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MULTI-TIER SPATIAL STOCHASTIC FRONTIER MODEL FOR COMPETITION AND COOPERATION OF EUROPEAN AIRPORTS

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This paper is devoted to a statistical analysis of spatial competition and cooperation between European airports. We propose a new multi-tier modification of spatial models, which will allow an estimation of spatial influence varying with distance. Competition and cooperation effects do not diminish steadily relative to distance from a given airport; their structure is more complex. The suggested model is based on a set of distance tiers, with different possible effects inside each tier.

We apply the proposed modification to the standard spatial stochastic frontier model and use it to estimate competition and cooperation effects for European airports and airport efficiency levels. We identify three tiers of spatial influence with different competition-cooperation ratios in each one. In the first tier (closest to an airport) we note a significant advantage for cooperation effects over competition ones. In the second, more distant, tier we discover the opposite situation; a significant advantage for competition effects. There is no significant advantage for cooperation or competition effects with the most distant tier. In this paper we also consider some other possible applications of the proposed spatial multi-tier model.

Keywords: spatial stochastic frontier, airport efficiency, competition, cooperation

1. Introduction

Late 1970s almost all airports and airlines were owned by government bodies. Therefore all interactions between airports were formalised and a level of competition and cooperation in the industry was insignificant. Monopolies and duopolies (supported by the famous “two airlines” law) didn’t have to care too much about efficiency of airports’ operations and thus weakly competed and cooperated. After a series of deregulation acts and privatisation decisions the industry was liberated; privately held companies positively influenced on a level of competition on the market.

Over the past few years, airports have been considered in the popular ‘competition vs. cooperation’ debates [1]. Before the recent economic crisis, discussion focused mostly and sometimes only on issues of competition. However, when airports met additional difficulties related to the overall decline in passenger traffic, cooperation became increasingly important and attracted the attention of researchers.

The area of competition between airports is wide and varied. It includes competition between adjacent airports in overlapping catchment areas for passengers and for local resources, competition to attract airlines, competition between airport groups (formal or informal), and other aspects. This research is oriented to the analysis of spatial competition for passengers between adjacent airports. The situation in which more than one airport serves a population is usual in Europe. This can be seen in major urban areas (London, Paris, etc) and also in peripheral areas which are not served by an airport in their immediate surroundings. When alternative airports are available to a population, competition effects appear [2].

In many cases when airports have overlapping catchment areas, cooperation effects also occur [3]. These effects can have different forms. Firstly, airports operating in the same areas, can be joined to different types of alliances or even have the same owners (for example, Heathrow and Gatwick, or Charles de Gaulle and Orly). Another common form of cooperation between airports is ’main airport plus satellites’. The main airport handles a significant part of the passenger traffic (usually international), while satellites serve special groups of customers (for example, domestic passengers or low-cost airlines). Finally, cooperation effects can appear without any formal or informal agreements between airports, but due to the nature of their operations. Often, if an airport operates successfully in a particular area, it promotes overall regional development, resulting in more businesses, more tourists, better infrastructure and better transport networks. Consequently, adjacent airports obtain additional utility, and therefore cooperation effects increase.

It is obvious that both competition and cooperation affect each airport areas of activity. However, much research is oriented towards the analysis of one aspect only (usually competition). In this research

we try to examine both aspects simultaneously. Note that the task of separating competition and cooperation effects completely appears very problematic (if not impossible), so the aggregative effects on an airport are estimated and observed for different distances from the airport.

The modern approach to analysis of dependences between adjacent economic units is spatial econometrics [4]. Spatial models utilise information about the units' geographical locations and distances between them to estimate interacting effects. The famous Tobler's Law says "everything is related to everything else, but near things are more related than distant things", and this statement is the basis of spatial models.

Usually spatial models are constructed focus on only one spatial effect (for example, competition between adjacent airports). However, we believe that spatial effects are not so straightforward, and It is possible that the effects of neighbours located in the immediate vicinity and the effects of more remote neighbours could be completely different, even differently directed. In this research we introduce a modification of spatial models (called *multi-tier*) and apply it to the data set of European airports.

