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The impact of recession on airports' cost efficiency

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► Airport cost efficiency worldwide dropped 5.85% between 2007 and 2009. ► This leads to a global loss of approximately USD 5.5 billion over this period. ► North American airports are the most severely affected by the recession. ► Results suggest a negative impact of outsourcing on cost flexibility. ► Privatization and corporatization seem to improve cost flexibility.

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The impact of recession on airports' cost efficiency

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ABSTRACT

The recent economic downturn took a severe toll on the aviation industry, leading to a significant contraction in air transport demand. In spite of that, airports' operating costs did not mirror the declining traffic trends and continued to increase during the same period. This paper sought to estimate the impact of the recession on airports' cost efficiency and financial performance. This is achieved by estimating the industry's short-run cost frontier over a balanced pool database of 194 airports observed between 2007 and 2009. Results show that airports struggled to control operating costs during the recession. Efficiency losses were estimated to be in excess of USD 5.5 billion, contributing to a significant reduction in industry operating margin. Results also suggest that airports that are corporatised and have not pursued extensive out-sourcing of activities are better able to manage their costs during periods of economic recession.

1. Introduction

The recent economic downturn has taken a significant toll on the air transport industry. As seen in Fig. 1, after a period of sustained growth between 2002 and 2007, worldwide passenger traffic stagnated in 2008 and then declined by 1.8% in 2009 (ACI, 2011). In spite of that, not all regions were equally affected, with major traffic losses in the mature markets of North America and Europe, showing a total variation of −8.3% and −4.1% in passengers, respectively, between 2007 and 2009. Other regions, such as Asia-Pacific, continue to grow (+6.1%), thriving on their booming domestic markets (Airbus, 2009). A similar trend can be observed for air cargo where total metric tons fell by 3.7% in 2008 and by 7.9% in 2009. In this case, all regions experienced traffic losses from the first moment, yet again, these were higher in Europe and North America (−11%) than in other regions (−2%).

As demand contracted, air carriers quickly reacted by reducing capacity and eliminating non-profitable routes in order to protect load factors and yields (ATA, 2010). From an airport perspective, this translates into reduced traffic levels, which are typically measured in terms of passengers, aircraft movements and cargo tonnage. This downward trend inevitably led to a reduction in airport revenues. ACI's Airport Economic Survey (ACI, 2011) notes that total industry income declined by 2% between 2008 and 2009, mirroring the traffic trend, from 96 to 94.5 billion USD. Unfortunately, a similar trend is not observed on the cost side. Even under a significant reduction in traffic, industry operating costs increased by 3.6% in the same period, from 55 to 57 billion USD. This includes labor and external charges, typically considered the truly variable costs of airports (Oum et al., 2008).

Airports are particularly infrastructure-intensive, which inevitably leads to massive investments, indivisibilities and step-changes in size and capacity. The presence of these fixities, either technological or regulatory, has been traditionally linked to an inherent inability within the airport sector to be able to adjust input demands (i.e. capital, utilities, and labor) to evolving traffic levels (Graham, 2008). This assumption is supported by the evidence presented above as airports were not able to control costs in spite of the decrease in traffic. In addition to the associated reduction in operating margins, this paper hypothesizes that this behavior has also led to a general reduction in airport cost efficiency worldwide.

With this background, the objective of this paper is to estimate the impact of the recession on airports' cost efficiency and financial performance. Results will serve to test the assumption that airports facing decreasing traffic are not flexible in costs, as empirical evidence in that regard has yet to be provided. Note that the latest downturn provides a unique background for this type of econometric research, as financial data on airports became increasingly available at a time when they were challenged to control costs. This study would be of interest for the airport industry, especially in the present context of privatization, where airport efficiency and profitability are major issues for regulators and practitioners (Sarkis and Talluri, 2004). In addition, any policy

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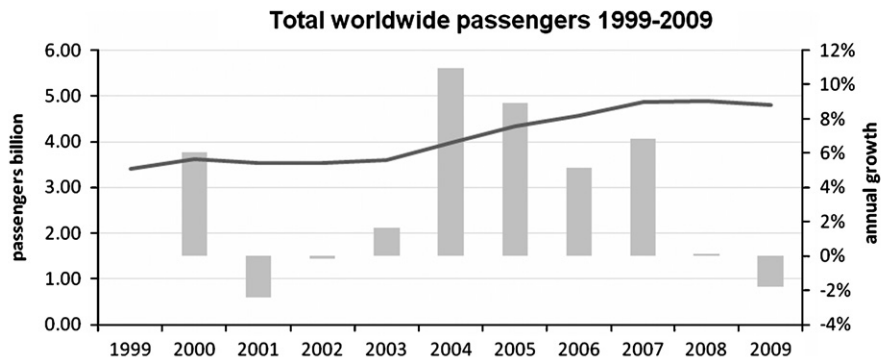

Fig. 1. Total worldwide passengers 1999–2009.

conclusion aimed at increasing flexibility can lead to cost savings which are crucial as airports struggle to maintain service quality through the financial crisis.

1.1. Literature review

In the last two decades there have been a growing number of empirical studies on airport efficiency and productivity. A representative sample of these contributions is shown in Table 1. During this period, the aviation industry suffered three different demand crises, all characterized by stagnation and then followed by a decrease in global passenger traffic (IATA, 2008): (i) 1991–1993, linked to the early 90's recession, (ii) 2001–2003, linked to the 9/11 attacks, and (iii) 2008–2010, linked to the latest global crisis. Regarding this last period, there is a clear literature gap as no published study features data on airports from developed regions for the key year 2009. In spite of that, some lessons on the impact of recession on airport efficiency could still be learned from studies undertaken in earlier periods.

Out of the 49 original studies in Table 1, 39 use panel data [Panel], which is a necessary requirement for a comparative analysis of efficiency over time. Of these, 26 cover any of the relevant crisis periods in their databases [Crisis], but thereof, only three papers consider the impact of recession on airport performance [Impact].

