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How scale and institutional setting explain the costs of small airports? - An application of spatial regression analysis

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Abstract

One of the main pillars of efficient airport operations is cost-minimization. Unit costs of operation with respect to the level of passengers served are a possible proxy to measure the cost efficiency of an airport. Due to compound production framework and sophisticated political-economic environment of airports, estimation of airport costs requires detailed specifications. Airport cost functions should be able to explain the total costs with the main inputs labor, material and capital as well as by taking the airport specific characteristics into account. In this paper, we apply such an approach and focus on airport specific characteristics. We use a spatial regression methodology to explain how these drive the unit costs and analyze the spatial relationship among the dependent variables. Two separate data samples from Norwegian and French airports are used in this research to test various hypotheses.

Because a large number of regional airports in both countries cannot reach financial break-even, our first research question deals with the effects of subsidies, which often follow regional and political considerations. One must therefore find an efficient way to maintain these airports without any distortions on the incentives. When evaluating the relationship between subsidies and unit costs, we find negative effect of subsidies on airport cost efficiency. Second, we evaluate the importance of economies of scale by focusing on the relationship between airport size and unit costs. Finally, the results of spatial regression show that a denser spatial distribution of airports results in higher unit costs as a consequence of lower capacity utilization, indicating the negative effect of spatial competition on airport unit costs within an airport network.

Keywords: Airport costs, airport subsidies, spatial regression, scale economies

JEL Classification: C23, C51, R11, R42

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1. Introduction

The need for high output levels for airports in order to be able to achieve cost-efficient operations has always been a challenging issue for airport managers and authorities, as well as the political decision makers. Airports serving a higher number of passengers are able to exploit the cost advantages of distributing the fixed costs over a larger output. Pels et al. (2003) find increasing returns to scale at European airports in terms of passenger traffic. Martin and Voltes-Dorta (2011a) show that, even for large major hubs around the world, advantages from increasing the scale of operations are still significant. For a large number of airports in Europe it is not possible to reach the minimum scale, for which the generated revenues would cover the fixed and operational costs. A small catchment area and insufficient inbound traffic at such airports can be considered as the most important reasons for such low output levels. This problem leads to a trade-offs: Either a cost efficient airport network can be sustained with a relatively lower number of airports, but then the quality of connectivity would suffer with a less dense airport network. Although competition is shown to increase the productive efficiency (Malighetti et al., 2008; Chi-Lok and Zhang, 2009) or financial efficiency (Starkie, 2008), airports within a network are generally not subject to competition. Instead they rely on joint operational planning with a need for direct or indirect subsidies for ongoing operations (Adler et al., 2013). Nonetheless, the negative effects of subsidies on the productive efficiency of firms should not be neglected.

In Norway, for example, the state-owned limited company Avinor AS is responsible for the operations of 46 airports in the country since 2003. The network of airports is characterized by a cross-subsidization scheme, where a few large profitable airports cover the losses of smaller airports, which are also subsidized by the Norwegian Ministry of Transport and Communications through the support of PSO[4] flights. These small airports serve a very low number of passengers (GAP-Project, 2012).

In France, on the other hand, airports are subject to individual ownership and operation, but those airports with financial losses are also in need of financial aid. They rely on direct local or federal government subsidies. The Directorate General of Civil Aviation publishes data over 80 airports annually, 64 out of which serve less than 1 million passengers (DGAC, 2009). Both in Norway

[4] Public Service Obligation

and France, airport density is above the European average.[5] The extent of subsidies varies significantly across airports in both countries, with Norway spending a much greater sum. Maximum subsidy per passenger served amounts to approximately 30 euro in France and 185 euro in Norway. In terms of average values, the average subsidy per passenger served equals to 3 euro in France and 26 euro in Norway.[6]

In this paper we investigate the determinants of airport unit costs by applying a spatial regression model, which allows for testing the locational interdependence of airports within a country. Next section presents an overview of the literature on airport cost functions as well as on the effect of subsidies on efficiency. In section 3, the research methodology and data are described. The results are illustrated in section 4, followed in the last section by concluding remarks and directions for further research.

2. Literature Review

The study of airport cost functions has attracted less attention until the 2000s, mainly due to methodological complexities and the detailed data requirements. Cost functions took either a translog or a Cobb-Douglas form. While some research has focused only on short-run cost function, others have estimated long-run cost functions allowing for variations in the assumed inputs. In most of these studies, "number of passengers" (PAX), "number of air traffic movements" (ATM) and "freight" were used as the outputs produced by an airport in multiple-output models. Often one of these variables has been used as the only output, indicating a single-output production technology. Labor, capital and material have mostly been used as inputs of airports, but the proxies used for inputs have changed according to the data availability.

In the literature we find that airport cost functions have been estimated to answer a wide range of questions concerning managerial, economic, social and political practices. Carlin and Park (1970) studies optimal pricing strategies to overcome the delay problem for LaGuardia airport. Keeler (1970) calculates the marginal costs of runway usage for 13 airport systems in the US and differentiates between capital and operational costs. According to Morrison (1983) cost functions should be estimated with a more sophisticated model that looks at capacity related usage, and the delay costs of the runways. Tolofari et al. (1990) estimate both short and long-run cost functions

[5] http://en.worldstat.info/Europe/List_of_countries_by_Number_of_airports_per_million_persons
[6] Although we do not have data on all subsidized airports in France, these summary figures enlighten the situation in comparing the two countries with respect to subsidy levels.