2. The Spatial Multi-Tier Autoregressive Stochastic Frontier Model

Operating efficiency is a key indicator for a company, acting in a competitive market. There are a set of methodologies developed to estimate company's efficiency in last decades; many of them take a multivariate, relative nature of efficiency indicator into consideration. Frontier-based approach is based on constructing of a set (real or hypothetical) of absolutely efficient companies (an efficiency frontier) and estimating of company's efficiency as a distance from this frontier. Stochastic frontier analysis utilises probabilistic philosophy to construct the efficiency frontier and estimate companies' efficiency levels.

The stochastic frontier model is usually presented as [5]:

$$\begin{aligned} &y = f(x,\beta) + \varepsilon, \\ &\varepsilon = v - u, \\ &v \sim N(0,\sigma_v^2), u \geq 0, \end{aligned}$$

The model specification considers economic units as producers of an output y which use resources x, but act with some level of inefficiency u.

Usually ([6], [7]) distance is included into spatial models in the form of a contiguity matrix W, whose components w_{ij} are metrics of spatial relation between objects i and j. Specification of the matrix W is usually under researcher's responsibility, and the main question here is to determine a power of interrelation between objects on the base of their geographical locations. There are some different approaches to specification of the matrix W, but first of all we need to distinguish two cases, related with a type of given geographical objects:

- Objects have geographical areas with borders (strictly defined or fuzzy). We always can specify if two objects of this type are adjacent and have a common frontier. For example, countries, regions within a country, districts of a city can be considered as objects with an area.
- A geographical border between two objects cannot be specified. For these object we cannot define exactly if two objects are neighbour, we just can measure a distance between them. Very often researchers consider these objects as mathematical points (without areas).

There are different approaches to define the contiguity matrix for objects of first and second types.

The easiest form of the matrix W for first type objects is a binary matrix of neighbourhood. In this approach a matrix item equals to 1 if two objects are adjacent (have a common border) and equals to 0 otherwise. For calculation purposes the matrix should standardised, so frequently matrixes values are divided by a total number of object's neighbours:

$$w_{ij} = \begin{cases} \dfrac{1}{count\ of\ objects\ adjacent\ with\ an\ object\ j}, if\ objects\ i\ and\ j\ are\ adjacent \\ 0, otherwise \end{cases}.$$

Generally speaking, the resulting matrix is not a stochastic one, because a data set can contain objects without neighbours, and the sum of values for this row will be equal to 0, not to 1.

Approaches for the second type objects are usually based on a distance between them. The distance d_{ij} should be considered as a geographical distance, but can be estimated in different ways [8]:

- An exact distance in kilometres between two objects. For relatively close objects the distance can be calculated as Euclidean distance for objects' coordinates, but objects are relatively far one from another (so a spherical form of the Earth becomes significant), a great circle distance should be used.
- Time required for a trip from one object to another. This metric is better than the previous one in case when accessibility should be included into consideration.
- Travel cost is also often used as a metric of a distance.

Travel time and cost should be used when we suppose a spatial structure related with human activities. For example, if we consider tourism in two cities and we assume that tourists travel from one city to another, we should use travel time or cost as a metric of a spatial dependence between cities. But if we study a spatial structure of farm production and we assume that local climate characteristics have an influence then physical distance metrics will be probably better.

Power of spatial interdependence can be non-linearly reduced with a distance between objects. In this case a distance decay function should be considered.

Finally, spatial influence can be limited with a predefined distance value h, so the objects located farther than h kilometres (or minutes, or Euros) one from another have 0 values for their relationship in the contiguity matrix.

We consider airports as objects of the second type (without borders) in this research. We used a great circle geographical distance as a metric of relation between airports, without any distance decay function. Different distance tiers are used in the model to separate different distance-related types of influence of neighbour airports.

Spatial interrelation is possible between all components of the stochastic frontier model, including the output y. We include the spatial dependence of the output in the specification and the resulting model is autoregressive.

