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Highlights

▶ This paper identifies the key drivers of airport cost flexibility in a recession context. ▶ The industry's short-run cost frontier is estimated using a worldwide airport sample. ▶ Average airport efficiency dropped 5.85% between 2007 and 2009. ▶ A higher level of outsourcing is shown to reduce cost flexibility. ▶ The share of low-cost flights is shown to improve cost flexibility. ▶ Airline dominance drags down flexibility of congested airports. ▶ Airports with mixed public–private ownership are the least flexible in costs.

Determinants of airport cost flexibility in a context of economic recession

Q1 Juan Carlos Martín [a], Héctor Rodríguez-Déniz [a], Augusto Voltes-Dorta [b,*]

[a] Universidad de Las Palmas de Gran Canaria, 35017 Las Palmas de Gran Canaria, Spain
[b] Universitat de Barcelona, Facultat d'Economia i Empresa, 6330, 08034 Barcelona, Spain

ABSTRACT

The recent economic downturn led to a significant contraction in the global demand for air travel and cargo. In spite of that, airports' operating costs did not mirror the traffic trends and kept increasing during the same period, showing evident signs of lack of flexibility. With this background, this paper aims at identifying the drivers of airport cost flexibility in a context of economic recession. This is done by estimating a short-run stochastic cost frontier over a balanced pool database of 194 airports worldwide between 2007 and 2009. Using the total change in cost efficiency during the sample period as a proxy for cost flexibility, the impact of variables such as ownership, outsourcing, airline dominance, low-cost traffic, and revenue diversification is tested in a second-stage regression. Contrary to the existing literature, a higher level of outsourcing is shown to reduce cost flexibility. Results also indicate that low-cost traffic, diversification, and corporatization increase the airports' ability to control costs. The negative impact of airline dominance suggests the need for more stringent regulations on slot allocation at congested airports in order to ensure optimal infrastructure usage.

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1. Introduction

The recent economic downturn has taken a significant toll on the air transport industry. After a period of sustained growth between 2002 and 2007, worldwide passengers stagnated in 2008 and declined by 1.8% in 2009 (see Fig. 1). Regarding global air cargo, total metric tons fell by 3.7% in 2008 and by 7.9% in 2009. While some regions, such as Asia–Pacific, kept growing despite the global recession – thriving on their booming domestic markets – the major traffic losses were concentrated in North America and Western Europe (Airbus, 2009).

As demand contracted, air carriers in the affected regions promptly reacted by reducing capacity in non-profitable routes to protect load factors and yields (ATA, 2010). In spite of the airports' efforts to develop their non-aviation business, the decreasing traffic trend was a leading cause for the falling airport revenues (ACI, 2011). Airports Council International notes that total industry income declined by 2% between 2008 and 2009, from 96 to 94.5 billion USD. On the cost side, however, a similar trend is not observed. Even under a significant reduction in traffic, industry operating costs (not considering capital expenses) increased by 3.6% in the same period, from 55 to 57 billion USD. This includes labor and external charges, typically considered the only variable costs of airports (Oum et al., 2008).

This contradiction between traffic and costs motivates this research. Airports are particularly infrastructure-intensive, which leads to massive investments and indivisibilities. The presence of these technological fixities has been traditionally

* Corresponding author. Tel.: +34 93 403 97 33; fax: +34 93 402 45 73.
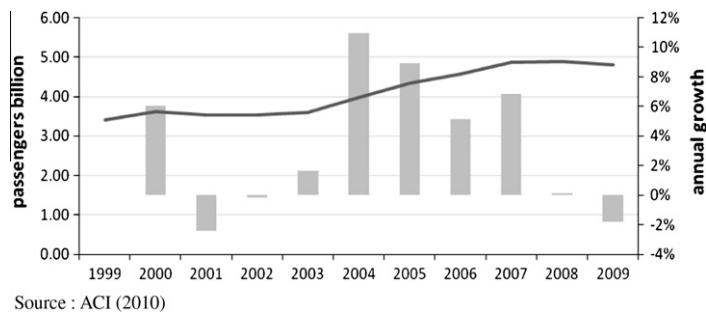E-mail address: avoltes@ub.edu (A. Voltes-Dorta).

Source : ACI (2010)

Fig. 1. Total worldwide passengers 1999–2009.

linked to lack of flexibility of airports in adjusting their input demands (especially the capital stock) to the evolving traffic levels (Graham, 2008). This is particularly obvious during expansive times, as airport capacity typically increases stepwise and always beyond existing demand. However, the figures discussed above suggest that airports are not being flexible during bad times either, and since capital costs were not included, one may argue for the existence of non-technological factors to explain this behavior: factors that may not manifest during expansive times or whose influence is exacerbated by the contraction in demand. The impact of this behavior on cost efficiency, regardless of the actual factors, is bound to be significant as it appears difficult to justify such increase in variable costs out of a falling traffic level.

With this background, the objective of this paper is precisely to identify the drivers of airport cost flexibility in a context of economic recession. This is done by estimating a short-run stochastic cost frontier over a balanced pool database of 194 airports worldwide between 2007 and 2009. Using the total change in cost efficiency during the sample period as a proxy for cost flexibility, the impact of variables such as ownership, outsourcing, airline dominance, low-cost traffic, and revenue diversification is tested in a second-stage regression. Results and policy implications are likely to be of interest for airport regulators and practitioners, especially in the present context of privatization and corporatization (Sarkis and Talluri, 2004). In addition, any policy lesson aimed at increasing flexibility can lead to cost savings which become crucial as airports struggle to maintain service quality through the recession.

The rest of this paper is organized as follows: Section 2 presents a literature review on the estimation of airport cost frontiers and determinants of airport efficiency. Section 3 introduces our cost frontier methodology and the second-stage regression. Section 4 describes the worldwide airport sample and data sources. Section 5 presents the results and discusses the policy implications. Finally, Section 6 summarizes the main findings.

2. Literature review

The latest recession provides a unique background for this empirical exercise, as financial data on airports became increasingly available at a time when they were much challenged to control costs and remain flexible. Also note that, while past studies adopted a static approach, this contribution is novel in the sense that the variable of interest is not the efficiency level on a certain year, but the variation in efficiency across a time period (proxy for cost flexibility). In spite of that, a high level of agreement with the previous studies is expected, as the most efficient airports would likely also be the most flexible in costs.

Table 1 summarizes all previous contributions and allows for a quick identification of the most relevant drivers of airport performance. Starting with the empirical paper by Parker (1999), who proposed a comparative study on the efficiency of UK airports before and after privatization, ownership has been the most widely studied determinant of airport efficiency. Perhaps the most comprehensive study on the subject is Oum et al. (2008). They analyzed the impact of ownership on airport cost efficiency worldwide using a high level of disaggregation in the variable of interest. Their results were in line with other previous contributions, as there seems to be a general consensus about the potential benefits of airport privatization, along with any movement towards increased corporatization.

The role of the airport and the scale of production are the next most common variables and they usually aim to characterize the difference between large hubs and small regional airports. In that respect, the consensus is that large airports tend to operate more efficiently than smaller ones, especially those serving less than 1 million annual passengers. This is arguably a consequence of significant returns to scale in airport operations (see, e.g. Martín et al., 2009). Similarly, Barros (2008) concluded that major hubs in Argentina had been relatively immune to the financial crisis while small airports appeared to be more vulnerable.

Q3   The impact of the level of outsourcing on airport performance was first explored by Oum et al. (2003), yet only Tovar and Rendeiro (2009) obtained enough evidence to conclude that outsourcing increased airport efficiency by allowing more flexibility and enabling the airport operators to focus on their core competencies. Since the actual variable is very difficult to measure, it is usually proxied by the share of "materials" costs. A similar consensus exists about the benefits of diversification (proxied by the share of commercial over total revenues) as airports can take advantage of the evident demand

Table 1
Determinants of airport productivity and efficiency.

