. UK Civil Aviation Authority (February 2003).
CAA, 2003b. Economic Regulation of Manchester Airport. CAA Decision. UK Civil Aviation Authority (March 2003).
CAA, 2003c. Go/Buzz/Ryanair on the CAA Recommendations to the Competition Commission: Stansted Price Cap 2003–2008. UK Civil Aviation Authority.
CAA, 2007. Airport Price Control Review – CAA Recommendations to the Competition Commission for Heathrow and Gatwick Airports. UK Civil Aviation Authority (March 2007).
CAA, 2011. Air Traffic Statistics. UK Civil Aviation Authority.
Carlin, A., Park, R., 1970. Marginal cost pricing of airport runway capacity. American Economic Review 60, 310–319.
Christensen, L., Jorgenson, D., Lau, L., 1973. Transcendental logarithmic production frontiers. Review of Economics and Statistics 55 (1), 28–45.
Competition Commission, 2002. Manchester Airport PLC: A Report on the Economic Regulation of Manchester Airport PLC. Competition Commission, London.
Competition Commission, 2009. BAA Airports Market Investigation: A Report on the Supply of Airport Services by BAA in the UK. Competition Commission, London.
Cuesta, R., 2000. A production model with firm specific temporal variation in technical inefficiency: with application to Spanish dairy farms. Journal of Productivity Analysis 13, 139–158.
Doganis, R., 1992. The Airport Business. Routledge, London.
Doganis, R., 2002. Consultancy Advice on Aviation Issues for the Department of the Taoiseach, Ireland. Rigas Doganis & Associates, London.
Doganis, R., Thompson, G., 1974. Establishing airport cost and revenue functions. The Aeronautical Journal 78, 285–304.
EC, 2001. White Paper: European Transport Policy for 2010: Time to Decide. European Commission.
Gillen, D., Forsyth, P., 2010. Airport Competition: The European Experience. Ashgate, Surrey.
Graniere, R., 1996. Almost Second-best Pricing for Regulated Markets Affected by Competition. The National Regulatory Research Institute. NRRI 96-10.
Griffin, J., Steel, M., 2007. Bayesian stochastic frontier analysis using WinBUGS. Journal of Productivity Analysis 27, 163–176.
Jara-Díaz, S., 2007. Transport Economic Theory. Elsevier, Amsterdam.
Keeler, T., 1970. Airport costs and congestion. The American Economist 14, 47–53.
Lei, Z., Papatheodorou, A., 2010. Measuring the effect of low-cost carriers on regional airports commercial revenue. Research in Transportation Economics 26 (1), 37–43.
Leigh-Fisher, 2011. UK Airport Statistics 2009/2010.
Link, H., Götze, W., Himanen, V., 2006. Estimating the Marginal Costs of Airport Operation by Using Multivariate Time Series with Correlated Error Terms. Institut für Verkehrswissenschaft Diskussionspapier Nr 11.
Lu, C., Pagliari, R., 2004. Evaluating the potential impact of alternative airport pricing approaches onsocial welfare. Transportation Research Part E 40, 1–17.
Lunn, D.J., Thomas, A., Best, N., Spiegelhalter, D., 2000. WinBUGS – a Bayesian modelling framework: concepts, structure, and extensibility. Statistics and Computing 10, 325–337.
Main, B., Lever, B., Crook, J., 2003. Central Scotland Airport Study. The David Hume Institute.
Martín, J.C., Voltes-Dorta, A., 2011a. The econometric estimation of airports' cost function. Transportation Research Part B 45 (1), 112–127.
Martín, J.C., Voltes-Dorta, A., 2011b. The dilemma between capacity expansions and multi-airport systems: empirical evidence from the industry's cost function. Transportation Research Part E 47 (3), 382–389.
Martín, J.C., Román, C., Voltes-Dorta A., 2006. Social Marginal Costs in Airports. Project GRACE. Deliverable 2.2. European Commission. <http://www.grace-eu.org/project.htm>.
Martín, J.C., Román, C., Voltes-Dorta, A., 2009. A stochastic frontier analysis to estimate the relative efficiency of Spanish airports. Journal of Productivity Analysis 31 (3), 163–176.
Martín, J.C., Román, C., Voltes-Dorta, A., 2011. Scale economies and marginal costs in Spanish airports. Transportation Research Part E 47 (2), 238–248.
Morrison, S., 1982. The structure of landing fees at uncongested airports – an application of Ramsey pricing. Journal of Transport Economics and Policy 16 (2), 151–160.
Morrison, S., 1983. Estimation of long-run prices and investment levels for airport runways. In: Keeler, T. (Ed.), Resarch in Transportation Economics I. JAI Press, Greenwich, pp. 103–130.
Morrison, S., Winston, A., 1989. Enhancing the performance of the deregulated air transportation system. Brookings Papers on Economic Activity: Microeconomics, 61–112.
NERA, 2001. The Application of Benchmarking to Airports Phase 1: Data Collection and Assessment: A Final Report for the Civil Aviation Authority, NERA, London.
ONS, 2010. UK Relative Regional Consumer Price levels for Goods and Services for 2010. Office for National Statistics.
Oum, T., Threteway, M., 1989. Hedonic versus general specifications of cost in translog functions. Logistics and Transportation Review 25 (1), 3–21.
Oum, T., Yan, J., Yu, C., 2008. Ownership forms matter for airport efficiency: a stochastic frontier investigation of worldwide airports. Journal of Urban Economics 64 (2), 422–435.
Parker, D., 1999. The performance of the BAA before and after privatisation. Journal of Transport Economics and Policy 33, 133–146.
Pels, E., Nijkamp, P., Rietveld, P., 2003. Inefficiencies and scale economies of European airport operations. Transportation Research Part E 39, 341–361.
Rendeiro, R., 1997. Airport pricing systems in Europe and an application of Ramsey pricing to Spanish airports. Transportation Research Part E 33 (4), 321–327.
Rendeiro, R., 2010. Ramsey pricing including CO_2 emission cost: an application to Spanish airports. Journal of Air Transport Management 16 (1), 45–47.