Barros (2008c) analyzed output efficiency (OE) of 32 Argentinean airports between 2003 and 2007, a period of recession after the collapse of the banking system, leading to a 50% reduction in traffic. Results indicate that major hubs were relatively immune to the crisis while small regional airports appeared to be more vulnerable. Nevertheless, average OE grew over the period. This conclusion, however, is not easily generalizable given the country-specific airport sample. In that regard, it is preferable to have international databases, which can provide a more comprehensive approach to the subject. Pathomsiri and Haghani (2004) and Pathomsiri et al. (2005) used a worldwide database to test differences in global OE between 2000 and 2002. These studies, however, remain unpublished and no relevant conclusions on the impact of 9/11 on airport efficiency are provided. Thus, it appears the impact of demand shocks (e.g. economic recessions) on airport efficiency has not been fully covered by previous studies. This paper seeks to address this gap in the literature.

The proposed methodology is based on the econometric estimation of stochastic cost frontiers. Even though the estimation of these models requires a significant amount of financial data, which is not always easy to obtain for airports, it has the enormous advantage of easily accommodating multi-production and panel data analysis (Jara-Díaz, 2007). In addition, cost frontiers can be adapted to a short-run context, more suitable to analyze cost flexibility[1]. Airport cost frontiers are relatively scarce in the literature, since early cost function studies did not consider inefficiencies in their sample airports. In addition, the use of very different data and methodologies provides inconsistent findings. For the long-run studies, these discrepancies are related to the extent to which airports enjoy returns to scale. Different studies have produced divergent views on the point at which returns to scale appear. These range from the constant returns in the pioneering single-output paper of Keeler (1970), using US airports; up to 1 million passengers in Doganis and Thompson (1974) using an UK sample, up to 3 million passengers in Jeong (2005), again with US airports; up to 20 million in Tolofari et al. (1990); and even beyond 120 million annual passengers in Martín and Voltes-Dorta (2011b), using a worldwide sample. This gives an indication as to how highly sensitive the estimation of a cost function is to the airport sample. Short-run cost functions are more scarce (e.g. Tolofari et al., 1990), as only Martín et al. (2011), using a sample of Spanish airports, provides individual estimates of short-run cost elasticities. Speaking strictly about stochastic frontier papers, one can highlight the long-run contribution of Martín et al. (2009) or the recent study of Barros (in press) using a small sample of African airports.

However, all of these studies are limited in the sense that they are restricted to analysis of single jurisdictions and it is difficult to apply their conclusions to the global airport industry. It is clear that, since the recession has affected many regions, the empirical study must feature a large number of airports worldwide observed before and after the onset of the global crisis. Continuing the selection started above, nine of the 26 relevant studies in Table 1 use a cross-country sample [Cross]. Among these, only six feature a large database (40 airports or more) [DB]. Adding the final restriction of a cost-efficiency [CE] approach (rather than OE[2]), only two papers can be cited as suitable methodological references.

Oum et al. (2008) provided the first example of a short-run multi-output airport cost frontier estimated using Bayesian

[1] Short-run models only include those costs that airports would theoretically be capable of controlling in the short-term, such as labor and utilities, as opposed to long-run models where capital costs are also considered. Cost flexibility during growth periods is commonly associated to flexible planning (modular terminals, etc.) with the objective to minimize long-run costs. On the contrary, during an economic recession, airports are stuck with existing capacity then try to minimize short-run costs. A long-run approach would be difficult to adapt to a recession context as airports delay capital investments by anticipating the contraction in demand, which introduces endogeneity in the model. Hence, a short-run approach is preferred.

[2] Cost efficiency studies focus on cost minimization, while output efficiency studies focus on output maximization. Estimating cost efficiency allows for further disaggregation between the technical and allocative components of efficiency.

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Table 1
Airport efficiency studies.
Source: own elaboration.