In general case, spatial data structure can have an influence on three components of the model:

- the efficiency frontier $f(X,\beta)$;
- the inefficiency term u as a distribution parameter;
- the dispersion of the inefficiency term u (heteroskedasticity).

Finally the general spatial autoregressive stochastic frontier model with Cobb-Douglass functional form of the frontier and truncated normal distribution of the inefficiency component can be specified as

$$\ln(y) = \rho \ln(W_1 y) + \beta \ln(X) + v - u,$$
$$u \sim N^{+}(\lambda W_2 y, W_3 \sigma_u^2),$$
$$v \sim N(0, \sigma_v^2)$$

Contiguity matrixes W_1, W_2, and W_3 show spatial dependences in the efficiency frontier, inefficiencies and inefficiency dispersions respectively. The model specification does not force matrixes to be the same, and the spatial structure can be different for all three components. The definition of the matrix W is critically important for the model specification.

The main problem we note in the standard model specification is unidirectional dependence on spatial components. The ρ coefficient shows the dependence between the output of a given unit and outputs of its neighbouring units, and only one conclusion (positive/negative influence or no influence) is possible.

Tobler's Law states that neighbouring objects influence one another, but this does not mean that they have the same influence, or even influence in the same direction. It is possible that objects located immediately around a unit have an influence in one direction, and objects located 1 km away influence in another direction.

Let's image a shopping centre with a set of shops, some of which are operating in the same market (clothes shops, for example). Obviously these are competitors. However, since these shops are located in the same shopping centre, cooperation between them (open or hidden) is also possible. If one of the shops runs an advertising campaign and attracts new customers to the shopping centre, the other competitors capture positive effects from this. So we can speak about the cooperation effects in this situation.

Now let's consider a new shopping centre located near to the first one. Customers who visit the second shopping centre buy their clothes there and rarely visit the first centre. In this case we can observe a high level of competition and a low level of cooperation.

Finally, let's consider a town where there are a lot of shopping centres and shopping tourists from all over the world visit this town for clothes. In this situation we also can note possible cooperation effects.

A similar situation can be observed with airports. Airports which are located near to each other can cooperate efficiently for several reasons:

1. An airport contributes to the overall development of a region in terms of businesses, tourists, and infrastructure. All these factors have positive influences on neighbouring airports.
2. An airport creates a culture of using air travel and forms passengers' habits. If a person gets accustomed to using airlines for his business and recreational trips, there is a higher chance that he will use neighbouring airports.
3. Airports can use the same infrastructure and other resources (R&D, for example)

However, beyond a certain distance cooperation effects become weaker, and competition effects can surpass them. For example, the development of airports in the neighbouring regions can lead to resources being redirected to this region. This is strengthening, and therefore increasing the level of competition pressure. We can speak about competition between regions in this case. Airports will be under the pressure of competition in without any of the positive effects of cooperation.

Therefore, the influence of neighbouring enterprises can differ depending on their distance. Mathematically speaking, we have a non-linear influence, and if we try to approximate this influence with a line we can obtain insignificant or even incorrect results. We suggest a modification of spatial models to prevent these problems. Instead of using one contiguity matrix which covers all the areas around the point, we can construct a set of matrices, each covering a ring around the point. For example, the first ring (first tier) includes all objects within 2 km of the point, the second – from 2 to 4 km, and so on (see Figure 1).

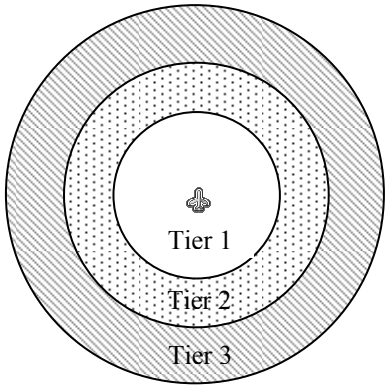

Figure 1. Airport tiers of spatial dependence

The specification of the suggested spatial multi-tier autoregressive model is (discrete case):

$$y = \sum_{tier=1}^{k} \rho_{tier} W_{tier} y + \beta X + \varepsilon ,$$

where

- W_{tier} are contiguity matrices, which contain real distances to objects within the tier and 0 for all objects outside the tier;
- ρ_{tier} are coefficients, which show the influence of the neighbours of this tier.