for 7 British airports, with PAX, ATM and freight as outputs; labor, equipment and capital stock as inputs as well as their prices and various operational attributes of airports. Carlsson (2002) estimates the marginal costs of 19 Swedish airports by using a log-log functional form with PAX as single output. Further, he compares the existing charging structure with marginal-cost prices derived from the analysis. Martin-Cejas (2002) determines the relative efficiency of 40 Spanish airports by estimating a translog cost function with a joint output of passengers and freight transported. The results show that the insufficient airport scale is the main reason behind efficiency differences observed. Craig et al. (2003) also estimate a cost function to compare the efficiency of authority-operated airports with their city-operated counterparts for 53 US airports. The cost function is based on a unique output, namely the ATM and three inputs labor, capital and materials. Main et al. (2003) estimate Cobb-Douglas cost functions for the short and long-run in order to investigate the necessity of a new airport in central Scotland. They conclude that total welfare can be significantly increased in case of developing the existing two airports instead of building a new, larger airport. By using data from 94 US airports Jeong (2005) estimates a translog cost function, in which various operational characteristics are incorporated such as share of international traffic, delay and the level of outsourcing of important activities of the value chain. He finds out that the minimum efficient scale is reached by serving 2.5 million passengers a year. Low and Tang (2006) show the degree of input substitutability at 9 Asian airports by estimating a translog cost function. A stochastic cost frontier in translog form is implemented by Barros (2008) to show the differences in efficiency levels of 27 airports from the United Kingdom. Oum et al. (2008) apply a similar translog cost frontier model to 109 airports worldwide and show that mixed public/private ownership structures lead to the least efficient production structure. Link et al. (2009) estimate the marginal costs for Helsinki airport to show the linear relationship between the number of aircraft movements and the number of employees. McCarthy (2010) estimates a short-run translog cost function for 35 US airports and determines increasing returns to scale in terms of runway utilization. Assaf (2010) utilizes a Bayesian stochastic cost frontier approach by using a Cobb-Douglas form to determine the level of cost efficiency for 13 Australian airports. The results show that none of the airports in the sample can attain the optimal scale. Pels et al. (2010) estimate various specifications of translog cost functions by using a dataset of 36 airports worldwide. Their results indicate the importance of economies of scale. The authors also discuss the infeasibility of marginal cost pricing. Barros (2011) deals with the heterogeneities between the airports in any sample and uses a latent class model to divide the airports into three clusters. After building the clusters, a translog cost function with PAX and ATM as outputs and labor, capital and capital-investment as inputs, is used to identify the efficiency levels for 17 airports in Africa. Martin et al. (2011) estimates various translog cost functions with single and multiple outputs by using data from 36 Spanish airports and conclude that the airports cannot achieve the minimum efficient scale and there exists limited possibility for input substitution. Martin and Voltes-Dorta (2011b) draws similar conclusions on minimum efficient scale with an enlarged dataset of 161 airports worldwide. The same model is implemented by Voltes-Dorta and Pagliari (2012) for 194 airports worldwide to estimate a short-run cost frontier. The authors conclude that the average cost efficiency decreased by 6 percent during the crisis between 2007 and 2009. Martin et al. (2013) use the results of the previous work to implement a second stage regression to measure the cost flexibility of airports and show the disadvantage of higher outsourcing level during a recession.

A look at this literature shows us, that despite addressing similar questions the conclusion may vary depending on the methodology chosen and data implemented. For example, the relationship between costs and the scale of operations is one of the most investigated topics. There is a consensus that airports enjoy scale economies, however the number of passengers necessary to reach efficient scale differs significantly from one study to another.

Furthermore, incorporating airport specific characteristics into cost functions helps to explain the differences in which inputs such as labor, capital and materials are allocated to the production. The literature shows us, that airport costs are driven by external factors, such as traffic structure (percentage of international passengers, percentage of business passengers, LCC share and share of cargo traffic), delays or the degree of competition between airports. The type of ownership and the level of outsourcing also matter. These last two points relate to the governance structure, an issue that we already noted in the study by Oum et al. (2008) concerning the negative effects of mixed ownership. How subsidies affect the operational performance or capital costs has however not been studied. For small airports with inadequate passenger throughput, subsidies play a very important role for their financial survival. Previous research on other industries (including transport sectors) very often point to the adverse effect of subsidies on the operational and capital costs. There has been an extensive research on urban public transport (transit) to find an answer to this question.

Bly et al. (1980) investigate 59 urban public transport companies worldwide and conclude that higher subsidies are associated with higher unit costs and higher number of employees, notwithstanding the positive effects on fares and quality of service. Anderson (1983) explores the changes in governance structure of bus transit companies in the US in detail. By estimating supply and demand equations for the market, the author shows a 28 percent increase in unit operating costs resulting from the introduction of local, state or federal subsidies. Pucher et al. (1983) use multiple regressions to find out the determinants of unit operating costs of urban public transport in the US. Their results indicate that increase in costs accelerated and productivity declines with higher subsidies. They recommend a better monitoring of operations as well as linking these subsidies to specific performance goals. In another paper, Pucher and Markstedt (1983) conduct a comparative analysis of unit costs over ten years for local US bus companies. They show that as the subsidies increased between 1970 and 1980, this led to higher unit costs. They argue that financial support by local governments rather than by the federal governments would enhance efficiency. Besides, performance based subsidies are necessary for better incentives. That, subsidies lead to an increase in unit costs as well as reduction in output per employee for transit companies is also shown by Bly and Oldfield (1986), who expand their study from 1980 to 117 cities. Further, with a time lagged regression they show that the rise in costs follows from a rise in subsidies. Karlaftis and McCarthy (1997) implement a factor analysis method, where they define the quality of transit system in Indiana with efficiency, effectiveness and overall performance. The adverse relationship between the subsidies and performance leads the authors to advocate a performance based subsidy system. In another study Karlaftis and McCarthy (1998) investigate the effects of subsidies and other governance characteristics on costs in transit industry by implementing a fixed effect regression. Their results show that subsidies coming from local, state or federal governments impact the costs differently. Furthermore, Granger causality exists between subsidies and performance. Nolan et al. (2001) estimate relative efficiency scores of transit companies in the US by using a Data Envelopment Analysis (DEA) followed by a second stage regression to determine the factors influencing efficiency. The regression results indicate that the local subsidies increase the efficiency, whereas the federal ones work in negative direction.

How subsidies influence the costs has also been examined for other industries. For instance, Oum and Yu (1994) conduct a DEA for 19 railway companies from OECD countries and test the determinants of efficiency with a second stage Tobit regression. According to their results, subsidized railways achieve lower efficiency scores than their unsubsidized counterparts. Cowie (2009) investigates British train operating companies. After the privatization, the government gradually decreased the subsidies to these companies. A DEA Malmquist Index shows that the efficiency changes were positively influenced by the reductions in subsidies. Bergström (2000) analyzes a similar question on the relationship between capital subsidization and firm performance for manufacturing industry. By employing a statistical model with data from Swedish manufacturing companies he concludes that there is a little evidence for a positive effect of capital subsidies on the productivity. Tzelepis and Skuras (2004) use a regression analysis for Greek food and drink-manufacturing sector and show that regional capital subsidies positively influence growth, but have insignificant effects on efficiency and profitability.

In the light of this literature on other industries, we expect to also find a positive relationship between subsidization and the level of costs for airports. Independent of the causality between those two variables with respect to the direction of the effect, i.e. whether higher costs lead to higher subsidies, or vice versa, it postulates that the incentives created by subsidies influence the costs in an undesirable course.

Further, some Baker and Donnet (2012) propose to promote an overall policy for Australia, in which all the stakeholders including federal, state, local governments as well as industry groups jointly take place in strategic decisions. Cohen (2002) also shows that the airport spending rises/decreases proportionally as airport grants increase/decrease.