Author(s)	Data sample	Method	Panel	Crisis	Cross	DB	CE	Impact
Hooper and Hensher (1997)	6 Australian; 88/89–91/92	TFP	x				x	
Gillen and Lall (1997)	21 US; 89–93	DEA	x	x				
Parker (1999)	22 UK; 88/89–96/97	DEA	x	x			x	
Salazar De La Cruz (1999)	16 Spain; 93–95	DEA	x				x	
Sarkis (2000)	44 US; 90–94	DEA	x	x		x	x	
Adler and Berechman (2001)	26 Worldwide; 96	DEA			x			
Martín and Román (2001)	37 Spain; 97	DEA					x	
Pels et al. (2001)	34 Europe; 95–97	DEA/SPF	x		x			
Abbott and Wu (2002)	12 Australian; 90–00	DEA/MI	x	x				
Bazargan and Vasigh (2003)	45 US; 96–00	DEA	x			x		
Pacheco and Fernandez (2003)	35 Brazil; 98	DEA					x	
Pels et al. (2003)	34 Europe; 95–97	DEA/SPF	x		x			
Oum et al. (2003)	52 Worldwide, 99	TFP			x	x		
Barros and Sampaio (2004)	10 Portugal, 90–00	DEA	x	x			x	
Yu (2004)	76 Worldwide; 00–01	VFP	x	x	x	x		
Pathomsiri and Haghani (2004)	63 Worldwide; 00 and 02	DEA	x	x	x	x		x
Yoshida and Fujimoto (2004)	67 Japan; 00	DEA/TFP				x		
Yu (2004)	14 Taiwan; 94–00	DEA/DDF	x					
Martín-Cejas (2005)	31 Spain; 97	LRCF					x	
Sarkis and Talluri (2004)	44 US, 90-94	DEA	x	x		x	x	
Craig et al. (2005)	52 US; 70–92	LRCF	x	x		x	x	
Pathomsiri et al. (2005)	72 Worldwide; 00 and02	DEA	x	x	x	x		x
Malighetti et al. (2007)	27 Italy; 05–06	DEA/MI	x					
Barros and Dieke (2008)	31 Italy, 01–03	DEA	x	x			x	
Oum et al. (2008)	109 Worldwide; 01–04	SCF (SR)	x	x	x	x	x	
Curi et al. (2008)	17 Italy; 00–04	DEA	x	x			x	
Barros (2008a)	27 UK, 00–05	SCF (LR)	x	x			x	
Barros (2008b)	13 Portugal, 90–00	SCF (LR)	x	x			x	
Barros (2008c)	32 Argentina, 03–07	DEA	x	x				x
Fung et al. (2008a)	25 China; 95–04	DEA/MI	x	x				
Fung et al. (2008b)	41 China; 02	DEA/TFP				x		
Yu et al. (2008)	4 Taiwan; 95–99	DEA/DDF/MI	x				x	
Pathomsiri et al. (2008)	56 US; 00–03	DEA/DDF	x	x		x		
Martín et al. (2009)	37 Spain; 91–97	SCF (LR)	x	x			x	
Lam et al. (2009)	11 Asia Pacific; 01–05	DEA	x	x	x		x	
Assaf (2009)	27 UK, 02/03 and 05/06	SFA	x				x	
Tovar and Rendeiro (2009)	26 Spain, 93–99	IDF	x					
Chow and Fung (2009)	46 China, 00	IDF				x		
Tovar and Rendeiro (2010)	26 Spain, 93–99	IDF	x					
Assaf (2010)	13 Australia, 02–07	SCF (LR)	x				x	
Abrate and Erbetta (2010)	26 Italy, 00–05	IDF	x	x				
Yang (2010)	12 Asia-Pacific, 98–06	DEA, SFA	x	x	x			
Perelman and Serebrinsky (2010)	148 Worldwide 95–07	DEA	x	x	x	x		
Martín and Voltes-Dorta. (2011a)	161 Worldwide, 91–08	**SCF (LR)**	**x**	**x**	**x**	**x**	**x**	
Lozano and Gutierrez (2011)	36 Spain, 06–07	DEA	x					
Tsekeris (2011)	39 Greece, 07	DEA						
Cunha-Marques (2011)	3 Portugal, 06	DEA						
Curi et al. (2010)	18 Italy, 00–04	DEA	x	x				
Barros (in press)	17 Africa, 00–10	SCF (LR)	x	x	x		x	
	Total studies	49	39	26	13	15	21	4
	Suitable contributions	-	39	26	9	6	2	0
Pagliari and Voltes-Dorta (present study)	194 Worldwide, 07–09	SCF (SR)	x	x	x	x	x	x

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

inference[3]. This paper used a pool of 109 airports worldwide between 2001 and 2004, and, while it discusses the difficulties in collecting comparable financial data, it does not solve to the problem of calculating airport-specific input prices (Purchasing Power Parities were used as proxy for the price of "materials"). Martín, Voltes-Dorta. (2011a) collected data on 161 airports worldwide between 1991 and 2008. The increase in observations allowed them to improve the (long-run) cost frontier estimation methodology with, for example, the specification of five outputs, the inclusion of take-off weight as an hedonic adjustment of aircraft operations (See Section 3), a new method to calculate input prices, and the joint specification of technical and allocative inefficiencies.

Taking all into consideration, we decided to adapt the method from Martín and Voltes-Dorta. (2011a) to a short-run context. A balanced pool database of 194 airports worldwide between 2007 and 2009 will be used, featuring a wide variety of airport sizes and output mixes. The present study is appended in Table 2 as described, in order to help place this contribution within the broad spectrum of airport efficiency research. The rest of this paper is organized as follows: Section 2 describes the worldwide sample and data sources and Section 3 introduces the cost frontier methodology. This is followed by Section 4 which analyzes the evolution of efficiency estimates during the sample

[3] Additional references for airport efficiency studies using Bayesian models include: Assaf (2009, 2010) and Barros (in press).

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Table 2
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	1,508	11
Mean	117,054	168,332	9,563,645	3,953,147	284,364	85,828	63	125,996	6,504	699
Geom	–	92,660	2,707,787	453,255	39,657	38,738	–	56,924	5,359	–
Std	179,786	171,394	12,494,829	7,880,956	576,752	125,984	34	160,413	4,134	1262

period and quantifies the impact of the recession on cost efficiency and operating margins. Finally, Section 5 summarizes the main findings.

2. Database and data Sources

The short-run cost frontier was estimated over a balanced pool database of 194 airports from all over the world, observed between 2007 and 2009[4]; producing a grand total of 582 observations. Starting from its onset in late 2007, the sample period was chosen to cover those years were the impact on traffic of the global crisis was more severe, as the first signs of recovery were observed during the first quarter of 2010 (Eurostat, 2011). Taking into account that major traffic losses were recorded in the "mature" markets in North America and Europe, the airport sample is clearly biased to these regions[5] . The geographical breakdown of the 194 sample airports is as follows: 72 observations from North America, 106 from Europe, and 16 from Asia-Pacific and Oceania (Appendix A).

Data collection was completed for the following variables: (i) variable costs (vc): labor (lab) and materials (mat); (ii) Outputs: Domestic-Schengen (dom) and international-transborder 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 of terminal buildings (ter), total runway length (run), total number of boarding gates (gat), check-in desks (chk), and baggage claim belts (bel) and (iv) Other: time (t), full-time equivalent employees (fte), share of the dominant carrier (sdc), Hirschman–Herfindahl index of airline traffic shares[6] (hh), share of charter traffic (scha), share of low-cost traffic (slcc) and ownership form. For homogeneity purposes, 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. Only the employees of the reporting authority, typically the airport operator, are considered. "Materials" costs include maintenance, utilities, external services and other administrative costs. Note that the share of materials will be correlated with the degree of outsourcing of each airport, thus serving as a proxy for this variable. Also note that these costs include all in-house activities, which vary widely across airports. Section 3 discusses how the calculated input prices take this heterogeneity into account.