A respective spatial specification of the stochastic frontier model:

$$\ln(y) = \sum_{tier=1}^{k} \rho_{tier} \ln(W_{tier} y) + \beta \ln(X) + v - u,$$

$$u \sim N^{+}(\mu, W\sigma_u^2), v \sim N(0, \sigma_v^2)$$

3. Data

In this research author use the same dataset as in the previous study [2]. New spatial components are calculated on the base of existing data. The data set includes the characteristics of European airport activities from 2003 to 2007.

Three main data sources are used:

1. The Eurostat (the Statistical Office of the European Community) database is a source of information about airport activities. The information about each airport includes the number of passengers carried (excluding direct transit passengers), the number of direct flights by destination country, the number of airport employees of (directly employed), and airport infrastructure (check-in facilities, gates, runways, and parking spaces)
2. The Atlas of Airports from the Ruimtelijk Planbureau, Netherlands. This supplements the Eurostat database.
3. The Digital Aeronautical Flight Information File (DAFIF) database and Google Earth as sources of the geographical coordinates of European airports.

Descriptive statistics of main indicators are presented in Table 1.

Table 1. Data descriptive statistics

Variable	Mean	Min	Max
Passengers carried, mln.	11.8	0.9	67.9
Check-ins	89.14	10	481
Gates	38.20	2	147
Parking spaces	7610.50	1	36500
Runways	1.91	1	6
Employment, persons	1856.23	87	15526

Detailed information about the parameters used is presented in [2].

4. Empirical Results

In this research we consider an airport as an economic unit which uses its resources to carry passengers (*PassengersCarried*). Airport resources include runways (*RunwaysNumber*), parking spaces (*ParkingSpaces*) and employees (Employees). In this research this basic set of resources was supplemented with spatial components.

The first empirical problem for spatial model specification is the principle of contiguity matrix selection. We investigated some approaches to matrix construction (distance-based, travel time-based, and cost-based) and chose the distance-based approach as it was the simplest from the point of view of calculation. We assumed that this was appropriate as there are usually no direct trips between airports. Two airports can be considered as neighbours if they service the same area (i.e. their catchment areas are intercepted). In this approach there is considered to be no significant difference in distance between airports regardless of whether there are connecting high-speed/low-cost road/railway links or not. The distance between two points on a sphere (the Earth) is correctly calculated using the great-circle distance formula.

At the first stage of the research we formulated the general model and calculated a set of contiguity matrices for circles with different radii around the airport. 10 standard spatial models were constructed starting from a model with a 220 km radius of spatial dependence (Model SPAT2) to a model with a 1210 km radius (Model SPAT11), with steps in 110 km distances (1 in Euclidean distance ≈ 110 km in great-circle distance). Estimated results for Model SPAT4 (440 km) and Model SPAT 10 (1100 km) are presented in Table 2.

Table 2. Model SPAT4 (440 km) and Model SPAT 10 (1100 km) estimation results

	Model SPAT4			**Model SPAT10**		
	Coefficient	*z*	*p-value*	*Coefficient*	*z*	*p-value*
Dependent variable Ln(PassengersCarried)						
Frontier						
Ln(ParkingSpaces)	0.095	3.850	0.000	0.102	3.490	0.000
Ln(RunwaysNumber)	1.205	12.910	0.000	1.152	12.120	0.000
Ln(Employees)	0.299	7.670	0.000	0.353	8.030	0.000
Ln(W· PassengersCarried), ρ	0.030	2.640	0.008	-0.155	-2.010	0.045
Constant	12.119	39.070	0.000	15.587	10.620	0.000
Inefficiency						
Ln(W· PassengersCarried), λ	0.308	0.560	0.577	-0.205	-1.770	0.077
Constant	-7.996	-0.520	0.606	4.518	2.120	0.034
Statistics						
γ	0.833			0.681		
Log likelihood	–252.135			–253.337		