The effects of the geographical proximity of airports to each other has been subject to various studies (Barrett, 2000; Pels et al., 2009; Fröhlich and Niemeier, 2011; Lian and Rønnevik, 2011). Yet, the main focus of these studies was to investigate the competition among airports. However, the spatial interdependence of airports relates also to broader topics such as the effects of network characteristics, airline-airport relationship, cost levels and productive efficiency rather than just competition effects. Moreover, Huber (2009) shows that a spatial concentration exists in the European airport network and there is a gap in the airport literature regarding the influence of spatial interdependence on a number of issues. The application of spatial relatedness is therefore an approach which includes geographical, cultural and economic factors in the analysis. First, the closeness between two airports means they are subject to similar geographical, climatic and natural characteristics. For example, airports lying on the oceanic coast in Norway mainly struggle with the frozen runways in winter compared to airports located on mountain ranges having to deal with snow, which leads to distinctly different cost characteristics. Second, spatial proximity also can be an expression of cultural similarities, as the behaviors of economic agents in the same regions of a country appear to be comparable. Last but not least, unique or very close economic conditions such as the GDP, growth rates and purchasing power of inhabitants in the same region make the economic environment, in which the airports work, also very close to each other. With the proposed regression specification we would therefore want to show the statistical significance of the spatial interaction of airports. From an econometric point of view, in addition, ignoring the spatial specifications when constructing the cost model could lead to biased estimates of the coefficients. For these reasons, one has to consider also the effects of the geographical distribution of airports and the spill-overs between them. (Pavlyuk, 2012)

To our knowledge, Pavlyuk (2009) is the first application of spatial econometrics to the airport industry. He investigates the relationship between the competitive pressure on an airport and its efficiency by introducing a new definition of airport catchment area. Pavlyuk (2010) tests whether proximity leads to cooperation or competition among airports in Europe by constructing a stochastic frontier model that incorporates spatial econometrics. The results show that airports located within a distance of 550 km tend to cooperate, while competition starts dominating for airports located within 550 km to 880 km. The stochastic frontier model applied also implies that many airports operate below the production frontier and exhibit high inefficiency levels. In another paper, he makes an extensive review of airport benchmarking literature and shows how the competition among airports was included as an explanatory variable in these studies (Pavlyuk, 2012). Finally, Pavyluk (2013) utilizes various spatial stochastic frontier models by using data from 122 European airports and estimates the production function of airports. A comparison of results from these various models shows the necessity of including the spatial characteristics in the stochastic frontier models, so that the biases can be eliminated from the estimations.

Following this review of the literature we first attempt to integrate the spatial interdependency of airports in the regression identifying the determinants of airport costs. By implementing a spatial regression model, we are able to include information about cost-relatedness between nearby airports resulting from geographical, cultural or economic resemblances. Second, we investigate the effects of airport subsidies on cost efficiency, which have so far been ignored in the literature. Third, we evaluate the level of scale economies at airports.

3. Methodology and Data

We introduce the economic interaction between the airports (that is their spatial autocorrelation) and their spatial heterogeneity (i.e. spatial structure) by using the methods of spatial econometrics to explain the determinants of airport unit costs from the perspective of spatial interactions and spatial effects (see Paelinck and Klaassen, 1979; Anselin, 1980, 1988 and 2001; LeSage and Pace (2009) and the references therein). According to Anselin (1988) and LeSage and Pace (2009), we can consider the following formulation of spatial regression models, namely spatial lag, error model and cross-regressive model:[7]

$$y = \rho \cdot W \cdot y + X \cdot \beta + \Upsilon \cdot W \cdot X + u \qquad (1)$$

$$u = \lambda \cdot W \cdot u + \varepsilon \qquad (2)$$

with $\varepsilon \sim N(0, \sigma_\varepsilon^2 I_n)$

W is an $n \times n$ spatial weights matrix which is crucial for incorporating the spatial effects into the regression model.[8] It specifies which spatial unit affects the other ones as well as in which way the interaction takes place (Anselin, 2001 and 2002; Elhorst, 2013; LeSage and Pace, 2009). In the simplest case, one considers the binary weights with the elements of W-matrix $w_{ij} = 1$, when i and j are neighbors, and $w_{ij} = 0$ otherwise. Another common way to model spatial interaction is to use a smooth or continuous distance decay function so that $w_{ij} = f(d_{ij})$ where d_{ij} is the distance between the unit i and j (Anselin, 2001 and 2002; Anselin et al.,2008; Elhorst, 2013).

When $\rho = \Upsilon = \lambda = 0$ and $\beta \neq 0$, it delivers a standard regression model, which reveals no spatial interaction. When $\rho \neq 0$, $\beta \neq 0$ and $\Upsilon = \lambda = 0$, it is a spatial lag model, which presents the spatial impact of the dependent variable in the host region on the dependent variable in the surrounding regions.[9] The coefficient ρ measures the intensity of the spatial effects. The higher the absolute value of ρ is, the stronger the spatial lag of the dependent variable y influences the calculation of the predicted value of $\hat{y}$. In most cases, the weights matrix is row-standardized for

[7] Their combinations result in a possibility for seven different specifications of the model.

[8] n presents the number of spatial statistical units considered in the analysis, which refers to the number of airports in this paper.

[9] A region in this context means simply the statistical unit. Again, in our context it is an airport.

better interpretation so that $W \cdot y$ is the term of the form such that it presents a weighted average of the value of y in the neighboring locations called spatial lag. If $\rho = 0$, $\beta \neq 0$, $\Upsilon = 0$ and $\lambda \neq 0$, it is a spatial error model, which reports the spatial effects in the errors. If $\rho = 0$, $\beta \neq 0$, $\Upsilon \neq 0$ and $\lambda = 0$, it represents a cross regressive model, which presents the spatial impact of the explanatory variables in the host region on the dependent variable in the surrounding regions. Last but not least, one can consider a combination of those models as well, e.g. spatial lag-spatial error model or spatial lag-cross regressive model with the corresponding formal representation.

The extension from a spatial regression model to a spatial panel model is straightforward, as in the case of the extension from a classical regression model to a classical panel model, with the usual model specification of individual effects α_i in fixed-effects model or of the error term $\varepsilon_i = \mu_i + v_{it}$ in the random effects model (see e.g. Anselin, 2001; Elhorst, 2001 and 2003; Anselin et al., 2008; Jeleskovic and Schwanebeck, 2012). It is obvious that the choice of the ''best'' specification of the panel model might not be a trivial task.[10] Hence, we will consider here only the basic specification of the fixed effects model, namely the spatial lag fixed effects model. The estimation of this model was done with Matlab and the codes made by Elhorst (2010) which include already the bias correction procedure of Lee and Yu (2010).