Author(s)	Data sample	Method	Drivers
Gillen and Lall (1997)	21 US; 89–93	DEA	Airport type
Parker (1999)	22 UK; 88/89–96/97	DEA	Ownership
Sarkis (2000)	44 US; 90–94	DEA	Airport type
Pels et al. (2003)	34 Europe; 95–97	DEA/SPF	Ownership
Oum et al. (2003)	52 World, 99	TFP	Ownership, scale, diversification, outsourcing, service quality
Oum et al. (2004)	76 World; 00–01	VFP	Ownership, scale, diversification, outsourcing, service quality
Pathomsiri and Haghani (2004)	63 World; 00 & 02	DEA	Airport type, 9/11
Yoshida and Fujimoto (2004)	67 Japan; 00	DEA/TFP	Airport type
Craig et al. (2005)	52 US; 70–92	LRCF	Ownership
Pathomsiri et al. (2005)	72 World; 00 & 02	DEA	Airport type, 9/11
Oum et al. (2008)	109 World; 01–04	SCF (SR)	Ownership
Curi et al. (2008)	Italy; 00–04	DEA	Ownership
Barros (2008)	32 Argentina, 03–07	DEA	Airport type, scale
Barros and Dieke (2008)	31 Italy, 01–03	DEA	Ownership, Airport type
Fung et al. (2008a)	25 China; 95–04	DEA/MI	Ownership, Airport type
Fung et al. (2008b)	41 China; 02	DEA/TFP	Ownership, Airport type
Tovar and Rendeiro (2009)	26 Spain, 93–99	IDF	Outsourcing, diversification
Chow and Fung (2009)	46 China, 00	IDF	Airport type
Assaf (2010)	13 Australia, 02–07	SCF (LR)	Ownership, price regulation
Abrate and Erbetta (2010)	26 Italy, 00–05	IDF	Outsourcing, diversification
Perelman and Serebrinsky (2010)	148 World 95–07	DEA	Ownership, economic development, demographics, airport type
Martín et al. (2009)	37 Spain, 91–97	SCF (LR)	Scale
Martín and Voltes-Dorta (2011)	161 World, 91–08	SCF (LR)	Ownership, price regulation
Tsekeris (2011)	39 Greece, 07	DEA	Seasonality, Scale
Curi et al. (2011)	18 Italy, 00–04	DEA	Scale, diversification, price regulation, airport competition
Barros (2011)	17 African, 00–10	SCF (LR)	Scale
Martín et al. (present study)	194 World, 07–09	SCF (SR)	Ownership, outsourcing, diversification, airline dominance, low-cost traffic, scale

DEA: Data Envelopment Analysis; TFP: Total Factor Productivity; VFP: Variable Factor Productivity; SFA: Stochastic Frontier Analysis; SPF: Stochastic Production Frontier; SCF: Stochastic Cost Frontier; IDF: Input Distance Function; DDF: Directional Distance Function; MI: Malmquist Index; LR: Long-run; SR: Short-run.

complementarity between air travel and commercial activities. Besides all of the above, this paper considers additional variables not previously covered in the literature, such as airline dominance and traffic mix, with special attention to low-cost carriers and their impact on airport development.

From a methodological perspective, it is clear that a dual approach to efficiency (i.e. cost minimization) is required in order to characterize airport behavior during the latest recession. In that regard, the econometric estimation of stochastic cost frontiers (SCFs) is proposed as a suitable approach, preferable to other methods such as Data Envelopment Analysis (DEA), or Total Factor Productivity (TFP). Even though SCF models require a large sample to yield robust results, they can easily accommodate multi-production, panel data, and can also be adapted to a short-run context[1] (Jara-Díaz, 2007). These three features make SCF clearly suitable for out data and research purposes.

Airport SCFs are scarce in the literature because early studies did not consider their sample airports to behave inefficiently, which led them to specify deterministic cost functions instead (see, e.g. Doganis and Thompson, 1974; Tolofari et al., 1990). Recent examples of airport SCFs are Martín et al. (2009) for Spanish airports, or Barros (2011), who used a small sample of African airports. These papers, however, do not provide results that are easily generalizable due to their small databases. Taking into account that the recession has affected many regions, a comparable empirical study must feature a large number of airports worldwide. In that respect, two papers can be cited as suitable methodological references. Oum et al. (2008) provided the first example of a short-run airport SCF estimated over a pool of 109 airports worldwide between 2001 and 2004. They discussed the difficulties in collecting comparable financial data for such a large sample, but it does not provide a satisfactory solution for the problem of calculating input prices. Martín and Voltes-Dorta (2011) collected data on 161 airports worldwide between 1991 and 2008. The increase in observations allowed them to improve the (long-run) SCF estimation methodology with the specification of five outputs, the inclusion of aircraft weight as a hedonic adjustment

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[1] SCF models only consider those costs that the airports would theoretically be capable of controlling in the short-run, such as labor and utilities, as opposed to long-run models where capital costs are also considered. The short-run approach also avoids introducing endogeneity in the model as airports delay capital investments by anticipating the contraction in demand.

119 of aircraft operations, a new method to calculate input prices, and the joint specification of technical and allocative
120 inefficiencies.
121 Taking all into consideration, we decided to adapt the SCF method from Martín and Voltes-Dorta (2011) to a short-run
122 context by dropping capital costs from the analysis. A balanced pool database of 194 airports worldwide between 2007
123 and 2009 will be used, featuring a wide variety of airport sizes and output mixes. The present study is appended in Table
124 1 in order to help placing the proposed contribution within the airport efficiency research.

3. Methodology

3.1. Short-run cost frontier

127 The econometric estimation of a short-run cost frontier requires data on variable costs (VC), outputs $\{Y \in \mathbb{R}_+^J\}$, input
128 prices ($\omega \in \mathbb{R}_+^H$) and fixed factors ($K \in \mathbb{R}_+^M$) of airports whose behavior is assumed to be cost-minimizing. The preferred func-
129 tional form is the transcendental logarithmic-translog (Christensen et al., 1973), which is the most commonly used in this
130 kind of empirical studies. A second-order translog expansion of a short-run variable cost function presents this general
131 structure:
132

$$lnVC = \alpha_0 + \sum_j \alpha_j lny_j + \sum_h \beta_h ln\omega_h + \sum_m \varphi_m lnK_m + \sum_h \sum_j \gamma_{hj} ln\omega_h lny_j + \sum_i \sum_m \gamma_{hm} ln\omega_h lnK_m + \sum_j \sum_m \gamma_{jm} lny_j lnK_m$$
$$+ \sum_j \sum_{k \neq j} \rho_{jk} lny_j lny_k + \sum_h \sum_{l \neq h} \rho_{hl} ln\omega_h ln\omega_l + \sum_m \sum_{n \neq m} \rho_{mn} lnK_m lnK_n$$
$$+ \frac{1}{2} \left[\sum_j \sum_j \rho_{jj} lny_j lny_j + \sum_h \sum_h \rho_{hh} ln\omega_h ln\omega_h + \sum_m \sum_m \rho_{mm} lnK_m lnK_m \right] + \varepsilon \tag{1}$$

135 where ε denotes statistical disturbance, and the subscripts $j = (1, \ldots, J)$, $h = (1, \ldots, H)$, and $m = (1, \ldots, M)$.
136 The translog equation is typically estimated jointly with its cost-minimizing input shares (s) by means of a Seemingly
137 Unrelated Equations Regression – SURE (Zellner, 1962). Input share equations are easily obtained by differentiating the cost
138 frontier (Eq. (1)) with respect to logged prices and applying Shephard's Lemma[2]:
139

$$s_h = \frac{\omega_h x_h}{VC} = \frac{\partial VC}{\partial \omega_h} \frac{\omega_h}{VC} = \frac{\partial lnVC}{\partial ln\omega_h} = \beta_h + \sum_j \gamma_{hj} lny_j + \sum_m \gamma_{hm} lnK_m + \sum_l \rho_{hl} ln\omega_l + \rho_{hh} ln\omega_h \tag{2}$$

142 If panel data is available, the model can be completed with the time variable (t) in order to account for technological
143 change in the industry (Stevenson, 1980).
144 A variable cost function provides insight on several technological indicators of interest from both management and policy
145 perspectives. The partial derivative of logged costs with respect to a logged output leads to the same output's cost elasticity
146 (η). The inverse of the sum of all specified outputs' cost elasticities leads to the airport's degree of economies of capacity uti-
147 lization (ECU). A value of ECU > 1 indicates that the airport is operating with excess capacity and there are opportunities for
148 reducing average operating costs by increasing the output. On the contrary, a value of ECU < 1 indicates that the airport has
149 pushed its output level beyond maximum capacity and it is experiencing increasing average operating costs a cause of it (e.g.
150 congestion, delays, etc.). Expansion should be considered at this stage. Finally, ECU = 1 indicates that, in theory, the airport is
151 operating at optimal capacity.
152

$$\eta_j = \frac{\partial lnVC}{\partial lny_j} \quad ECU = \frac{1}{\sum_j \eta_j} \tag{3}$$