Data was mainly extracted from annual reports published online by the respective airport authorities. In certain cases (i.e. UK, France and Turkey) comprehensive financial reports at a country level[7] were consulted (Sharp et al., 2010; 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, 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[8]. 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 2009–2007 ACI, 2010 and IATA Airport Capacity and Demand profiles 2003 IATA, 2003. Average landed MTOW, dominant carriers, 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)[9] .

Table 2 provides descriptive statistics for the most relevant variables in the cost frontier estimation: variable costs, outputs, and fixed factors. The scale of production ranges from 1,500 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, and 284,000 t of cargo. Geometric means are also relevant as they provide the approximation point for the translog cost function. In total, the 194 sample airports served 2.44 billion passengers and 46.5 million tons of cargo in 2009, which represent 50% and 58% of worldwide traffic, respectively.

Table 3 provides a disaggregated look at the financial and traffic figures in order to check if the database is representative of the global trends described in Section 1. As expected, total passenger traffic at sample airports remained flat in 2008 and decreased significantly in 2009, with the percentages being very close to ACI's worldwide estimates (in parentheses). The similarity extends to the regional estimates, which, where there were sharp reduction in both the North American and European

[4] One could argue for the time series to be broader in scope in order to provide a necessary contrast in cost flexibility between growth and recession periods. However, as argued before, that analysis would require separate models (long-run for growth and short-run for recession), which would hamper a comparative analysis.

[5] The availability of financial data was the main criterion for inclusion in the database and it explains the absence of some large European hubs. In spite of that, the final sample provides enough variability in terms of cost structures, ownership forms, price regulations, and traffic mixes to remain representative of the global airport industry.

[6] The Hirschmann–Herfindahl is a well-known indicator of market concentration and competition. In this particular case, it was calculated as the sum of the squares of traffic shares of all airlines operating at each airport over a given year. Traffic shares were based on total flights using OAG data.

[7] Data for Spanish airports was available only for the year 2009, which did not allow for a balanced panel 2007–2009.

[8] 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.

[9] 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).

Table 3
Evolution of passenger traffic and operating costs at sample airports 2007–2009.

	2007	2008	VAR 07–08	2009	VAR 08–09	VAR 07–09
NORTH AMERICA						
PAX (million)	14	1379	−3% (−3.1%)	1309	−5% (−5.2%)	−8%
CARGO (thousand tons)	28,261	26,262	−7%	23,503	−11%	−17%
COST (PPP million)	8844	9198	4%	9567	4%	8%
LAB	3274	3433	5%	3655	6%	12%
MAT	5570	5766	4%	5912	3%	6%
EUROPE						
PAX (million)	802	817	2% (1.2%)	784	−4% (−5.4%)	−2%
CARGO (thousand tons)	13,225	13,400	1%	11,790	−12%	−11%
COST (PPP million)	11,414	12,420	9%	12,387	–	9%
LAB	4682	4952	6%	4948	–	6%
MAT	6732	7467	11%	7439	–	11%
ASIA – PACIFIC/OCEANIA						
PAX (million)	327	333	2% (1.2%)	350	5% (+4.9%)	7%
CARGO (thousand tons)	11,735	11,478	−2%	11,284	−2%	−4%
COST (PPP million)	2322	2563	10%	2746	8%	18%
LAB	534	648	21%	656	2%	23%
MAT	1788	1915	7%	2090	10%	17%
TOTAL SAMPLE						
PAX (million)	2546	2529	−0.0 (+0.1%)	2443	−3% (−1.8%)	−3%
CARGO (thousand tons)	53,221	51,140	−4% (−3.7%)	46,577	−9% (−7.9%)	−13%
COST (PPP million)	22,580	24,181	7%	24,700	2% (+3.6%)	9%

In parentheses are the ACI estimates.

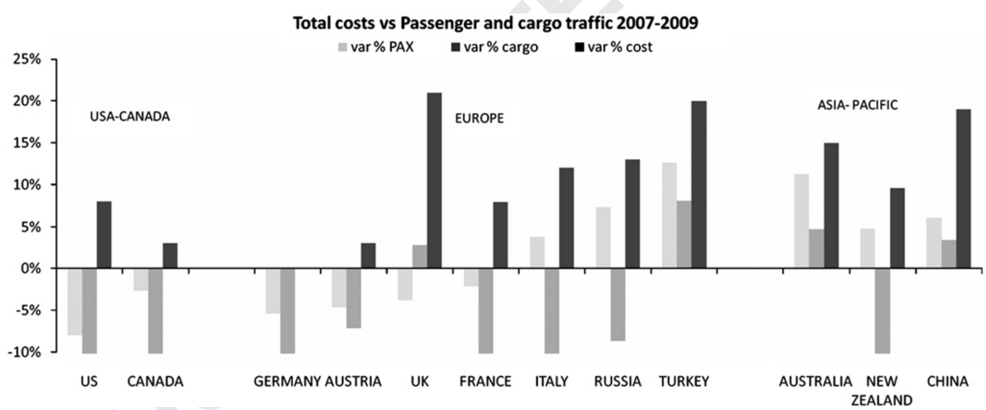

Fig. 2. Total costs vs passenger and cargo traffic 2007–2009.

markets. The temporary deceleration and early recovery of the Asia-Pacific cluster is explained by the sample as well. A similar picture is drawn for air cargo activity, which started to decline in 2008 and then followed by further contraction in 2009. While there are no estimates for industry operating costs in 2007, the sample variation between 2008 and 2009 (2%) is also reasonably close to the global change (3.6%).