General conclusions were the same for all 10 models:

1. All basic resources (runways, parking spaces, and employees) have positive significant coefficient estimates, which match our expectations.
2. Stochastic frontier models are significantly better than simple OLS estimate (γ-statistic values are close to 1) and a significant level of inefficiency is present in the data.
3. The influence of the spatial components is not stable over the models; frontier and inefficiency coefficients change significance and even direction.

We do not pay significant attention to overall model analysis in this paper, but concentrate on the analysis of spatial components. Estimates of frontier (ρ) and inefficiency (λ) coefficients for all 10 models are presented in Table 3 and on Figure 2.

Table 3. Estimates of frontier and inefficiency coefficients for 10 standard spatial models

Model		**Frontier component, ρ**			**Inefficiency component, λ**		
	Approx. distance, km	*ρ*	*z*	*p-value*	*λ*	*z*	*p-value*
SPAT2	220	0.008	1.15	0.249	0.195	0.53	0.597
SPAT3	330	0.042	1.68	0.093	0.066	2.3	0.021
SPAT4	440	0.030	2.64	0.008	0.308	0.56	0.577
SPAT5	550	0.044	3.13	0.002	0.719	0.77	0.443
SPAT6	660	0.052	2.12	0.034	1.258	0.38	0.702
SPAT7	770	0.045	1.04	0.298	0.883	0.53	0.596
SPAT8	880	-0.125	-1.55	0.121	-0.203	-1.78	0.075
SPAT9	990	-0.138	-1.78	0.075	-0.194	-1.73	0.084
SPAT10	1100	-0.155	-2.01	0.045	-0.205	-1.77	0.077
SPAT11	1210	-0.164	-2.11	0.035	-0.212	-1.85	0.065

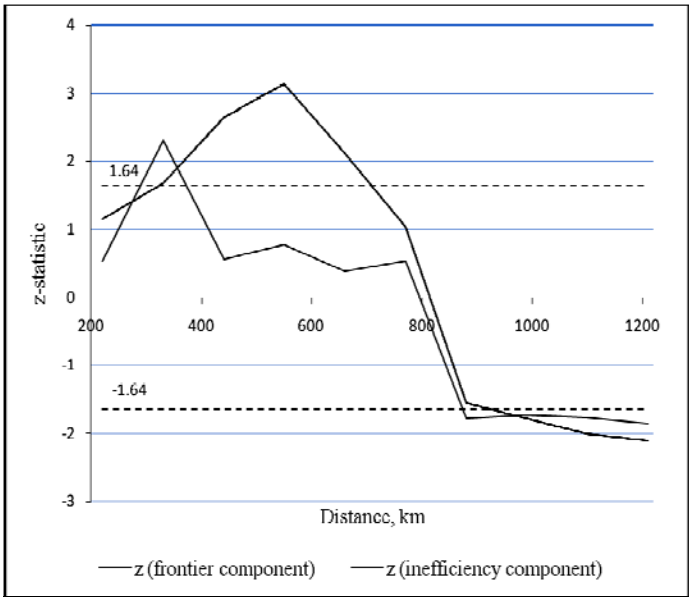

Figure 2. Dependence between frontier and inefficiency coefficients and a radius of spatial dependence

Positive values of the frontier coefficient ρ indicate that passengers carried by neighbouring airports increase the 'production' of a given airport, so this can be considered as a resource. This influence can be interpreted as a cooperation effect, and we can see that these effects are significant for Models SPAT4, SPAT5, and SPAT6 (440-660km radius).

Negative values of the frontier coefficient ρ indicate that the successful operations of neighbouring airports decrease a given airport's production. These can be explained as competition effects and are noted for model SPAT10 and SPAT11 (1100+ km radius).