155 Following Martín and Voltes-Dorta (2011), our short-run cost model features five outputs: commercial aircraft movements
156 (ATMs), domestic/Schengen passengers (dom), international/transborder passengers (int), metric tons of cargo (cgo), and
157 commercial revenues (rev) – measured in Purchasing Power Parity USD –. Furthermore, ATMs will be hedonically adjusted
158 (ATMh) using the airport's average landed Maximum Take-Off Weight (MTOW) as a quality variable.[3] This technique was
159 developed in the seminal paper of Spady and Friedlaender (1978):
160

$$lnATMh = lnATM + \psi \cdot lnMTOW \tag{4}$$

163 where $\psi > 1$ indicates that ATM-related costs increase more than proportionally with aircraft weight.
164 The cost function also features two input prices: materials (ω_m), and labor/personnel (ω_p). The price of labor is obtained
165 by dividing labor costs by the full-time equivalent employees (ftes) of the airport authority. The calculation of the price of
166 materials is more complex: materials costs are divided by a quantity index based on marginal productivity ratios, calculated
167 among a predefined set of inputs assumed to represent the airport's overall demand for utilities and maintenance ("shadow

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[2] Differentiating costs with respect to an input price leads to the same input demand function (Shephard, 1953), i.e. $\frac{\partial C}{\partial \omega} = x$.
[3] Average MTOW is calculated as total landed weight divided by total ATMs.

168 inputs"). Marginal productivities are estimated from a ray production frontier provided by the reference paper.[4] The "sha-
169 dow" inputs considered were check-in desks, boarding gates, and total warehouse area.

170 As prices are related to the observed costs, they reflect each airport's specific circumstances (i.e., labor policies, scope of
171 outsourcing, leased terminals, etc.). This reduces the need for data homogenization and, provided there are enough sample
172 airports with the same internal characteristics, it allows for fair efficiency comparisons between airports from different
173 regions.[5]

174 Regarding fixed factors (K), our paper follows the approach from Martín et al. (2011) and includes both terminal floor area
175 (ter) and total runway length (run).

176 In addition, it is likely that some, if not all, sample airports have incurred in technical and/or allocative inefficiencies (AI)
177 during the period under study.[6] Both impacts can easily be included the model. For example, an additional disturbance term (u)
178 can be introduced in order to account for technical inefficiency, leading to a stochastic frontier specification (Aigner et al., 1977).
179 The impact of AI on operating costs is formulated using the shadow price method of Kumbhakar (1997). This method introduces
180 an allocative distortion (ξ) in the price vector, i.e. $\omega = [\omega_m, \omega_p e^{\xi}]$, that represents input over- or under-use given the observed
181 prices. The resulting specification, however, is non-linear in parameters and thus too complex to be estimated using classical
182 techniques. In these cases, Bayesian inference and numerical models are the preferred alternative (Van der Broeck et al.,
183 1994). For its simplicity, the WinBUGS software (Lunn et al., 2000) will be used in that task, as well as the codification proposed
184 in Griffin and Steel (2007). This assumes that the dependent variable (i.e. the logarithm of variable costs) is normally distributed,
185 with the aforementioned translog equation as the mean and σ_v^2 as the white noise variance:

188
$$lnVC_{it}^a \sim N(lnVC_{it}^0(\omega, Y, K, \psi, t) + lnVC_{it}^{AI}(\omega, Y, K, \psi, t, \xi) + u_{it}, \sigma_v^{-2}), \tag{5}$$

189 where VC^a represents actual costs, VC^0 is the cost frontier (i.e. minimum cost), VC^{AI} represents the percentage increase in
190 costs linked to the allocative distortions (ξ), and u is a positively-valued error term measuring technical inefficiency. Once
191 the corresponding partial derivatives are taken, factor share equations present a similar structure.[7]

192 The parameter of technical inefficiency u is allowed to vary systematically over time allowing firm-specific effects ζ_i, as in
193 Cuesta (2000), i.e.

196
$$u_{it} \sim \exp\{\zeta_i(t - T)\}u_i, \quad \text{where } u_i \sim \exp(\lambda) \tag{6}$$

197 Note that a negative ζ_i indicates that the airport increases efficiency over time (T is the baseline year 2007). Thus, u_{it} de-
198 noted technical inefficiency of firm i in time period t. The firm's average inefficiency u_i is assumed to be exponentially dis-
199 tributed with mean λ^{-1}.

200 Prior distributions must be assigned to the parameters. The cost frontier coefficients (β) follow a non-informative normal
201 distribution with zero mean and infinite variance.[8] In the same spirit, a gamma distribution (0.01,0.001) is assigned to the
202 white noise inverse-variance. The distributional structure of technical inefficiency, via the λ parameter, allows us to impose
203 prior ideas about mean efficiency (r^*) in the airport industry. This is set at 0.854 as indicated in Martín and Voltes-Dorta
204 (2011). The allocative distortion ξ is specified as a normally distributed variable with mean zero and inverse-variance 18, based
205 on the notion that average AI is likely to be small (Kumbhakar and Tsionas, 2005) and input proportions are not expected to
206 deviate more than twice from the optimal ones. The prior distribution of ζ_i was also chosen to be a zero-mean normal distri-
207 bution representing the prior indifference, despite the recession, between increasing or decreasing efficiency at each airport.
208 An inverse-variance of 10 allows for a reasonable spread. The same applies to the ψ coefficient of the hedonic ATM equation
209 that is assigned a uniform distribution $U(0,2)$.

212
$$\beta \sim N(0,0), \sigma_v^{-2} \sim G(0.01, 0.001), \lambda \sim \exp(-logr^*), \xi \sim N(0,18) \quad \zeta_i \sim N(0,10), \psi \sim U(0,2) \tag{7}$$

213 Since the estimation process will benefit from any additional information that can be added to the cost system and no col-
214 linearity problems will arise in this kind of Bayesian estimation, both factor share equations (materials and labor) are in-
215 cluded. The full model specification is shown in Appendix A. It features a second-order Taylor expansion of the cost
216 frontier (see Eqs. (1) and (5)), the hedonic ATM equation, the corresponding factor shares, plus an additional expression
217 G_{it} (Kumbhakar, 1997), that characterizes the impact of AI on factor shares. Note that all explanatory variables are logged
218 and deviated with respect to their sample means. The model is completed with parametric restrictions to impose linear
219 homogeneity in input prices.

---

[4] See Appendix B in Martín and Voltes-Dorta (2011).
[5] German airports tend to perform a wider range of core activities in-house, which inevitably leads to higher operating costs than similar airports in other countries. However, the application of this calculation method leads to higher input prices, which, in turn, will also translate to higher frontier costs. In this way, each airport faces a cost frontier that adapts to its particular cost structure.
[6] The airport is said to be technically inefficient if, given an output target and the actual input proportions, it fails to achieve the minimum operating cost. Furthermore, the airport will be allocatively inefficient if there is an alternative input combination that would reduce costs even further.
[7] Note that technical inefficiency does not affect factor shares as all inputs are overused in the same proportion.
[8] Normal distributions in Eq. (7) follow WinBUGS' notation: N(mean, inverse-variance).