Fig. 2 shows that all regions have flexibility problems regardless of the traffic trend. The picture is clear for the "mature" markets in North America and Europe: traffic falls and costs increase. The problem persists, however, in the developing regions as there was a disproportionate increase in operating costs relative to traffic, thus perhaps indicating that airport technology is cost-elastic with respect to output. This contradicts the likely existence of economies of capacity utilization in the short-run (Oum et al., 2008). We assume that the discrepancy between the "expected" trend (i.e. costs falling with traffic) and the actual trend is entirely due to the lack of cost flexibility during the recession. This is bound to lead to increased inefficiency worldwide, the estimation of which is the objective of the next section.

3. Cost frontier estimation

The econometric estimation of a short-run cost frontier requires data on variable costs (VC), outputs (Y), input prices (ω) and fixed factors (K) of airports whose behavior is assumed to be cost-minimizing. The preferred functional form is the transcendental logarithmic-translog (Christensen et al., 1973), which is the most commonly used in this kind of empirical study. A second-order translog expansion of a short-run variable cost function has this general structure, where ε represents statistical disturbance:

$$\begin{aligned}\ln VC = {} & \alpha_0 + \sum_j \alpha_j \ln y_j + \sum_h \beta_h \ln\omega_h + \sum_m \varphi_m \ln K_m + \sum_h \sum_h \gamma_{hj} \ln\omega_h \ln y_j \\ & + \sum_i \sum_m \gamma_{hm} \ln\omega_h \ln K_m + \sum_j \sum_m \gamma_{jm} \ln y_j \ln K_m \\ & + \frac{1}{2}\left[\sum_j \sum_k \rho_{jk} \ln y_j \ln y_k + \sum_h \sum_l \rho_{hl} \ln\omega_h \ln\omega_l \right. \\ & \left. + \sum_m \sum_n \rho_{mn} \ln K_m \ln K_n \right] \end{aligned} \quad (1)$$

The translog equation is typically estimated jointly with its cost-minimizing input shares (s) by means of a Seemingly Unrelated Equations Regression—SURE (Zellner, 1962). Input share equations are easily obtained by differentiating and applying Shephard's Lemma[10] :

$$s_i = \frac{\omega_i x_i}{VC} = \frac{\partial VC}{\partial \omega_i}\frac{\omega_i}{VC} = \frac{\partial \ln VC}{\partial \ln \omega_i} = \beta_i + \sum_j \gamma_{ij} \ln y_j + \sum_m \gamma_{im} \ln K_m + \sum_m \rho_{ih} \ln \omega_h \tag{2}$$

If panel data is available, the model can be completed with the time variable (t) in order to account for technological change in the industry (Stevenson, 1980).

A variable cost function provides insight on other technological indicators of interest from both management and policy perspectives. The partial derivative of logged costs with respect to a logged output leads to the same output's cost elasticity (η). The inverse of the sum of all specified outputs' cost elasticities leads to the airport's degree of economies of capacity utilization (ECU). A value of ECU > 1 indicates that the airport is operating with excess capacity and there are opportunities for reducing average operating costs by increasing the output. On the contrary, a value of ECU < 1 indicates that the airport has pushed its output level beyond maximum capacity and it is experiencing increasing average operating costs, possibly caused as a result of the need to employ additional resources to cope with pressures caused by congestion. Expansion should be considered at this stage. Finally, ECU = 1 indicates that, in theory, the airport is operating at optimal capacity.

$$\eta_j = \frac{\partial \ln VC}{\partial \ln y}\; \mathrm{ECU} = \frac{1}{\sum_j \eta_j} \tag{3}$$

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

$$\ln ATM_i^{MTOW} = \ln ATM_i + \psi(\ln MTOW_i) \tag{4}$$

This is intended to account for the significant heterogeneity in aircraft mixes across the sample as different aircraft impose different operating costs to the airports. The hedonic coefficient ψ provides an estimate of the cost elasticity of aircraft weight. A value of $\psi > 1$ indicates that the variable costs imposed by an aircraft during either landing or take-off increase more than proportionally with its *MTOW*.

The cost function also features two input prices: materials (ω_m), and labor/personnel (ω_p). The price of labor is obtained by dividing labor costs by the full-time equivalent employees (*fte*) of the airport authority. The calculation of the price of materials is more complex: materials costs are divided by a quantity index based on marginal productivity ratios, calculated among a predefined set of inputs assumed to represent the airport's overall demand for utilities and maintenance ("shadow inputs"). Marginal productivities are estimated from a ray production frontier provided by the reference paper[11]. The "shadow" inputs considered were check-in desks, boarding gates, and total warehouse area. As prices are related to the observed costs, they reflect each airport's specific circumstances (i.e., labor policies, scope of outsourcing, leased terminals, etc.). This reduces the need for data homogenization and, provided there are enough sample airports with the same internal characteristics, it allows for fair efficiency comparisons between airports from different regions[12] .

Regarding fixed factors, this paper follows the approach from Martín et al. (2011) and considers total floor area of terminal buildings (*ter*) and total runway length (*run*). The full specification of the proposed cost system is shown in Appendix B. Note that all explanatory variables are logged and deviated with respect to their sample means. Additional parametric restrictions are included in order to impose linear homogeneity in input prices.