Estimated values of both coefficients take as significant positive as significant negative values, which support our hypothesis about the non-stable influence of neighbouring airports on a given airport.

Behaviour of the inefficiency coefficient λ looks similar to the frontier coefficient. For models with cooperation effects on the frontier we note positive (significant or near-significant) influences of the spatial component on inefficiency (increasing it), and for models with competition effects – negative influences are noted (decreasing inefficiency). So competition appears to lead to the more efficient operation of airports. This conforms to economic theory.

Note that the spatial components of the estimated models are nested, because greater circles of spatial dependence contain smaller ones. For example, the influence of the spatial component in Model SPAT6 (660 km) includes the influence of the Model SPAT5 (550 km) spatial component and adds the influence of airports located in the 550-660 km ring around an airport. This cumulative effect makes analysis difficult. For example, the positive significant value of ρ for Model SPAT6 indicates cooperation effects, but as we can see on the chart, the influence of airports within 550 km, and the 550-660 km tier only reduces these effects.

To avoid this difficulty, and to separate the influences of each tier, we modified the standard spatial model and instead of one circle spatial component we included a set of spatial tiers (rings) around an airport. We noted on the chart that cooperation effects increase up to 550 km distance (Model SPAT5), but decrease after that until 880 km (Model SPAT8), and stabilise after this distance. Therefore we chose three tiers:

1. 220-550 km
2. 550-880 km
3. 880+ km

Respective tier spatial matrices were calculated and included in the spatial multi-tier autoregressive stochastic frontier model specification. Models estimation results are presented in Table 4.

Table 4. Spatial multi-tier autoregressive stochastic frontier model estimation results

	Coefficient	*z*	*p-value*
Dependent variable Ln(PassengersCarried)			
Frontier			
Ln(ParkingSpaces)	0.103	4.04	0.000
Ln(RunwaysNumber)	1.255	13.93	0.000
Ln(Employees)	0.350	9.45	0.000
Ln($W_{2\text{-}5}$· PassengersCarried), ρ_1	**0.032**	2.75	**0.006**
Ln($W_{5\text{-}8}$· PassengersCarried), ρ_2	**-0.057**	-4.83	**0.000**
Ln(W_{8+}· PassengersCarried), ρ_3	**0.010**	1.21	**0.227**
Constant	12.386	36.20	0.000
Statistics			
γ	0.936		
Log likelihood	-239.733		

The most interesting values (in terms of the model's specification) are marked in bold in the table.

The estimated influence of the number of passengers carried by neighbouring airports is significantly positive within the 220-550 km distance tier. From this we can form a conclusion about significant cooperation effects between airports located in one region.

The influence of airports located in the 550-880 km tier is significantly negative, so competition effects for these airports are significantly higher than cooperation effects.

Finally, there is no significant dependence of airports located at 880 km and further from an airport, so cooperation and competition effects are absent, or compensate for each other.

A possible pattern of cooperation-competition effect power is presented on Figure 3.

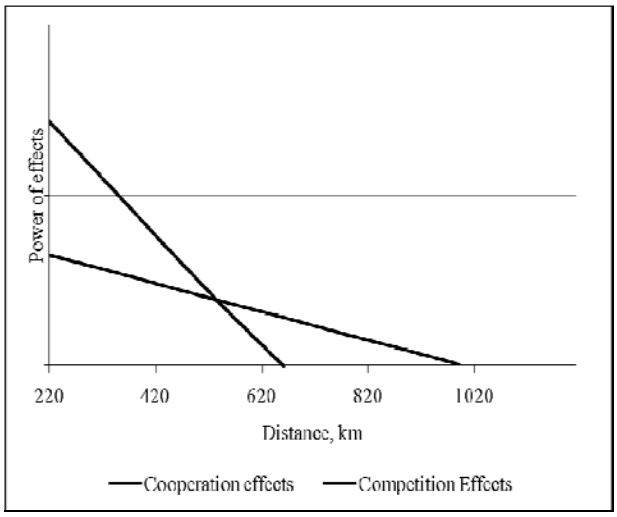

Figure 3. Possible pattern of competition-cooperation effects

According to the graph, cooperation effects are stronger immediately around an airport, but diminish much faster than the effects of competition. This pattern exactly matches observable behaviour; there is significant cooperation influence within the first tier, competition influence within the second tier and no significant effects for greater distances.