Table 2
Drivers of cost flexibility: linear correlation matrix.

	eff07	varpax	mppa	ssm	srev	scha	slcc	hh	mtow
eff07	1.00	0.15	0.19	0.18	0.14	−0.06	0.04	−0.05	0.23
varpax	0.15	1.00	0.04	0.00	−0.19	−0.06	0.11	−0.05	0.21
mppa	0.19	0.04	1.00	0.11	−0.03	−0.37	−0.14	−0.07	0.42
ssm	0.18	0.00	0.11	1.00	−0.01	−0.17	0.00	−0.06	0.11
srev	0.14	−0.19	−0.03	−0.01	1.00	0.17	0.17	−0.02	−0.05
scha	−0.06	−0.06	−0.37	−0.17	0.17	1.00	−0.14	0.22	−0.16
slcc	0.04	0.11	−0.14	0.00	0.17	−0.14	1.00	−0.05	0.04
hh	−0.05	−0.05	−0.07	−0.06	−0.02	0.22	−0.05	1.00	−0.19
mtow	0.23	0.21	0.42	0.11	−0.05	−0.16	0.04	−0.19	1.00

3.2. Second-stage regression

Once the cost frontier is estimated, the change in efficiency for the individual airports will be regressed against several institutional and external factors, similar to those used in the past to explain airport efficiency. As mentioned in the introduction, ownership is the most commonly studied variable and the airport sample features eight different forms: (i) public–individual, i.e. a single airport managed by the municipal Department of Aviation (e.g. Atlanta); (ii) public–group, which can be either a multi-airport system or an airport group under public ownership (e.g. Manchester Airport Group); (iii) public-corporation: typically an evolution of the public–individual case, when a new Airport Authority is created as an independent body with increased commercial orientation (e.g. Graz); (iv) port authority: typical of the US, these corporations manage all airports and seaports in a metropolitan area (e.g. Seattle); (v) public–private partnership (e.g. Vienna); (vi) long-term concessions, either publicly or privately owned (e.g. Canada, Australia); (vii) privatized-individual (including minority public shares); and (viii) privatized-group (e.g. British Airport Authority – BAA). These will be introduced as dummy variables into the model, with public–individual used as the reference category.

Additional drivers of cost flexibility considered in this stage are: the Hirschman–Herfindal index of airline traffic shares (hh), the share of charter traffic (scha) and share of low-cost carrier flights (slcc). Instead of using a hub/non-hub dummy variable, the airport size and its role are measured by annual passenger traffic in millions (mppa), as well as the average landed Maximum Take-off Weight (mtow). It is assumed that large hubs will combine high passenger throughput with heavier aircraft for long-haul routes.[9] In addition, this allows us to consider separate effects for landside and airside infrastructures. Outsourcing and diversification are proxied by the share of "materials" costs (ssm), and the share of commercial over total revenues (srev). In order to allow for fair comparisons between airports affected by the recession in different ways, the variation in passenger traffic between 2007 and 2009 (varpax) is also included. The model is completed with the pre-crisis efficiency level (eff07) and the corresponding geographical dummies (Asia–Pacific and Europe), which are included to account for differentiated effects across regions.[10] All variables, except when indicated, refer to the year 2009.

Table 2 shows the linear correlation matrix between all non-binary explanatory variables in order to evaluate any possible threat of multicollinearity in the specification. It is clearly seen that no strong relationships are present as even the correlation between passenger traffic and aircraft size (a priori the most evident) is only 42%.

The variation in economic efficiency (eff) between 2007 and 2009 is used as a proxy for cost flexibility (flex), which is then specified as dependent variable in a linear regression model:

$$FLEX_i = eff_{09} - eff_{07} = \alpha_0 + \sum_j \alpha_j Z_{ij} + \varepsilon_i, \tag{8}$$

where Z is a vector including all of the above-mentioned regressors. The Bayesian estimation was used again, with similar distributional assumptions than the cost frontier (i.e. normally distributed parameters, Gamma disturbance, etc.).

4. Database and data sources

The cost frontier was estimated over a balanced pool database of airports worldwide between 2007 and 2009 (582 observations). The sample period was chosen to cover those years were the impact of the global crisis on air traffic was more severe,[11] as the first signs of recovery were observed during the first quarter of 2010 (Eurostat, 2011). Taking into account that the major traffic losses were recorded in the mature markets in North America and Europe, the airport sample is clearly biased

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[9] Cargo hubs, on the other hand, will combine smaller passenger traffic with even heavier aircraft size.

[10] Price regulation and service quality have also been used as drivers of airport efficiency but they could not be included in this paper because of data restrictions.

[11] One could argue for the time series to be broader in scope in order to provide the necessary contrast in cost flexibility between growth and recession periods. Even though data was available, this idea was dropped because flexibility during expansive times was considered a long-run problem that shifts to short-run cost minimization if demand does not grow as planned. For obvious reasons, the second approach is the one featured in this paper and therefore, the sample period was restricted to the economic recession, using 2007 as a baseline.

Table 3
Overview of the airport sample: variable costs, outputs, and fixed factors.

	vc (PPP'000)	atm	dom	int	cgo (t)	Rev (PPP'000)	mtow (t)	ter (sqm)	run (m)	fte
max	1,708,449	981,402	80,858,789	63,323,180	3,840,941	1,080,547	397	1,382,000	24,505	13,979
min	831	1,528	0	0	0	242	15	500	1508	11
mean	117,054	168,332	9,563,645	3,953,147	284,364	85,828	63	125,996	6504	699
geom	–	92,660	2,707,787	453,255	39,657	38,738	–	56,924	5359	–
std	179,786	171,394	12,494,829	7,880,956	576,752	125,984	34	160,413	4134	1262

to these regions.[12] The geographical breakdown of the 194 airports is as follows: 72 observations from North America, 106 from Europe, and 16 from Asia–Pacific and Oceania (See Appendix B).

According to the methodological requirements outlined in the previous section, data collection was completed for the following variables: (i) variable costs (vc): labor (lab) and materials (mat); (ii) Outputs: Domestic-Schengen (dom) and international passengers (int), air transport movements (atm), average landed Maximum Take-off Weight (mtow), metric tons of cargo (cgo), and non-aviation revenues (rev); (iii) Fixed factors: gross floor area in m^2 of terminal buildings (ter), total runway length in m (run), total number of boarding gates (gat), check-in desks (chk), and warehouse area (war); (iv) Other: time (t), full-time equivalent employees (fte), Hirschman–Herfindahl index of airline traffic shares (hh), share of charter traffic (scha), share of low-cost traffic (slcc) and ownership form. All monetary variables were converted to 2009 Purchasing Power Parity (PPP) USD using OECD's exchange rates.

Labor costs include all types of employee compensation, such as salaries and wages, retirement, and health benefits. "Materials" costs include maintenance, utilities, external services and other administrative expenses. Note that these costs include all activities performed in-house, which vary widely across airports. Section 3 discussed how the calculated input prices take this heterogeneity into account.

Regarding financial data sources, the observations were mainly extracted from annual reports and financial statements published online by the respective airport authorities. In certain cases (i.e. UK, France and Turkey) comprehensive financial reports at a country level were consulted, produced by either academic institutions (Sharp et al., 2010) or by the respective Civil Aviation Authorities (DHMI, 2010; DGAC, 2010). For the US sample, besides the annual reports, the main source is the CATS financial database provided online by the Federal Aviation Administration (FAA, 2011). Additional data on costs and revenues for specific airports (e.g. Portugal, Japan, Romania, and Ukraine) is available online from ICAO/ATI statistics portal (ICAO, 2011). Even though most annual reports follow the International Financial Reporting Standards (IFRS), efforts were made to improve comparability.[13] Regarding the other variables, in most cases airports' annual reports and master plans provide enough data on traffic activity and infrastructure. Other relevant sources are: ACI World Airport Traffic Reports WATR 2007–2009 (ACI, 2011), ICAO/ATI Airport Traffic Summary reports (ICAO, 2011), and IATA Airport Capacity and Demand profiles 2003 (IATA, 2003). Average landed MTOW, airline concentration, and the shares of charter and low-cost flights were calculated using data on ATMs disaggregated by either aircraft type or published operator from the Official Airline Guide iNet Schedules tool (OAG, 2011).[14]

Table 3 provides the mean, range, and std. deviation of the most important variables for the cost function estimation: variable costs, outputs, and fixed factors. The scale of production ranges between 1500 annual ATMs at Carcassonne (Southern France) in 2009, to slightly over 980,000 ATMs at Atlanta in 2007. The average sample airport serves about 168,000 annual ATMs, 9.5 million domestic and 3.9 million international passengers, as well as 284,000 tons of cargo. Geometric means are smaller yet also relevant as they provide the approximation point for the translog cost function that will be estimated in the next section. In total, the 194 sample airports served 2.44 billion passengers and 46.5 million metric tons of cargo in 2009, which represent 50% and 58% of worldwide traffic, respectively.