In addition, it is likely that some, if not all, sample airports have incurred in technical and/or allocative inefficiencies (AI) during the sample period[13]. Both impacts must be specified separately in the model in order to avoid estimation biases (Kumbhakar and Tsionas, 2005). An additional disturbance term can be introduced in order to account for technical inefficiency, leading to a stochastic frontier specification (Aigner et al., 1977), while the impact of AI on operating costs is formulated using the shadow price method of Kumbhakar (1997). The resulting specification, however, is non linear in parameters and thus too complex to be estimated using classical techniques. In these cases, Bayesian inference and numerical models are the preferred alternative (Van der Broeck et al., 1994). For its simplicity, the WinBUGS software (Lunn et al., 2000) will be used in that task, as well as the codification proposed in Griffin and Steel (2007). This assumes that the dependent variable (i.e. the logarithm of the variable costs) is normally distributed, with the aforementioned translog equation as the mean and σ_v^2 as the white noise variance:

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

VC^a represents actual costs, $VC^0(\omega,Y,K)$ is the cost frontier (i.e. minimum cost), VC^{AI} represents the percentage increase in costs linked to the allocative distortions (ξ), and u is a positively-valued error term measuring technical inefficiency. Once the corresponding partial derivatives are taken, input share equations suffer a similar transformation (See Appendix B).

The parameter of technical inefficiency u_i is allowed to vary systematically over time allowing firm-specific effects η_i (Cuesta, 2000). Note that a negative η_i indicates that the airport increases efficiency over time (T is the baseline year 2007). Thus, u_{it} indicates the level of technical inefficiency of firm i in the time period t. The firm's average inefficiency u_i is assumed to be exponentially distributed[14] with mean λ^{-1}

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

Prior distributions must be assigned to the parameters. The cost frontier coefficients (β) follow a non-informative normal distribution with zero mean and infinite variance[15] . In the same spirit, a gamma distribution (0.001, 0.001) is assigned to the

[10] Differentiating costs with respect to a price leads to the input demand function (Shephard, 1953), $\frac{\partial C}{\partial \omega} = x$.

[11] See Appendix B in Martín and Voltes-Dorta (2011a).

[12] German airports tend to cover a wider range of core activities in-house, which inevitably leads to higher operating costs than similar airports in other countries. However, since they have also higher input prices, their frontier costs will be also higher. Thus, each airport will face a cost frontier adequate to its cost structure.

[13] From a cost perspective, 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.

[14] The exponential distribution was preferred because it only requires a single coefficient to be estimated. Martín et al. (2009) estimated cost efficiencies for Spanish airports under exponential, truncated normal and half-normal distributions finding no significant differences in the estimated efficiencies.

[15] Normal distributions in Eq. 7 follow WinBUGS' notation: N (mean, inverse-variance).

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Table 4
Short-run cost function parameter estimates.

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

Note: ATMh: hedonically-adjusted aircraft movements; dom: domestic passengers; int: international passengers; cgo: cargo tonnage; rev: commercial revenues; ter: terminal surface; run: runway length; wm: price of materials; wp: price of labor; t: time trend. Bold indicates non-significant coefficients (5%).

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 0.854 as indicated in Martín and Voltes-Dorta (2011a). The allocative distortion ξ is specified as a normally distributed variable with mean zero and inverse-variance 18, based on the notion that average AI is likely to be small (Kumbhakar and Tsionas, 2005) and input proportions are unlikely to deviate more than twice from the optimal ones. The prior distribution of η_i was also chosen to be a zero mean normal distribution representing the prior indifference, despite the circumstances, between increasing or decreasing efficiency at each airport. An inverse-variance of 10 allows for a reasonable spread. The same applies to the ψ coefficient of the hedonic ATM function that is specified as a uniform distribution $U(0,2)$.

$$\beta \sim N(0,0), \sigma_v^{-2} \sim G(0.001,0.001), \lambda \sim \exp(-\log r^*)$$
$$, \xi \sim N(0,18) \eta_i \sim N(0,10), \psi \sim U(0,2) \tag{7}$$

Since the estimation will benefit from any additional information that can be added to the system, both factor share equations (materials and labor) are included. The results of the Bayesian estimation are shown in Table 4. The R^2 coefficient (built in the estimation code) provides an average 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 e.g. a t-ratio test) that the vast majority of parameters (35 out of 39) are significantly different from zero at a 5% 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 positive and significant, implying the existence of some degree of short-run disequilibrium. The degree 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 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[16]. This is seen in the case of London Heathrow, which presents diseconomies of capacity despite the recent terminal expansion (ECU = 0.96). In this case, the exceptionally congested runways are offsetting any cost advantages related to the excess 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 suggests that airports are outsourcing more than would be desirable. Nevertheless, the quality of the data does not allow for a detailed analysis of AI. Therefore, the next chapter combines both technical and allocative components in a single indicator of cost efficiency (*CE*) upon which the impact of the recession will be analyzed. The individual *CE* estimates can be obtained by multiplying each airport's technical and allocative efficiencies ($CE = TE \times AE$) calculated from the following expressions (Kumbhakar, 1997):

$$VC^a = VC^0 VC^{AI} e^u; VC^{TE} = VC^0 VC^{AI}$$
$$TE = VC^{TE}/VC^a; AE = VC^0/VC^{TE}; CE = TE \times AE$$
$$= VC^0/VC^a TE_{it} = exp(-u_{it}); AE_{it} = \left(VC^{AI}{}_{it}\right)^{-1} \tag{8}$$

4. Results and Discussion

The estimated cost frontier provides technological evidence upon which a preliminary analysis on cost flexibility can be carried out. Knowing that most sample airports operate with excess capacity (*ECU* > *1*), therefore, costs should not increase more proportionally than traffic; the operating trends shown in Fig. 2 are clearly a symptom of decreasing cost efficiency worldwide. Even allowing for inflation and its impact over input prices, the significant increase in operating costs will hardly be explained by a falling output.

[16] Note that $\psi > 1$, which indicates that short-run marginal ATM costs increase more than proportionally with MTOW. Nevertheless, our short-run value is lower than previous long-run estimates (Martín and Voltes-Dorta, 2011), which makes sense since ATMs are particularly capital-intensive.

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Table 5
Impact of increased inefficiency on industry EBIT margin (airport sample).
Source: own elaboration.