As already mentioned, the critical point of the spatial regression is the weight matrix which has to be assumed as an exogenous one (Anselin, 1980 and 1988). Using a distance matrix for spatial weights, one uses some smooth declining function for individual weights in most cases:

$$w = \frac{1}{d^{\alpha}} \qquad (3)$$

where d stands for the distance (e.g. in km) between two spatial units and α is a smooth parameter usually an integer $\alpha = [1,2]$ (Anselin, 1988 and 2002).

However, in the sense of the spatial clustering one can assume that some first kilometers around an airport do not make a difference, and after these first kilometers the impact and catchment area are vanishing in a steep grade, and then kilometers far away do not make a big difference again.[11] Thus, we use a non-linear weighted function of decaying distances which we construct by using a

[10] Given several possibilities for different specifications for either fixed or random effects models.
[11] See a similar argumentation of Pavlyuk (2009).

so-called sigma-shaped function between two airports i and j as depicted in the following equation:

$$W_{ij} = 1 - \frac{1}{1 + a * exp(-b * distance_{ij})} \qquad (4)$$

where $i \neq j$, $a > 0$ and $b > 0$ and d_{ij} is the distance between airports i and j measured in km. Next, we deal with the question how to find out the optimal values of a and b. Anselin (2002) points out that, model validation techniques, such as a comparison of goodness-of-fit, can be used to find out the best specification of the weight matrix or the parameter of distance decay function. We use the Akaike information criterion-AIK (Akaike, 1974) to solve the problem of best parameter values in our distance decay function.[12] Hence, parameters a and b are calibrated due to the best value of AIK by estimating the regression model for each combination of a and b values. We apply a grid search algorithm over a and b in such a way that all distance decay functions in the parameter space of a and b are unique.[13] Hence, we do not have the identification problem by the parameters a and b. Finally, we use the row-standardized weight matrix W, where the sum of each row is equal to one (Anselin, 1988 and 2002; LeSage and Pace, 2009).

In this paper we apply the second specification because of the assumption that the airport unit costs (dependent variable in our model) at nearby locations show similarities to each other because they use the same production technique. Hence, the regression model we use takes the following final specification:

$$y_{it} = \rho W y_{it} + \beta X_{kit} + \alpha_i + \varepsilon_{it} \qquad (5)$$

where y is the vector of dependent variable for airport i in year t, ρ is the spatial autoregressive parameter, W is the weighted distance matrix, X is a matrix of k independent variables, β is the vector of coefficients to be estimated, α is the fixed effect parameter for each airport i and ε is a vector of independent error terms.

[12] This is applied according to Fotheringham et al. (1998 and 2000) and Eckey et al. (2007). These authors provide for using the AIK criterion to optimize the bandwidth parameter in the distance decay function in a geographically weighted regression approach, which is very similar to our econometric approach used in this research.

[13] We take over the assumptions of Anselin and Bera (1998) that the weights matrix is exogenously incorporated into the model

The dependent variable we use in the spatial regression is the unit costs of airport operations (*costppax*), calculated by dividing the total operational costs by the annual number of passengers served. Total operational costs include the labor costs, material costs and outsourcing costs but exclude the depreciation. Hence, the analysis ignores the investments undertaken at the airports and focuses merely on the operational level. The matrix of independent variables composes of 7 variables. A year dummy variable is introduced into matrix of independent variables in order to identify time trend of unit costs (*year*). As we utilize a panel dataset between 2002 and 2010 for Norway and 2002 and 2009 for France, *year* dummy variable controls for the annual changes in average cost levels. To examine how important the scale of operations at an airport for the unit costs is, work load unit (*wlu*) is used as an independent variable. *wlu* is a combination of number of passengers and amount of cargo served by the airport and is a good proxy for the cumulative output of the airport. Due to the fact that there are a lot of small sized airports in our dataset, we expect to find out significant economies of scale. In order to analyze the influence of subsidy levels on the cost efficiency, we follow the idea of Oum and Yu (1994) and calculate the ratio of subsidies to the operational costs (*subs*). This variable shows to what extent the losses are covered by either cross subsidies or direct financial installments.

Although the share of commercial revenues increased on average in the last decade, the aeronautical revenues are the core revenue source of most airports, particularly the smaller regional airports that dominate our sample. These mainly include the fees paid by the airlines for using the airport infrastructure. Especially smaller airports with limited possibilities of generating commercial revenues rely mainly on the aeronautical revenues. Hence, including aeronautical revenues per passenger (*aerrev*) delivers valuable results in interpreting the extent of cost coverage by airport charges. This variable has occasionally been used as a proxy for the level airport charges in the literature (Bilotkach et al., 2012).

In spite of the fact that our dataset comprises of commercial airports, these airports serve non-commercial flights as well. These flights are those which are not authorized for public transportation and include flights such as military, ambulance, school, instruction and general aviation. Non-commercial flights constitute a high share of the traffic at some airports in our dataset. For example for the airports in our dataset they make up one fifth of all the flights in Norway and two thirds of all flights in France in 2009. By including the share of non-commercial air traffic movements in total air traffic (*noncommatm*), we test how these flights drive the airport unit costs.

Whether an airport serves any flights through public service obligation (pso) is included as another dummy variable.

In addition investments in terms of either expansion or modernization will influence the operational costs by altering productivity. By having a capital-intensive production technology, airports can benefit from modernization investments in terms of efficiency. Furthermore, investments directly influence the level of capacity utilization at an airport. For these reasons, the total investments should be included in the regression function. However, the data on such investments are not fully available for the whole period of analysis. For this reason, we include the depreciation per passenger (*depr*) as a proxy of capital.

For the spatial regression analysis two separate data samples, i.e. from Norwegian and French airports, are used: A balanced panel dataset of 41 airports in Norway for the years between 2002 and 2010 and a balanced panel dataset of 26 airports[14] in France between 2002 and 2009. Table 1a and 1b present the descriptive statistics for the variables.