Fig. 2 provides a snapshot of the airport sample, showing the percent change in operating costs against the variation in passenger and cargo traffic between 2007 and 2009 for the most important geographical clusters. This figure illustrates the uneven impact of the economic recession on airports worldwide, thus providing the necessary heterogeneity that will support the empirical identification of the drivers of airport cost flexibility. Furthermore, it is clearly seen that all regions had problems to control operating costs during the sample period. The picture is clear for the mature markets in North America and parts of Europe as traffic and costs evolved in opposite directions. In developing regions, however, the flexibility problem is still present. Assuming the existence of economies of capacity utilization in the airport industry (see, e.g. Oum et al., 2008), operating costs should not increase, under optimal conditions, more than proportionally than traffic. In view of this evidence, the main conclusion is that the airport industry has not been flexible enough to adjust capacity to demand and significant efficiency losses can be expected, the estimation of which is the objective of the next section.

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[12] The availability of financial data was the main criterion for inclusion in the database and it explains the absence of some large European hubs.

[13] Homogenization of reporting periods (financial vs calendar year) was not possible. However, this issue was taken into account when specifying the time variable in the cost function specification.

[14] Since OAG only accounts for scheduled ATMs, charter flights are obtained by subtracting the OAG figure to the total ATMs. They are then assigned a representative aircraft for the MTOW calculations, defined for each airport in relation to their major charter operator's fleet (typically A320 or B737).
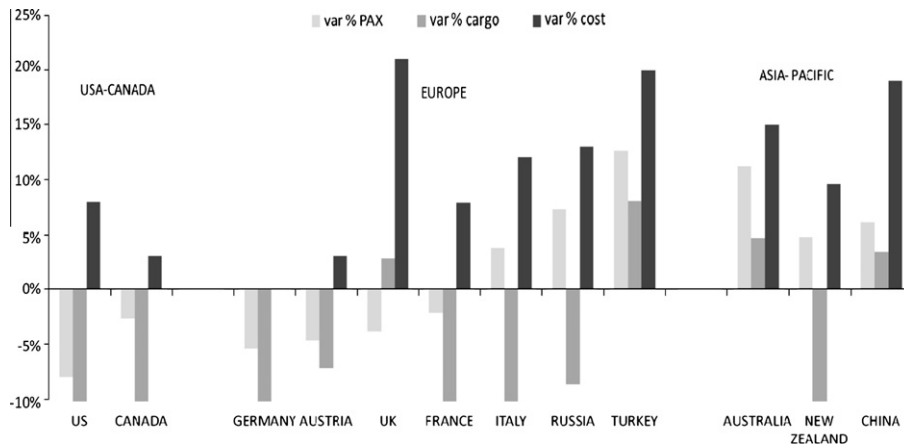
Fig. 2. Total costs vs passenger and cargo traffic 2007–2009.

5. Results and discussion

5.1. Cost frontier and efficiency

The results of the Bayesian estimation are shown in Table 4. The R^2 coefficient (built in the estimation code) has an average value of 0.928, which indicates excellent goodness-of-fit of the proposed model. In addition, the standard F-test against global significance is clearly rejected. The posterior densities of the cost function coefficients are characterized by their means and standard deviations. From these values it is straightforward to show (using a t-ratio test) that the vast majority of parameters (35 out of 39) are significantly different from zero at a 95% confidence level. The first-order output variables all have the expected positive signs. Apart from that, and since it was imposed in the estimation code, linear homogeneity in variable input prices also holds in the approximation point, as proven by a built-in Wald test (probability = 0.78) on the first-order price coefficients.

The coefficients associated to the fixed factors are significant, implying the existence of some degree of short-run disequilibrium. The indicator of economies of capacity utilization (ECU) at the average airport is calculated as the inverse of the sum of the first-order output coefficients. This yields 2.13, showing a significant degree of excess capacity in the airport industry. Additional conclusions can be drawn from the squared output interactions, which show that overall capacity is exhausted much faster by increasing ATMs than any other output. This is seen in the case of London Heathrow, which presents diseconomies of capacity despite the 2008 terminal expansion (ECU = 0.96). In this case, the exceptionally congested runways are offsetting any cost advantages related to the new terminal capacity.

The posterior density of *lambda* indicates that average technical inefficiency is 6×97^{-1} = 0.143 for the baseline year 2007. Regarding AI, a stochastic node was built into the model (VC^{AI}) in order to measure the percentage increase in costs linked to AI. Results show that airports, on average, would be able to reduce their TE costs by almost 4.8% if input proportions were adequate to the observed prices. Taking into account the cost shares at the average airport (58% materials), this

Table 4
Short-run cost function parameter estimates.

Node	mean	sd	Node	mean	sd	Node	mean	sd
Constant	10.80515	0.007084	int * ωm	0.001371	0.000788	0.5 * dom^2	0.009318	0.000642
ATMh	0.087782	0.010035	int * ωp	−0.001283	0.000893	0.5 * int^2	0.004085	0.000421
dom	0.077115	0.004552	cgo * ωm	−0.014463	0.001163	0.5 * cgo^2	0.000434	0.000623
int	0.055495	0.002554	cgo * ωp	0.005759	0.001323	0.5 * rev^2	0.019821	0.003722
cgo	0.024325	0.002584	rev * ωm	−0.014278	0.002978	0.5 * ter^2	0.092963	0.011691
rev	0.228644	0.006306	rev * ωp	0.031942	0.002804	0.5 * run^2	−0.063740	0.023838
ter	0.103969	0.008433	ter * ωm	0.072283	0.003415	ATMh * ter	−0.105387	0.010645
run	0.261125	0.013009	ter * ωp	−0.069291	0.003564	ATMh * run	0.066675	0.009158
ωmat	0.582029	0.002093	run * ωm	−0.054149	0.004796	t	−0.007450	0.001314
ωper	0.417254	0.002159	run * ωp	0.051693	0.004896	t * ter	−0.009222	0.001587
ATMh * ωm	0.009087	0.003801	0.5 * ωm^2	0.064102	0.002833	t * run	0.031722	0.003326
ATMh * ωp	−0.010673	0.003818	ωm * ωp	−0.056771	0.002526	psi (hedonic)	1.034736	0.069224
dom * ωm	0.008857	0.001035	0.5 * ωp^2	0.051046	0.003094	lambda	6.973433	6.866274
dom * ωp	−0.001369	0.000883	0.5 * ATMh^2	0.067594	0.008978	VC^{AI}	1.047803	0.039951

Italics indicates non-significant coefficients (5%).

Table 5
Evolution of cost efficiency estimates 2007–2009.

	2007	2008	2009	VAR 2007–09 (%)
Total North America	0.830	0.789	0.765	−6.49
Canada	0.808	0.780	0.760	−4.83
US	0.831	0.790	0.765	−6.61
Total Asia–Pacific	0.895	0.824	0.835	−5.94
Australia	0.868	0.840	0.848	−1.97
New Zealand	0.883	0.861	0.857	−2.59
China – Far East	0.903	0.812	0.830	−7.35
Total Europe	0.796	0.772	0.748	−4.77
Austria	0.766	0.750	0.737	−2.92
France	0.772	0.731	0.723	−4.90
Germany	0.772	0.772	0.740	−3.23
Italy	0.813	0.795	0.806	−0.69
Russia	0.644	0.641	0.633	−1.08
Turkey	0.802	0.802	0.820	1.74
UK	0.834	0.780	0.748	−8.63
Total sample	0.828	0.788	0.769	5.85

Table 6
Drivers of cost flexibility.