PPP USD billion	2007	2008	2009
A. Aviation revenues	24.54	25.96	26.21
B. Commercial revenues	17.86	18.94	18.27
C. Total revenues (A+B)	42.40	44.90	44.48
D. Operating costs (labor+materials)	22.58	24.18	24.70
E. Depreciation and amortization	8.38	8.81	9.79
F. Total costs (D+E)	30.96	32.99	34.49
G. EBIT margin (C−F)/C	26.98%	26.53%	22.46%
D'. Operating costs at 2007 efficiency		23.21	23.26
G'. Corrected EBIT margin (C−D'−E)/C		28.68%	25.71%
Difference (G'−G)		2.15%	3.25%

Table 6
Evolution of cost efficiency estimates 2007–2009.
Source: own elaboration.

	2007	2008	2009	VAR 2007–09 (%)	Losses (PPP'000)
Total North America	**0.830**	**0.789**	**0.765**	**−6.49**	**−620,094**
Canada	0.808	0.780	0.760	−4.83	−32,878
US	0.831	0.790	0.765	−6.61	−587,217
Total Asia-Pacific	**0.895**	**0.824**	**0.835**	**−5.94**	**−197,932**
Australia	0.868	0.840	0.848	−1.97	−5,469
New Zealand	0.883	0.861	0.857	−2.59	−17,336
China—Far East	0.903	0.812	0.830	−7.35	−175,127
Total Europe	**0.796**	**0.772**	**0.748**	**−4.77**	**−434,716**
Austria	0.766	0.750	0.737	−2.92	−15,000
France	0.772	0.731	0.723	−4.90	−21,109
Germany	0.772	0.772	0.740	−3.23	−115,453
Italy	0.813	0.795	0.806	−0.69	−2,507
Russia	0.644	0.641	0.633	−1.08	−9,068
Turkey	0.802	0.802	0.820	1.74	0
UK	0.834	0.780	0.748	−8.63	−271,578
TOTAL SAMPLE	**0.828**	**0.788**	**0.769**	5.85%	**−1,252,743**

As expected, the average cost efficiency of the airport sample drops approximately 6% during the recession (exactly 5.85%), from 82.8% in 2007 to 78.8% in 2008 and finally 76.9% in 2009. At first sight, it is surprising that the largest impact on airport efficiency occurred during 2008. However, it was in this year that the largest gap between traffic and operating costs was recorded. The question of whether 5.85% is a significant drop can be answered by determining its impact on global operating margins. Since ACI does not provide data on depreciation for the global industry, the airport sample will be used instead (See Table 5). The global EBIT margin[17] in 2007 (baseline) was 26.98%. The significant increase in operating costs during 2008 was partially offset by a parallel increase in airport charges and concession fees, which had an impact on both aeronautical and commercial revenues (Airport Charges Monitor, 2008; ACI, 2009). Thus, the EBIT margin remained relatively stable at 26.53%. As expected, a slight decrease in revenues, coupled with the lack of cost control led to a significant fall in the year 2009 (22.46%). Assuming that the sharp decrease in cost efficiency during the recession can be exclusively linked to the lack of flexibility, it is possible to determine its impact on EBIT margins by just recalculating the operating costs for 2008 and 2009 under the baseline efficiency level (82.8%). The corrected margins would be approximately 2.15% and 3.25% higher than the actual ones in absolute terms (7.5% and 12.6% higher in relative terms), which gives an idea of how significant this problem is. Using a similar method, these losses can be extrapolated to the global industry, considering the baseline year 2007, and using ACI estimates (USD 55 and 57 billion in operating costs in 2008 and 2009, respectively). The calculations yield an estimated USD 5.5 billion in global losses associated to the lack of cost control and flexible management during the recession.

Going back to the sample, for 2009 the average loss across the 194 airports is estimated at USD 1.3 billion. In spite of that, it is clear that the global impact of the recession is unevenly distributed, even within the same region. The breakdown and evolution of these cost efficiency estimates[18] by geographical clusters is shown in Table 6. The 72 North American airports are the ones more significantly affected, dropping 6.5% in cost efficiency during the recession. US airports dropped almost 4% in 2008, clearly as a consequence of the impact of increasing fuel prices on airline activity. Taking the aggregate variable costs in 2009 from Table 3 as reference, this downward trend translates into USD 620 million in financial losses, an amount that would be more than enough to finance the airport authorities of two major hubs in the US, such as e.g. Atlanta or Chicago. Considering that both US and Canadian samples feature almost every large airport in each country, it can be assumed that these estimates are a good indicator of the total losses for the respective national airport systems.

In Australia and New Zealand cost efficiency estimates drop between 2 and 2.6%, respectively, while the Far East lost about 7.4%. Even though the Asian sample is not comprehensive (7 airports), these results characterize two alternative approaches to airport development: the first one linked to severe land restrictions and lengthy planning procedures, and the second one characterized by fast growth and unlimited expansion. The impact of such policies on cost flexibility is clear, as significant step-changes in size and capacity are observed, affecting not only the capital expenditures, but also the supposedly "variable" labor and material costs (e.g. Beijing Terminal 3 in 2008). Thus, even though Asian airports are experiencing explosive growth, their average cost efficiency dropped from first to third place in 2008, immediately below Australia and the new top-performer, New Zealand. Indeed, both countries managed to avoid the worst part of the economic recession because of their robust financial systems and increased trade flows with China Treasury, 2010. These results also suggest a positive impact of privatization and long-term management leases on cost flexibility, as both features are characteristic of Australian and New Zealand airports. This agrees with previous studies on the impact of ownership on airport efficiency, such as Oum et al., 2008 or, more specifically, the studies by Hooper and Hensher (1997) and Abbott and Wu (2002) on Australian airports.