Table 1a: Descriptive Statistics for Norwegian Airports, 2002-2010

Variable	costppax	wlu	subs	aerrev	noncommatm	pso	depr
Minimum	3.42	5850	0	2.80	0.02	0	0.79
Maximum	247.00	1,649,847	1.50	25.98	0.83	1	142.26
Average	38.62	206,035	0.52	7.91	0.23	0.74	10.50
Standard Deviation	35.45	342,347	0.31	2.69	0.16	0.44	15.01

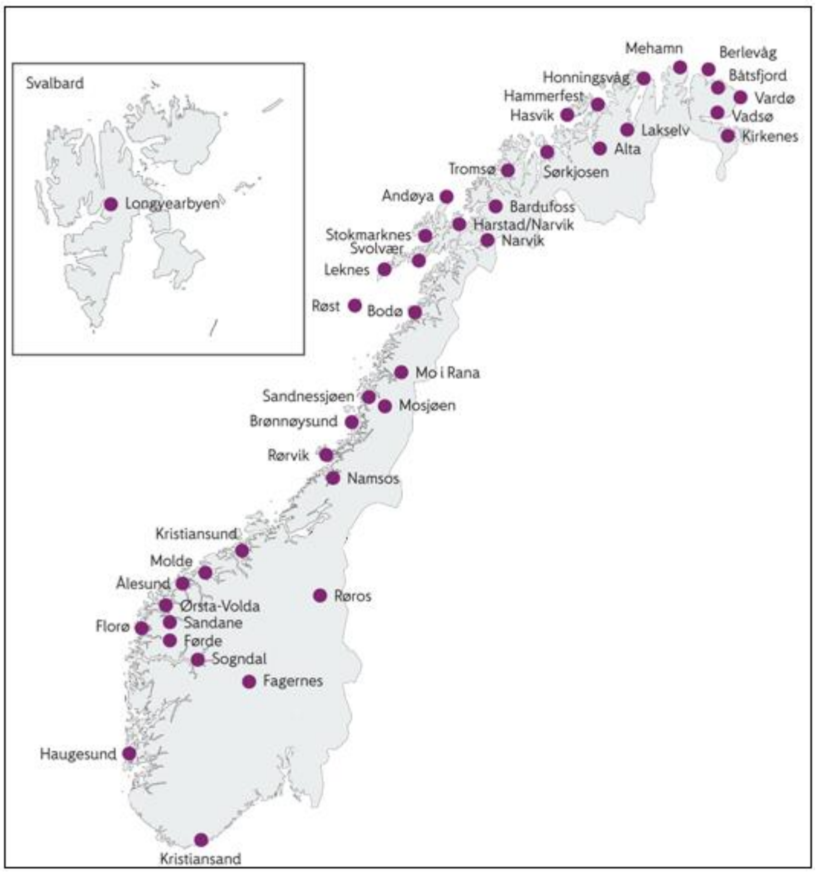
Table 1b: Descriptive Statistics for French Airports, 2002-2009

Variable	costppax	wlu	subs	aerrev	noncommatm	pso	depr
Minimum	8.25	14,441	0	4.50	0	0	0
Maximum	66.46	7,295,964	0.70	22.15	0.96	1	18.66
Average	16.67	826,325	0.15	8.45	0.66	0.53	3.21
Standard Deviation	8.89	1,274,584	0.16	1.90	0.26	0.50	2.70

[14] of which 4 are on the island of Corsica

In Figure 1, the 41 Avinor airports used in the analysis are shown on the map. Especially on the northern part of the country, the density of the airports is very high. Topographical peculiarities of the country and their social policies towards better connectivity are responsible for such a high number of airports (Lian, 2010). But, on the other hand, total demand is distributed among airports instead of being concentrated at one key airport in a region. Hence, having a close competitor is decreasing the volume of total output at each airport, therefore driving up operating costs per movement.

Figure 1: Norwegian Airports used in the Regression Analysis

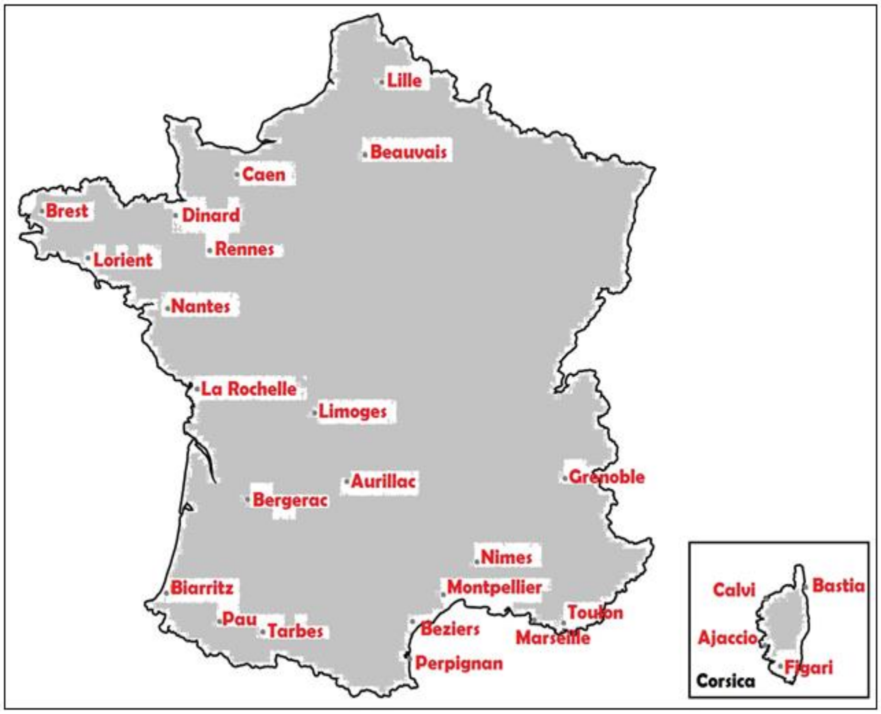


Source: Avinor

Figure 2 displays the 26 French airports used in the analysis on the map[15].

[15] It should be noted that the proportion of the airports, which we are able to include in the analysis, in comparison to the total number of airports is very low for France, while in Norway we could obtain data on almost all the airports.