Node	Mean	Sd	Node	Mean	Sd	Node	Mean	Sd
Constant	−0.069020	0.034628	**slcc**	**0.004354**	**0.002770**	PUB-CRP ∗ eur	0.032043	0.014793
varpax	0.207730	0.034878	**slcc ∗ eur**	**0.004770**	**0.002869**	PUB-MAS	0.016720	0.006797
eff07	0.106413	0.034801	hh	0.046360	0.016679	**PAUTH**	**0.009787**	**0.012227**
mppa	−0.000626	0.000311	hh ∗ ap	−0.069933	0.027868	PPP	−0.080356	0.033284
ssm	−0.105624	0.036860	hh ∗ eur	−0.053299	0.019904	**PPP ∗ eur**	**0.065621**	**0.040366**
ssm ∗ eur	0.072441	0.033879	**mtow**	**−0.000323**	**0.000192**	**CCS**	**0.014199**	**0.009060**
srev	**0.038068**	**0.028425**	mtow ∗ ap	0.000965	0.000287	**PRIV**	**0.012271**	**0.008135**
scha	**0.000291**	**0.022162**	**PUB-CRP**	**−0.019312**	**0.011155**			

Note: Bold indicates non-significant coefficients (5%).

suggests that airports are outsourcing more than it would be desirable. The quality of the data, however, does not allow for a more detailed analysis of AI. Therefore, economic efficiency estimates are obtained by multiplying each airport's technical and allocative efficiencies (TE, AE) obtained from the following expressions:

$$TE_{it} = \exp(-u_{it}); AE_{it} = (VC_{it}^{AI})^{-1} \tag{9}$$

The average economic efficiency of the airport sample drops 5.85%, from 82.8% in 2007 to 78.8% in 2008 and finally 76.9% in 2009. A significant drop indeed, yet unevenly distributed across, and even within, sample regions.

Table 5 provides the breakdown and evolution of average cost efficiencies for all featured geographical clusters. It is clearly seen that North American airports have been, on average, the most significantly affected by the recession. Nevertheless, the explosive infrastructure developments in China have also taken its toll on cost efficiency. European airports appear to be the most flexible, but also showing great variability. These differences between sample regions would suggest the influence of variables such as airport size, traffic mix, ownership, or outsourcing on cost flexibility. However, results are too heterogeneous to draw general conclusions at-a-glance. In that regard, an econometric method is the most suitable option.

5.2. Determinants of cost flexibility

Second-stage estimation results are shown in Table 6. The fitted equation has an R^2 of 0.423, but the F-test against global significance is rejected. Note that many parameters are not significantly different from zero at 95% confidence. In these cases, instead of doing inference on the actual value, an odds-ratio[15] based on its posterior density will be calculated in order to confront the mutually exclusive hypotheses of the variable having either a positive or negative impact in cost flexibility.

As expected, results show a direct relationship between the actual variation in passenger traffic and the variation in estimated efficiency. This allows for a fair comparison of cost flexibility between airports with different traffic trends. Otherwise it would appear that, e.g. North American airports are systematically less flexible than those from other regions. The model also identifies a clear positive relationship between pre-crisis efficiency and cost flexibility during the recession.

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[15] The odds-ratio will be defined as the positive density divided by the negative density. This gives an indication about how much likely is one hypothesis against the other.
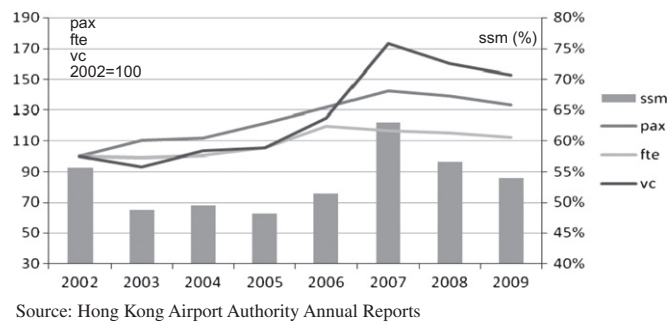
Source: Hong Kong Airport Authority Annual Reports

Fig. 3. Operational indicators Hong Kong Airport 2002–2009.

Conversely, as passenger traffic increases, airports become less flexible in costs. This was also expected given the significant step-changes in landside capacity experienced by large airports. In all such cases included in the sample, e.g. London Heathrow or Beijing, operating costs have increased well beyond the cost elasticities defined by the cost function. The other variable expected to capture the impact of airport size, MTOW, also has a negative impact on flexibility, yet not fully significant. This can be explained by the fact that the provision of airside infrastructures, such as runways and movement areas, is very capital intensive, but these costs have not been included in our short-run analysis.

A higher level of outsourcing (ssm) is surprisingly shown to significantly reduce cost flexibility (−10%) in America and Asia/Pacific, with a lower elasticity in Europe (−4%). This result appears to be in disagreement with what it is traditionally accepted in the literature regarding outsourcing and flexibility. However, it may also indicate that not everything that works during growth periods applies necessarily to recessions as well. In the first case, the airport may be able to cut down operating expenses by contracting out non-core activities at a much lower cost than the in-house alternative. However, during a period of significant (and unforeseen) contraction in demand, the airport may end up being less flexible as it is bound by contract with the external suppliers, who, under the same circumstances, will not be willing to renegotiate the terms of service. In addition, given the high level specialization of outsourced personnel, it is also more difficult to reallocate idle resources to other areas.

In support of this evidence, a deeper analysis of the most efficient sample airport, Hong Kong, was carried out. Hong Kong International (HKG) saw its total traffic reduced in more than 3 million passengers (−6%) and 350 thousand metric tons of cargo (−10%) between 2007 and 2009 and was still able to become more cost efficient (+1%). The exceptional performance of HKG is explained by Fig. 3, which shows the evolution of several operational indicators between 2002 and 2009. This period covers not only the recent downturn but also the SARS pandemic in early 2003. During both crises, HKG adopted a similar strategy to control costs. First, a hiring and salary freeze led to a net reduction in their staff numbers (fte), and consequently in their in-house labor expenses (HKG, 2009). Second, the relative level of outsourcing also experienced a sharp decrease (ssm), as the airport succeed in renegotiating their supply contracts. The combination of both effects (reduced staff, reduced outsourcing) leads to the conclusion than internalization, combined with increase labor productivity was actually their main strategy to reduce costs.[16] The same applies to Frankfurt Airport (FRA), the most flexible large European hub in the sample. The policy lesson is that airports with a higher share of in-house labor may be more capable to implement cost-saving programs as they have more control over their cost structures.

Revenue diversification (srev) is shown to have a positive impact on flexibility. Even though the actual parameter is not significant at a 95% confidence level, it is possible to calculate an odds-ratio (OR) based on the posterior density of the estimated coefficient. From the density shown in Fig. 4 (left), it can be concluded that a positive impact is approximately nine times more probable than a negative one, assuming a normal distribution (OR ≈ 9). This result was also expected since increased diversification allows the airport to reduce risks by linking its overall performance to that of many different sectors (air travel, cargo, retail, real state, advertising, etc.) which may not be equally affected by the recession.

Regarding the mix of traffic, the share of low-cost carrier flights is shown to increase cost flexibility as well (Fig. 4 right, OR > 15). In Europe, the effect of low-cost airlines is even larger, probably as a result of the number of very small sample airports dominated by this type of traffic. De Neufville (2007) notes that, during the last decade, airports serving low-cost traffic have succeed in departing from traditional master planning in order to adapt to the higher volatility of low-cost traffic. This allows airport managers to match the infrastructure development to the way the traffic unfolds, leading to increased flexibility.

Airline dominance is also shown to have a significant impact on cost flexibility, though very much differentiated across the sample regions. In North America, flexibility increases with the level of concentration, measured by the HH index. This result is likely related to the existence of dedicated terminals, fully operated by the incumbent airline, which is more likely to shut down operations or significantly reduce frequencies during an economic downturn. On the contrary, in Europe and Asia/