This analysis could be very important for airport managements, airport associations and government bodies.

One of stochastic frontier model's advantages is a resulting set of individual levels of efficiency for every airport and every time point. The analysis of efficiencies, its patterns, and dynamics is not presented in this paper; here we just discuss a difference between efficiency estimates, received from the non-spatial and spatial models.

First of all, we can't directly compare efficiency levels in two models. Spatial components change the specification of the frontier, so the resulting values are not comparable. So in this research we compare not efficiency levels directly, but their ranks. Spearman's rank correlation coefficient, frequently used for these purposes, has been calculated:

$\rho = 0.9387$,

$P\{\rho = 0\} = 0.000$.

Spearman's ρ shows a strong positive relationship between efficiency ranks in the non-spatial and spatial models. We calculated differences of ranks in two models to investigate it in details. The extreme difference values are presented in Table 5.

Table 5. Differences of efficiency ranks for the non-spatial and spatial models.

Airport name	**Country**	**Difference of efficiency ranks,** $Rank_{non\text{-}spatial} - Rank_{spatial}$
Malta/Luqa	Malta	-17
Larnaka	Cyprus	-17
Toulouse Blagnac	France	-8
Stockholm/Arlanda	Sweden	-8
Bologna/Borgo Panigale	Italy	-6
…	…	…
Koln/Bonn	Germany	6
Bruxelles/National	Belgium	8
Paris/Orly	France	8
Faro	Portugal	24
Sevilla	Spain	25

As we expected the most significant changes in efficiency estimates turned out for airports with the smallest or the biggest number of powerful neighbour airports. The ranks are affected both by competition and cooperation effects, so there is no general explanation of differences, each airport should be considered separately. Negative rank difference values show that airport's rank in the spatial model is higher than in the non-spatial model; the non-spatial model underestimates efficiency levels. We can note from the Table 5 that these airports are generally located far from the nearest big neighbours, so cooperation effects are low for them. The non-spatial model overestimates efficiency levels for airports with positive ranks in Table 5, which means that the airports are supported by positive cooperation effects from adjacent airports.

5. Conclusions

In this paper the author suggests new modifications of spatial models called spatial multi-tier stochastic frontier models. The feature of these models is an embedded possibility to estimate changes in the influence of spatial components, depending on the distance from a given economic unit. This type of model can be useful in situations where the influence of neighbouring units is not unidirectional, but can vary, and where this variation is related to the distance between units. Incorporating spatial components into the model for different distance borders (tiers) separately in order to analyse the differences in the relationships are suggested.

The proposed spatial model modification has a various areas of application. Competition vs. cooperation between economic units, positive vs. negative effects of new buildings/enterprises in a city,

new directions in social sciences and other applications presuppose that its influence has different power and directions. In cases where these differences are spatial and can be explained by the distance between units, the new model specification seems to be useful. One possible direction for further research is the development of a spatial model without discrete tiers, but with non-linear (possibly functional) dependency from spatial components.

In this research the suggested model to analysis of European airports and their efficiency levels is applied. The data from 2003 to 2007 is used and estimates of airport efficiency levels are received. A conclusion about a significant level of inefficiency in airports operations was made.

The assumption about the varying influence of neighbouring airports was confirmed. Cooperation effects outweigh competition effects for airports located inside the 550 km circle. In the next tier, (550-880 km), completion effects become stronger and cooperation is weaker, and so the aggregate influence is one of competition. Finally, for the third tier, 880 km and more, no competition or cooperation effects are noted.

Finally, the author has investigated individual airport efficiency levels and discovered a significant effect of including spatial components into the model for some airports.

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