Figure 2: French Airports used in the Regression Analysis



Source: own compilation

4. Results

Table 2 displays the results of the spatial regression analysis from model (5) for the airports in Norway and France separately. To start with, we evaluate the results from the spatial perspective by interpreting the coefficient ρ and the corresponding t-values. The coefficient is statistically significant for both countries. This indicates a significant spatial dependence among the airports, as far as the unit operating costs is concerned. Furthermore, the coefficients are positive. Hence, costs of one airport are positively influenced by the weighted average of costs of neighboring airports; that is by the spatial weights matrix W calculated with the Equation (4). This, as well, leads to the interpretation that airports located close to each other seem to have similar cost structures. It should be noted that zero values on the diagonal of W matrix assures that the interaction of the same observation in the regression equation is excluded. The coefficient for Norway is significantly higher than that for France, which indicates that the positive correlation between costs of nearby airports in Norway is stronger than in France. It is not a surprising fact, not only because Norwegian airports are centrally managed by the Avinor Headquarters, but also because Avinor has built four administrative sub-units[16] of its local airports according to their geographical position. This evidently leads to similar management techniques for the airports in the same group. These local airports make up 28 of 41 sample airports; the remaining 13 airports are grouped as national and regional airports. On the other hand, French airports in the sample are managed individually and have no administrative links to each other, which possibly enable them to introduce own strategies regarding the cost structures.[17]

Table 2: Estimation Results from the Spatial Regression

Variable	*Norway*	*France*
year	0.050* (9.23)	0.026* (6.46)
wlu	-0.816* (-18.81)	-0.443* (-10.46)
subs	0.203* (3.87)	0.219* (2.76)
aerrev	0.113* (3.25)	0.223* (4.39)
noncommatm	0.229*** (1.65)	-0.266* (-2.85)
pso	-0.018 (-0.67)	-0.046*** (-1.75)
depr	0.032** (2.20)	0.014*** (1.71)
$\boldsymbol{\rho}$	0.685* (12.36)	0.365* (3.55)
$\mathbf{R}^2$	0.98	0.94
Adjusted $\mathbf{R}^2$	0.84	0.56
Log-Likelihood	307.00	185.14

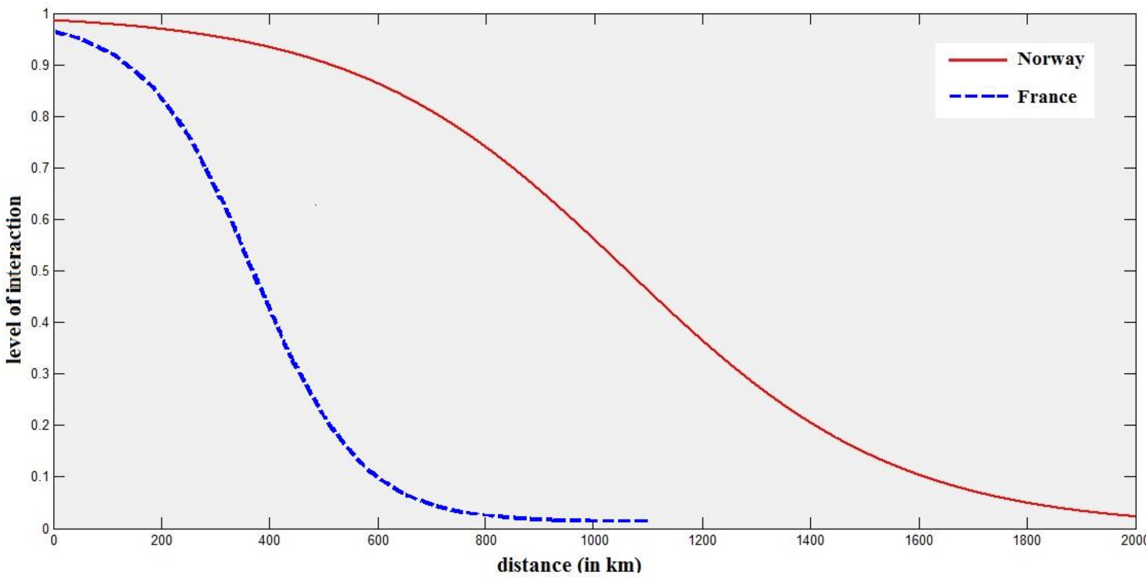
1. Dependent variable is "costppax" (Operating costs per passenger)
2. Independent variables "wlu", aerrev" and "depr" are in natural logarithms.
3. t-values are in parentheses
4. * 1% significance; ** 5% significance; *** 10% significance

Figure 3 plots the interaction level as a function of distance from Equation (4) for our sample airports from Norway and France. According to these two figures, the interaction levels remain

[16] These four sub-units are: *Finnmark, Ofoten/Lofoten/Vesterålen, Helgeland/Namdalen* and *Southern Norway*
[17] The private company Vinci has concession contracts for the management of Dinard, Rennes and Nantes airports, however this happened in 2010, after the timeframe of this analysis.

much higher in Norway, as the distance between airports increases. This leads to the implication that the presence and strength of links between airports in Norway is much higher than in France in our sample.

Figure 3: Non-linear weighted functions of decayed distances for Norway and France



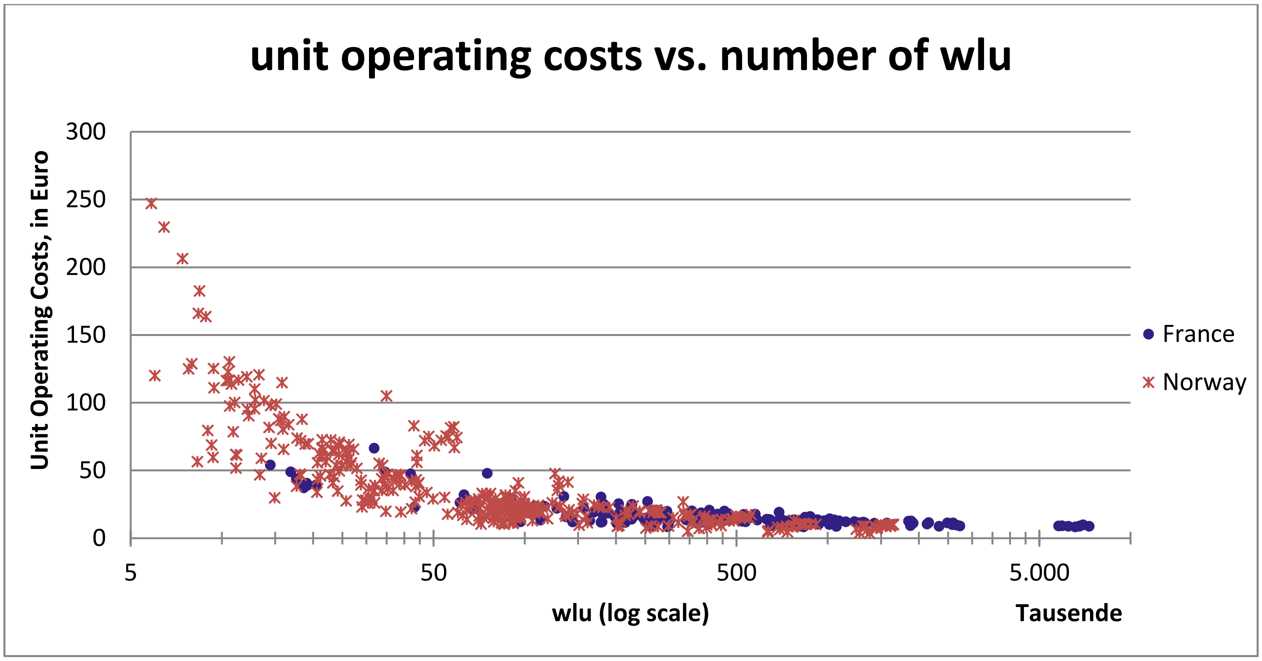
The coefficients for the time trend for both countries are highly significant and have positive signs. It can be concluded that the unit operating costs have increased since 2002. For the 41 Norwegian airports, we observe approximately 5 percent annual increase in average costs. On the other hand, the yearly increase in average costs amounts to 2.6 percent for 26 French airports in the sample[18].