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[16] To improve labor productivity, HKG introduced variable compensation schemes during the SARS crisis, and more recently, the airport shifted to a "cost and profit centers" structure.
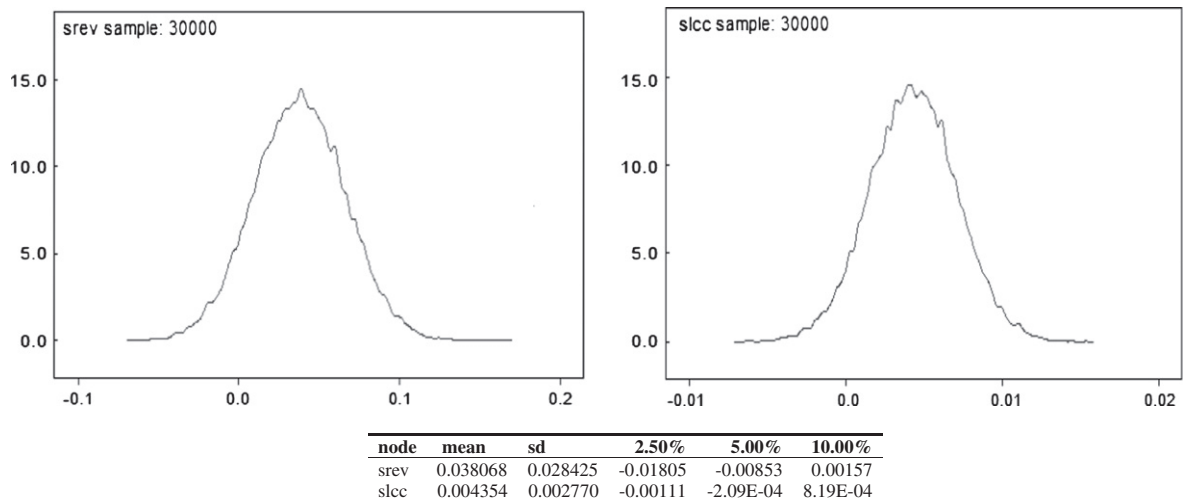
node	mean	sd	2.50%	5.00%	10.00%
srev	0.038068	0.028425	-0.01805	-0.00853	0.00157
slcc	0.004354	0.002770	-0.00111	-2.09E-04	8.19E-04

Fig. 4. Impact of revenue diversification (srev) and low-cost traffic (slcc) on cost flexibility.

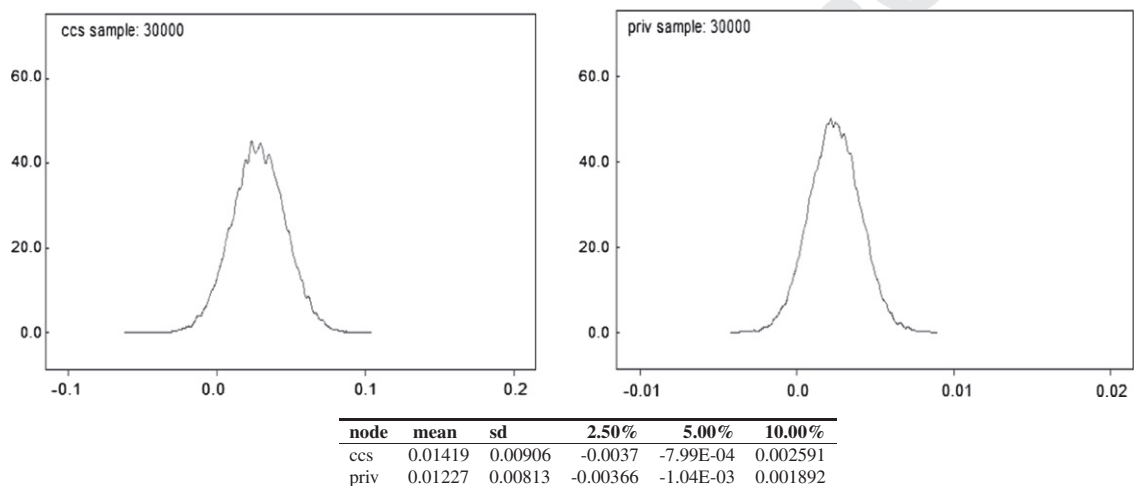| node	mean	sd	2.50%	5.00%	10.00%
ccs	0.01419	0.00906	-0.0037	-7.99E-04	0.002591
priv	0.01227	0.00813	-0.00366	-1.04E-03	0.001892

Fig. 5. Impact of long-term concessions (ccs) and privatization (priv) on cost flexibility.

Pacific, airline dominance is typically associated to legacy carriers operating massive hub-and-spoke networks at congested airports. Even during the most severe economic downturn, these dominant carriers have an incentive to hold onto underutilized (yet enormously valuable) runway slots and terminal spaces in order not to lose them to the competition. Therefore, they end up reducing the level of cost flexibility (and economic efficiency) of themselves and of the airport operator. In that regard, it would be beneficial to introduce more stringent regulation on slot allocation in order to ensure optimal utilization of congested airport capacity.

Public corporatization in Europe (PUB-CRP) has a significant and positive impact on cost flexibility (+2.3%) in comparison with the reference public-institution model. Increased commercial orientation, plus the lack of Government subsidies in most cases, is likely to move cost minimization up in the priority list. A positive impact is also associated to those multi-airport systems under public ownership (PUB-MAS). Again, the reason may be found in the diversification of traffic (full service, low cost, business, general aviation, etc.) which is often seen in these airport systems. Since all markets have not been equally affected by the recession, the airport authority has the option to reallocate resources across different business units for increased cost flexibility. In spite of that, this does not seem to apply to US airports operated by Port Authorities (PAUTH), such as e.g., Seattle, New York, which are not significantly more/less flexible than the reference ownership type. Our interpretation is that specialization does not allow for straightforward transfers between airports and seaports.

In a similar result than Oum et al. (2008), public–private partnership (PPP) is the least desirable ownership form in the airport industry with an average 8% less flexibility than a 100% publicly-owned airport. Long-term concessions (CCS), either publicly (Canada) or privately owned (Australia) are also shown to increase flexibility (Fig. 5 left, OR > 15) regardless of the number of airports managed by the concessionaire. Finally, full privatization (PRIV) is also beneficial for airports (Fig. 5 right,

OR ⪴ 13) as the driving force of profit maximization provides the right incentives to control costs during an economic recession. The policy recommendation, in terms of flexibility, is that public airports should move to any form of corporatization, including long-term concessions or full privatization, as mixed ownership may lead to conflicts between public and private shareholders (Boardman and Vining, 1989) regarding the objective of the airport business.

6. Summary and conclusions

The most recent economic downturn led to a significant contraction in the global demand for passenger travel and air cargo. In spite of that, airports' operating costs did not mirror the traffic trends and kept increasing during the same period, thus showing important signs of lack of flexibility. With this background, this paper aims at identifying the drivers of airport cost flexibility in a context of economic recession. This is achieved using a two-stage method. First, we estimate the industry's short-run cost frontier over a balanced pool database of 194 airports worldwide observed between 2007 and 2009. Results indicate that average economic efficiency of the airport sample dropped 5.85% between 2007 and 2009. However, the impact of the recession varies significantly across geographical regions, which suggests the influence of external variables on cost flexibility. In order to test that assumption, the efficiency change at the individual airports is then regressed against institutional variables and other descriptors of airport operations.

Results show that flexibility decreases with the scale of production, given the significant step-changes in capacity experienced by large airports. A higher level of outsourcing is shown to reduce cost flexibility, thus contradicting the existing literature. This is a relevant result as it proves that not everything that works during growth periods applies necessarily to recessions as well. When an airport decides to outsource non-core activities at a lower price, it is actually losing control over its cost structure, which may become problematic during a recession. Thus, outsourcing implies a clear trade-off that the airports need to balance carefully. A sound policy is to ensure that external service contracts can be renegotiated if traffic does not evolve as expected, and that internal solutions can temporarily be provided.

Regarding the mix of traffic, the share of low-cost flights is identified as another driver of cost flexibility. Note that planning and development of low-cost dominated airports is closely linked to the peculiarities of this business model, with significantly lower infrastructure demands than legacy carriers. Airline dominance is also shown to affect cost flexibility as well, yet in opposite directions: in North America, airline dominance leads to increased flexibility, most likely as a consequence of dedicated terminals. On the contrary, airline dominance drags down flexibility in Europe. The reason may be found in airport congestion that drives up slot valuation and gives dominant carriers an incentive to hold onto underutilized slots. In that respect, it would be beneficial to introduce more stringent regulation on slot allocation in order to ensure optimal utilization of airport capacity.

Nevertheless, much of the observed differences in cost flexibility across sample regions can be attributed to an institutional component, i.e. ownership. Public corporations, multi-airport systems, long-term concession contracts, and privatized airport authorities are empirically shown to outperform fully public airports, port authorities or public–private partnerships. The policy recommendation, in terms of cost flexibility, is that public airports should move to any form of corporatization, including 100% privatization. However, they should avoid mixed ownership arrangements as they may lead to conflicts between public and private shareholders regarding the very own objective of the airport business.

7. Uncited reference

Q4   ACI (2010).