The European results provide some insight on the likely determinants of cost flexibility in the airport industry: internalization, corporatization and airport size. European Airports were, on average, more flexible than their American and Asian counterparts, which is surprising given the reduced level of outsourcing (traditionally linked to increased cost flexibility) at many European clusters, such as Austria or Germany. Indeed, previous studies, such as Oum et al. (2004) and Tovar and Rendeiro (2010) found a positive impact between outsourcing and cost efficiency. This contradiction between our results and the existing literature

[17] EBIT margin (Earnings Before Interest and Tax) is defined as the operating income (operating revenues minus operating costs) divided by operating revenues.

[18] Traffic-weighted efficiency averages (related to passenger numbers) were calculated. The efficiency estimates for the individual airports can be consulted in Voltes-Dorta (2011).

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suggests that what works during expansive times does not necessarily apply to recessions as well. A deeper analysis of the largest European sample airport, Frankfurt, reveals a strategy of staff reduction, combined with increased internalization and improved labor productivity in order to control operating costs (FRA, 2010). Thus, airports with a higher share of in-house activities may be more capable of implementing such policies as they have more control over their operating expenditures. The reason is that airports that outsource commit themselves to paying fixed price contracts for services to third-party suppliers that cannot be re-negotiated in the short-term if demand does not grow as planned. Furthermore, the gradual shift to public corporatization in both countries, along with Italy and Russia, is proposed as another plausible explanation for this result, especially compared to the French regional airports, which remain largely controlled by local chambers of commerce. Referring again to Fig. 2, it appears surprising that Austria outperforms Germany, which were the only ones actually successful in controlling operating costs. The likely reason is that German sample airports are, on average, larger than the Austrian and hence more cost elastic. In particular, note the relatively high cost elasticity at Frankfurt (0.86). From a technological point of view, German airports are required to cut costs much more than other smaller clusters in order to remain efficient. A similar argument can be drawn for e.g. US airports above, suggesting a negative relationship between airport size and cost flexibility. Similarly to the outsourcing example discussed above, airport size, which has been identified as a positive driver of cost efficiency by many studies (e.g. Gillen and Lall, 1997; Sarkis, 2000; Barros, 2008a; Martín et al., 2009) is likely to hamper the implementation of cost-saving programs during an economic recession due to increased organizational complexity.

The least flexible European cluster is UK. Total efficiency losses in the UK airport industry amount to USD 271 million against the pre-crisis baseline (note that the UK airport sample is comprehensive). As in the Beijing case, these losses can be mostly associated to the significant step-change in labor and material costs observed in Heathrow Airport after T5 was inaugurated in 2008, aggravated by a decrease in passenger and freight traffic during the same period. Regarding developing regions, Turkish Airports, especially Istanbul Ataturk and Antalya, reveal themselves as a model for flexible growth in Europe, becoming one of the top-performing clusters in the sample (82%). Many of these airports' international terminals are leased to companies that provide expertise in airport management (e.g. Fraport, TAV) and who have been able to capitalize on the booming leisure and low-cost markets.

5. Summary

The most recent economic downturn led to a significant contraction in the global demand for passenger travel and air cargo. In spite of that, the trend in airports' operating costs did continue to increase, thus indicating a lack of flexibility. With this background, the objective of this paper is to estimate the impact of the recession on airports' cost efficiency and financial performance. This is achieved by estimating the industry's short-run cost frontier over a balanced pool database of 194 airports worldwide observed between 2007 and 2009. Taking into account that the major traffic losses were registered in the "mature" markets of Europe and North America, the airport sample is biased to these regions. However, data clearly shows that all regions have problems with cost flexibility, as operating costs grow more than proportionally than traffic in all cases.

The estimated cost function parameters reveal the existence of very significant economies of capacity utilization at the average airport (ECU=2.13). If this result is contrasted with the actual trends in costs and traffic, it is not surprising to find a global drop of 5.85% in cost efficiency for the airport sample between 2007 and 2009. Extrapolating this figure to the worldwide industry (using ACI estimates), the aggregated financial loss associated with the failure of cost control measures and flexible development programs during the recession is estimated at approximately USD 5.5 billion. Using a similar method, the impact on industry EBIT margins is also estimated between 7%–12%, in relative terms, showing that airports should indeed prepare for any contraction in demand as operating costs, for several reasons, are not quite as volatile as traffic and commercial revenues.

Efficiency results differ significantly across regions, with North American airports being the ones most severely affected by the recession. This would suggest a negative relationship between airport size and cost flexibility, which comes to no surprise given the significant step-changes in capacity experienced at large hubs. The airport's cost structure also appears to have its influence on cost flexibility, yet in this case, the findings appear to challenge conventional views which advocate the outsourcing of airport core functions. Results suggest that reduced outsourcing may be beneficial for cost flexibility. Hence, airports with a higher share of in-house labor will be more successful at implementing cost-saving programs. The same applies to European public corporations and airports operated under long-term management leases (e.g. Turkey, Australia), as both seem to provide the right incentives to control costs and protect margins through the recession.

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Appendix A. Sample airports

See Table A1

Appendix B. Short-run model specification

$$\ln VC_{it}^{a} = \ln VC_{it}^{0} + \ln VC_{it}^{AI} + u_{it} + v_{it}$$

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

$$\begin{aligned}\ln VC_{it}^{AI} = {} & \beta_{10} \xi_p + \gamma_{12} atmh\ \xi_p + \gamma_{14} dom\ \xi_p + \gamma_{16} int\ \xi_p \\ & + \gamma_{18} cgo\ \xi_p + \gamma_{20} rev\ \xi_p + \gamma_{22} ter\ \xi_p + \gamma_{24} run\ \xi_p \\ & + \delta_{26} \omega_m\ \xi_p + \delta_{27} 0.5\ \xi_p\ \xi_p + \ln G_{it}\end{aligned}$$

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

Appendix A

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 Int		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		Indianapolis		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
	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				

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

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

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

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

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

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

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

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