Please cite this article in press as: Voltes-Dorta, A., Lei, Z. The impact of airline differentiation on marginal cost pricing at UK airports. Transport. Res. Part A (2013), http://dx.doi.org/10.1016/j.tra.2013.08.002

Sharp, R., Starkie, D., Marchant, J., 2010. Airports Statistics 2008/2009. Centre for Regulated Industries, University of Bath.
Spady, R., Friedlaender, A., 1978. Hedonic cost functions for the regulated trucking industry. Bell Journal Economics 9, 159–179.
Starkie, D., 2008. Aviation Markets: Studies in Competition and Regulatory Reform. Ashgate, Aldershot.
Starkie, D., 2012. European airports and airlines: evolving relationships and the regulatory implications. Journal of Air Transport Management 21, 40–49.
Tolofari, S., Ashford, N., Caves, R., 1990. The Cost of Air Service Fragmentation. Department of Transport Technology, University of Loughborough.
Van der Broeck, J., Koop, G., Osiewalski, J., Steel, M., 1994. Stochastic frontier models: a Bayesian perspective. Journal of Econometrics 61, 273–303.
Voltes-Dorta, A., Pagliari, R., 2012. The impact of recession on airports' cost efficiency. Transport Policy 24, 211–222.
Zhang, A., Zhang, Y., Clougherty, J., 2011. Competition and regulation in air transport. In: de Palma, A., Lindsey, R., Quinet, E., Vickerman, R. (Eds.), A Handbook of Transport Economics. Edward Elgar, Northampton.

Please cite this article in press as: Voltes-Dorta, A., Lei, Z. The impact of airline differentiation on marginal cost pricing at UK airports. Transport. Res. Part A (2013), http://dx.doi.org/10.1016/j.tra.2013.08.002