How scale affects the unit operational costs are investigated by using the variable *wlu*. The negative sign of the coefficients for both countries indicates that the unit costs decrease with increasing output, i.e. airport size. One percent increase in the level of *wlu* leads to approximately 0.82 percent decrease in the costs per passenger in Norway and approximately 0.44 percent decrease in France. Figure 4 visualizes the relation of unit costs with respect to the airport size, where the unit operating costs are shown against the number of work load units (in log scale). Due to the larger number of very small airports in the sample, Norwegian airports operate on a steeper curve. Especially those airports serving less than 50,000 annual work load units suffer

[18] GAP-Project (2012) finds out that security costs at small Norwegian airports increased more than proportionally between 2002 and 2010, which is a partial explanation of increasing overall costs.

from very high average costs. A detailed analysis of average costs in order to determine the minimum efficient scale of airport operations is beyond the scope of current work and is left for further research.

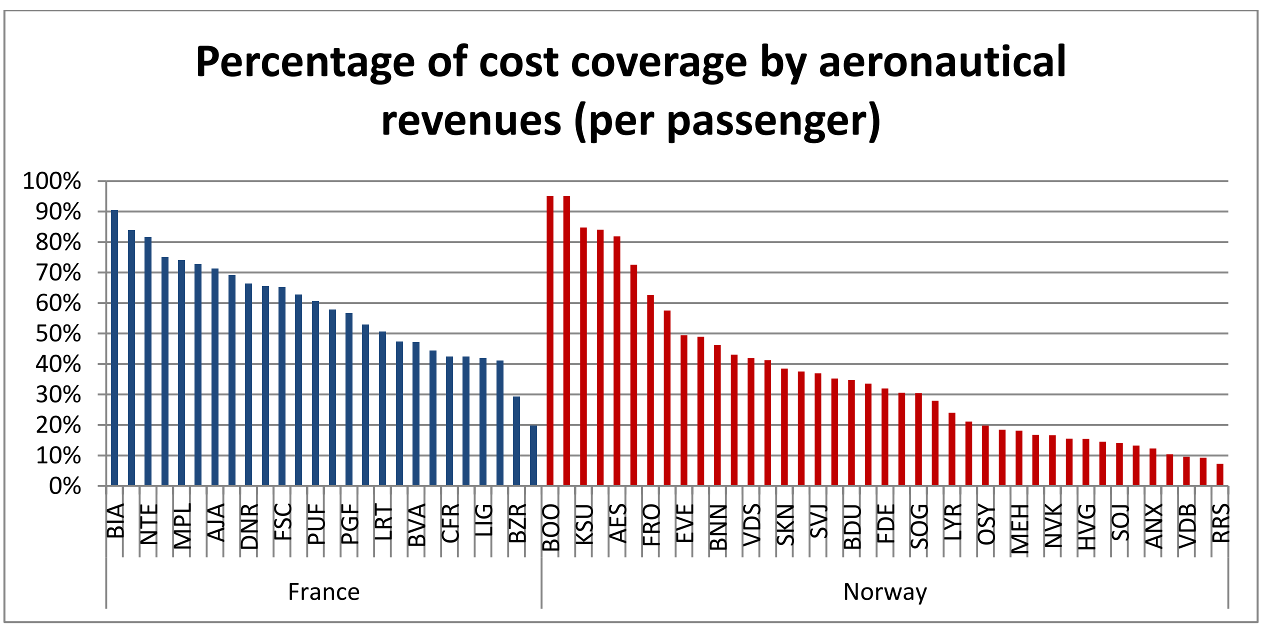
Figure 4: Scale Effect on Unit Operating Costs



The coefficient of the variable *subs* enables us to confirm the relationship between the level of cost coverage by the subsidies and the unit costs of airports. Having a positive coefficient in both countries indicates that higher subsidies lead to higher unit costs and this relationship is statistically significant. To our best knowledge, this is the first attempt in the literature of airport economics, which statistically analyses the relationship between the two variables. The results suggest that if the subsidies relative to costs increase by one percent, the unit costs increase by approximately 0.2 percent both in Norway and France. It should be noted again that the ratio of subsidies to costs is used as the independent variable in the regression, because the absolute values of the subsidies are not relevant due to different scale of various airports.

Next, it can be seen that the revenues from the aeronautical charges per passenger have a significant positive relationship with the unit operating costs by observing the results for the variable *aerrev*. Furthermore direct correlation between the unit costs and aeronautical revenues per passenger amounts to 0.25 in Norway and 0.28 in France. Despite the obtained significant and positive relationship, the coefficients and the correlation values are relatively small indicating that the aeronautical revenues are insufficient, given the operational costs. This raises concerns whether determination of airport charges follow calculations based on the costs. The challenge airport managers are facing is the question to what extent the airport fees can be increased, which are paid by the airline companies. Elasticity of demand for air travel increases as the travel length decreases. Normally for long-haul flights, we observe inelastic demand. However elastic demand can characterize the short-haul flights, because the airport charges constitute a higher proportion of total airline costs. Following this argument, if we assume a price elastic demand of airlines for airport services (Intervistas, 2007; Starkie and Yarrow, 2013), the aeronautical revenues will further decrease when the airport fees are increased and this leads to a vicious circle of whether the aeronautical revenues may be increased at all. The dataset implies no significant relationship between airport size and the share of aeronautical revenues in total revenues. This is driven by the fact that relatively small airports dominate the sample. Following figure shows that none of the airports in the sample was able to cover the operational costs by the aeronautical revenues on average over the time span. The average value amounts to 36 percent and to 58 percent, for the 41 Norwegian and for the 26 French airports respectively.

Figure 5: Relationship between Costs and Aeronautical Revenues, 2002-2009 or 2010



The variable *noncommatm* delivers different results for the two countries regarding the direction of the influence of non-commercial air traffic share on the unit costs. While unit costs increase in

Norway with increasing share of non-commercial air traffic, they decrease in France. In order to explain the conflicting results, further analysis regarding the components of non-commercial air traffic is necessary. Despite not having detailed data, we assume that the general aviation traffic constitutes an important part of non-commercial activities at French airports, hence lowering the overall unit costs. In contrast, Norwegian airports serve mainly other type of non-commercial activities such as ambulance flights.