Appendix A. Short-run model specification

$$lnVC_{it}^a = lnVC_{it}^0 + lnVC_{it}^{AI} + u_{it} + v_{it}$$

$$
\begin{aligned}
lnVC_{it}^0 = {} & \alpha_1 + \alpha_2 atmh + \alpha_3 dom + \alpha_4 int + \alpha_5 cgo + \alpha_6 rev + \varphi_7 ter + \varphi_8 run + \beta_9 \omega_m + \beta_{10}\omega_p + \gamma_{11} atmh \cdot \omega_m + \gamma_{12} atmh \\
& \cdot \omega_p + \gamma_{13} dom \cdot \omega_m + \gamma_{14} dom \cdot \omega_p + \gamma_{15} int \cdot \omega_m + \gamma_{16} int \cdot \omega_p + \gamma_{17} cgo \cdot \omega_m + \gamma_{18} cgo \cdot \omega_p + \gamma_{19} rev \cdot \omega_m \\
& + \gamma_{20} rev \cdot \omega_p + \gamma_{21} ter \cdot \omega_m + \gamma_{22} ter \cdot \omega_p + \gamma_{23} run \cdot \omega_m + \gamma_{24} run \cdot \omega_p + \delta_{25} 0.5 \cdot \omega_m \cdot \omega_m + \delta_{26} \cdot \omega_m \cdot \omega_p + \delta_{27} 0.5 \\
& \cdot \omega_p \cdot \omega_p + \rho_{28} 0.5 \cdot atmh \cdot atmh + \rho_{29} 0.5 \cdot dom \cdot dom + \rho_{30} 0.5 int \cdot int + \rho_{31} 0.5 \cdot cgo \cdot cgo + \rho_{32} 0.5 \cdot rev \cdot rev \\
& + \rho_{33} 0.5 \cdot ter \cdot ter + \rho_{34} 0.5 \cdot run \cdot run + \rho_{35} atmh \cdot ter + \rho_{36} atmh \cdot run + \tau_{37} t + \tau_{38} t \cdot ter + \tau_{39} t \cdot run
\end{aligned}
$$

$$lnVC_{it}^{AI} = \beta_{10}\xi_p + \gamma_{12}atmh \cdot \xi_p + \gamma_{14}dom \cdot \xi_p + \gamma_{16}int \cdot \xi_p + \gamma_{18}cgo \cdot \xi_p + \gamma_{20}rev \cdot \xi_p + \gamma_{22}ter \cdot \xi_p + \gamma_{24}run \cdot \xi_p + \delta_{26}\omega_m \cdot \xi_p$$
$$+ \delta_{27}0.5 \cdot \xi_p \cdot \xi_p + lnG_{it}$$

$$atmh = atm + \psi \cdot mtow$$

$$S_m^a = (\beta_9 + \gamma_{11}atmh + \gamma_{13}dom + \gamma_{15}int + \gamma_{17}cgo + \gamma_{19}rev + \gamma_{21}ter + \gamma_{23}run + \delta_{25}\omega_m + \delta_{26}\omega_p + \delta_{26}\xi_p)/G_{it}$$

$$S_p^a = (\beta_{10} + \gamma_{12}atmh + \gamma_{14}dom + \gamma_{16}int + \gamma_{18}cgo + \gamma_{20}rev + \gamma_{22}ter + \gamma_{24}run + \delta_{26}\omega_m + \delta_{27}\omega_p + \delta_{27}\xi_p)/G_{it} \cdot exp\xi_p$$

$$G_{it} = (\beta_9 + \gamma_{11}atmh + \gamma_{13}dom + \gamma_{15}int + \gamma_{17}cgo + \gamma_{19}rev + \gamma_{21}ter + \gamma_{23}run + \delta_{25}\omega_m + \delta_{26}\omega_p + \delta_{26}\xi_p) + (\beta_{10} + \gamma_{12}atmh$$
$$+ \gamma_{14}dom + \gamma_{16}int + \gamma_{18}cgo + \gamma_{20}rev + \gamma_{22}ter + \gamma_{24}run + \delta_{26}\omega_m + \delta_{27}\omega_p + \delta_{27}\xi_p)/exp\xi_p$$

$$\beta_9 + \beta_{10} = 1$$

$$\gamma_{11} + \gamma_{12} = 0; \gamma_{13} + \gamma_{14} = 0; \gamma_{15} + \gamma_{16} = 0; \gamma_{17} + \gamma_{18} = 0; \gamma_{19} + \gamma_{20} = 0$$

$$\gamma_{21} + \gamma_{22} = 0; \gamma_{23} + \gamma_{24} = 0$$

$$\delta_{25} + \delta_{26} = 0; \delta_{27} + \delta_{28} = 0$$

Appendix B

Sample airports.

Country	Airport	Country	Airport	Country	Airport	Country	Airport
Canada	Calgary	US	BWI	US	Louisville	US	Pittsburg
	Edmonton		Charlotte		Memphis		Portland
	Fredericton		Cincinnati		Miami		Pt. Columbus
	Gander		Cleveland		Midway		Raleigh Durham
	Halifax		Dallas-FW		Milwaukee		Reagan
	Moncton		Dayton		Minn/St Paul		Reno
	Montreal		Denver		Nashville		Richmond
	Otawa		Detroit		New Orleans		Salt Lake City
	Toronto		Dulles		NY-EWR		San Antonio
	Vancouver		Ft Lauderdale		NY-JFK		San Diego
	Victoria		Honolulu		NY-LGA		San Francisco
	Winnipeg		Houston		O'hare		San Jose
	Albany		Indiannapolis		Oakland		Santa Ana
US	Albuquerque		Jacksonville		Ontario		Seattle
	Anchorage		Kansas City		Orlando		St Louis
	Atlanta		Knoxville		Palm Beach		Sw Florida
	Austin		Las Vegas		Philadelphia		Tampa Intl
	Boston		Los Angeles		Phoenix		Tucson
Austria	Graz	Germany	Bremen	Russia	Moscow Sheremet	UK	Coventry
	Innsbruck		Dortmund		Moscow Vnukovo		East Midlands
	Klagenfurt		Dresden		Nizhny Novgorod		Edinburgh
	Linz		Düsseldorf		Novosibirsk		Exeter
	Salzburg		Frankfurt		Omsk		Glasgow
	Vienna		Hahn		St. Petersburg		Humberside
Belgium	Brussels		Hamburg	Slovakia	Bratislava		Leeds
	Ostend		Hannover	Slovenia	Ljubljana		Liverpool
Croatia	Zagreb		Köln/Bonn	Sweden	Arlanda		London City
Denmark	Copenhagen		München	Switzerland	Geneva		London Gatwick
Estonia	Tallin		Stuttgart		Zurich		London Heathrow
France	Beauvais	Greece	Athens	Turkey	Adana		London Luton
	Bordeaux	Hungary	Budapest		Adnan Menderes		London Stansted

Appendix B (continued)

Country	Airport	Country	Airport	Country	Airport	Country	Airport
	BSL/MLH/FRE	Italy	Bologna		Antalya		Manchester Intl
	Carcassonne		Firenza		Ataturk Int		Newcastle
	Cayenne		Orio Al Serio		Dalaman		Sheffield
	Clermont		Palermo		Esenboga		Southampton
	Grenoble		Pisa		Milas/Bodrum		Southend
	Lille		Torino		Trabzon		Teesside
	Marseille		Venezia	Ukraine	Kyev		
	Nantes	Latvia	Riga		Lviv		
	Noumea	Malta	Malta		Simferopol		
	Pau	Netherlands	Amsterdam	UK	Aberdeen		
	Perpignan		Eindhoven		Belfast		
	Pointe A Pitre	Norway	Oslo		Birmingham		
	Rennes	Portugal	Faro		Blackpool		
	Strasbourg		Lisboa		Bournemouth		
	Tolouse		Ponta Delgada		Bristol		
	Toulon	Romania	Bucharest		Cardiff		
Australia	Adelaide	China	Baiyun	New Zealand	Auckland		
	Alice Springs		Beijing		Christchurch		
	Brisbane		Hainan Meilan		Wellington		
	Darwin	Hong Kong	Hong Kong	South Korea	Incheon		
	Perth	Indonesia	Yakarta				
	Sydney	Japan	Tokio Narita				

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