Some airports benefit from the centrally-organized and government-subsidized PSO routes by increasing the number of passengers served. These services help airports improve the unfavorable situation of having too little traffic, which leads to higher average costs. Furthermore some airports entirely rely on PSO flights. Regression results deliver negative coefficients for the *pso* variable. In France, an airport with PSO flights operates with 4.6 percent less average costs than those airports without any PSO flights. We observe the same, but weaker, relationship for Norway as well, however the coefficient is statistically insignificant.

Finally, the coefficients of the variable *depr* are positive indicating that the value of depreciation per passenger influences the average costs in the same year positively. The interpretation of the positive coefficients is somewhat difficult, but intuitionally one can explain this with the lagged effect of investments on the unit costs. It is to say, some investments require a couple of years to be utilized effectively. Furthermore the lumpiness of airport investments such as runway or terminal expansions leads to lower capacity utilization in the time period following the investment. The higher unit costs might be associated with the low utilization of capacity at those airports, which undertook recent expansions. In addition, the coefficients of the depreciation variable are significant only at 5 and 10 percent levels for Norway and France respectively. It can be driven by the fact that that there is no differentiation in the depreciation data with regard to the lifetime of the investment made. Both small investments such as computers or office supplies and large investments such as for runways and terminals are included in the depreciation data. A further distortion to the depreciation data relates to the establishment of Avinor in 2003, which from then on was responsible for the whole airport infrastructure in the country. Upon establishment Avinor made an immense investment to improve the infrastructure at airports that where before operated by the communes or regional bodies. This led to a sudden jump in the data for depreciation[19].

5. Conclusion and Directions for Further Research

Our study is based on two separate data samples that consisted of subsidized airports in Norway and France, with which a number of hypotheses could be tested. The spatial lag regression model indicated a significant level of spatial relatedness among airports, namely the spatial impact of the dependent variable (unit costs) at the host airport on the unit cost of the surrounding airports. We also studied the relationship between subsidies and costs as well as the importance of scale economies. Furthermore, the annual changes in average cost levels, cost coverage via aeronautical revenues, importance of non-commercial air traffic movements, the effects from PSO routes and the level of investments were evaluated in this paper.

The unit costs of airports show a statistically significant level of spatial interdependencies which was estimated by the ρ variable in the regression specification. The spatial relationship in Norway is much stronger than in France. Thus, it can be concluded that once the airports are managed as a group, the interaction among them tend to be stronger mainly due to the organizational similarities. Although competition is assumed to improve the cost efficiency, one should treat this issue with special care and evaluate the spatial distance between airports in detail. In terms of overlapping catchment areas, where airports are located very close to each other with limited aggregate demand in the area, positive effects due to competition are offset by factors like insufficient exploitation of scale that lead to negative results in terms of the costs, or technical efficiency of airports.

From a methodological point of view, the significance of the results of the spatial parameters indicates that the model specification enables us to avoid biased estimates. An F-test can be implemented to test the efficiency of the model in comparison to a non-spatial regression specification. However, in further research indirect effects should be introduced in order to improve the analysis. These include the secondary relationships between a host airport and a third airport, where the spatial dependence of unit costs is transited via an airport located between

[19] Total depreciation for the 41 airports in the sample increased by approximately 53 percent between 2002 and 2003.

those two airports. Nonetheless it is believed that these effects would only lead to negligible changes in the results we have obtained.

The significant positive relationship between the share of costs covered by the subsidies and the unit costs indicate that subsidies may provide distorted incentives. Thus policies regarding the subsidization of airports and routes should be re-evaluated. Subsidization policies should include mechanisms, which will better align the incentives of the airports with the government rather than merely encouraging non-market driven traffic as riskless financial support. Moreover, fiscal decentralization would enhance the way subsidies are allocated to the necessary nodal point, which should replace the centrally organized installments to cover any expenses accrued at an airport. For instance, the local governments can be endowed with a yearly sum of financial support and the allocation between different nodes of public good provision such as airports; ports; highways; rail or water, gas and electricity infrastructure should be undertaken according to the needs of the region. Another, but a similar option would be to decide the level of subsidy each airport will receive prospectively, rather than paying for the costs ex-post irrespective of the magnitude. We believe that the causality between the two should be investigated in more detail by applying a more in-depth regression analysis, in which time lagged variables can determine the direction of the causal links as well as a Granger-causality test.

Inadequate demand at the airports is the most important reason behind high unit costs. Some airports are not able to achieve a break-even point due to scale, although they might be technically efficient with regard to the input output combinations chosen. Hence, policies towards increasing the demand for the airport services on the one hand and closing very small airports on the other can help to overcome this problem. In most of the airports, traffic is considered to be an exogenous variable, on which the managers have no influence. Bel (2009) defines this situation for Spanish airports as "a hand tied behind back", however presents the example of Girona, where local institutions express a great interest in the situation of the airport due to financial spillover effects in the region. In addition, airline-friendly policies are applied by the airport. These resulted in a tenfold increase in the number of passengers served. However, it should be kept in mind that such policies should be applied with a special care. Girona airport almost exclusively relied on the services by its main customer Ryanair, which constituted approximately 90 percent of the total traffic in 2007. Such a dependency on a single customer certainly leads to concerns about a sustainable business model. Nevertheless, Ryanair started reducing the offers from or to Girona airport, reducing the total number of passengers at the airport continuously after 2009.

In some other cases, traffic stimulation via PSO grants appears to be the only solution to increase the demand at the airports. However, our results show that the unit costs at PSO airports are not statistically different than those at other airports in Norway. This is in line with the results of Pita et al. (2014), who suggest that the PSO system in Norway can be enhanced. In France, on the other hand, PSO services seem to improve the airport unit costs. Airports with PSO share tend to operate with approximately 4.6 percent lower unit costs. Precise information about the PSO shares for the airports would further enhance the analysis.

As regards scale economies, it should finally be noted that an estimation as to the minimum efficient scale of operations at the airports was not undertaken in this research, because based on previous literature it is assumed that the airports in the sample serve a very low number of passengers, so that the results of such an analysis could not be generalized to larger airports.

Low capacity utilization accelerates the problems with respect to high unit costs, as shown with the depreciation variable in our regression specification. From this finding, it can be concluded that an optimal long-term strategy for small-sized airports should be not to increase the capacity unless a certain threshold for the utilization of current capacity is reached.

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