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Regions' efficiency and spatial disparities in Tunisia

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Abstract

In post-revolution Tunisia, promoting balanced regional development represents one of the main objectives in the development program of the government. Therefore, economic efficiency is an essential condition to reduce region inequality.
The purpose of this article is to investigate regional efficiency and spatial dependence in Tunisia. We propose a two-stage approach, which involves: in the first place, applying data envelopment analysis (DEA) for the evaluation of efficiency across Tunisian delegations in the year 2010, the year preceding the Tunisian revolution; and, in the second place, using spatial statistical techniques and spatial logistic regression to estimate the impact of spatial dependence on efficiency results. The findings show the regions 'efficiency is driven by structure and spatial factors.

JEL Classification: R11, R15, O18,
Keywords: efficiency, data envelopment analysis, regional disparities, exploratory spatial data analysis, spatial regression, Tunisia.

I. Introduction

The regional disparity in Tunisia is now a matter of serious concern. High levels of inequality and regional disparities are at the core of the root problems that led to the Tunisian Revolution in 2011.TheTunisia's interior and coastal regions don't have the same access to basic public services such as water services (99% in Tunis sand 54.6%in Sidi Bouzid), sanitation (96%in Tunis, and 26.4% in Mednine), proximity to school and the availability of a health center. These inequalities between the regions are accentuated by the concentration of economic activities in the coastal region, with coastal area areas receiving 65% of public investment, hosting alm almost 90% of enterprises and attracting 95 % of foreign investment in companies. Conversely, the hinterlands are less served in terms of infrastructure and public service. These deprived regions accommodate only 30% of the Tunisian population and less than 8% of enterprises. These regional disparities threaten social stability and national unity.

The main issue of regional disparities problem is concerning with the regional efficiency. The term regional efficiency mentioned under this article is used to measure the region's ability to use its basic productive resources in an economic way, to sustain economic growth and development.
This article analyses the efficiency of 252 Tunisian delegations[2] for the year 2010, the year preceding the revolution. Paying particular attention to the role played in this context by spatial interactions and geographical location. For this purpose, efficiency analysis is conducted by using the well-known method of Data envelopment analysis and the spatial interactions are modeled using the techniques of spatial econometrics. These techniques allow us to measure the extent to which the efficiency of one delegation depends upon that of its neighbors, or whether the allocation of regional resources has a significant impact on the efficiency of the targeted regions and on the one of their neighbors(Cliff and Ord, 1973, Anselin, 1988). The study of spatial externalities is essential to understanding the phenomena of agglomeration of people , institutions, activities and its effect on regional efficiency. This paper employs spatial analysis, particularly exploratory spatial data analysis (ESDA) and spatial Logistic regression, to investigate regional efficiency of Tunisian delegation using cross-section data.

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[2] As of 2014 there are in Tunisia 24 governorates (cities)which are divided into 264 delegations(as delegation is the principal division within the governorate).

II. Evaluation of regions' efficiency indicator using data envelopment analysis (DEA)

Data envelopment analysis method evaluation was initiated by Charnes, Cooper and Rhodes (1978) and was extended by Banker, Charnes, Cooper (1984) by including variable returnsto scale. DEA is a non-parametric method that uses linear programming techniques to analyze consumed inputs and produced outputs of the decision making units (DMUs) and builds an efficient production frontier based on best practices. The efficiency of each decision making unit is then measured in relation to this frontier. This relative efficiency is calculated based on the ratio of the weighted sum of all outputs and the weighted sum of all inputs.

Several regional applications of DEA have emerged. Charnes et al. (1989) applied this method to evaluate economic performance of 28 Chinese cities in 1983 and 1984.

Tong (1996, 1997) used DEA to investigate the changes in production efficiency in 29 Chinese provinces. Bernard and Cantner (1997) applied the empirical DEA to selected regions of the French economy from 1978-89. In a recent study, Maudos, Pastor and Serrano (2000) analyzed the relationship between efficiency and production structure in Spain 1964-93. Ilkka Susiluoto and Heikki A. Loikkanen (2001) studied inter-regional and inter-temporal differences in efficiency (or productivity) in Finnish regions during the period 1988-1999. IlkkaSusiluoto (2003) examined efficiency rates for the 83 Finnish and 81 Swedish regions during the period 1988-1999. Axel Schaffer, Léopold Simar and Jan Rauland (2010) identified and examined efficiency in 439 German regions. They show that the regions' efficiency is driven by an arguably spatial and a non-spatial structural factor. Soo Nah and Hong YulJeong (2010) measured the efficiency of the Korean and Chinese large cities and then explored the implications on the two countries' efficiency in these cities. Danijela Rabar (2013) evaluated regional efficiency of Croatian counties in three-year period (2005-2007) using VRS data envelopment analysis model. The study identifies efficient counties as benchmark members and inefficient counties that are analyzed in detail to determine the sources of inefficiency. Finally,Giedrė Dzemydaitė, Birutė Galinienė (2013) applied DEA analysis to evaluate Lithuanian regions efficiency.The results identified four efficient regions (Vilnius, Klaipėda, Utena and Marijampolė) and five inefficient regions (Alytus, Tauragė, Kaunas, Šiauliai, Panevėžys). The study helped to formulate the benchmarks for regional development.

In this study we consider a Variable Returns to Scale (VRS) Data Envelopment Analysis (DEA) model and we use the output-oriented method of Banker, Charnes and Cooper(1984). We assess the relative efficiency of individual Tunisian delegations for 2010, within each of the above-mentioned twenty four governorates defined according to the Tunisian nomenclature of territorial units having already considered the desegregation level.

A. Data

To use the DEA approach in order to obtain efficiency measures, we need data about the delegation's inputs and outputs. The selection of inputs and outputs is based on the available information and indicators. In Table 1, we present the main variables taken into consideration in calculating the DEA.

The first goal indicator to be maximized is the per capita income growth. However, no local income measures used by local governments were available. To overcome this problem, we selected human capital indicators registered in delegation accounts for the year 2010 as a measure for the delegation's economic growth; a better measurement tool would be that of productivity growth. Since we do not observe outputs, it is hard to measure productivity (Glaeser E, Kallal H.D Scheinkman, J.A and Shleifer.A (1992)). For Glaeser E. L and Saiz A(2003) education share is a particularly powerful predictor of income growth. The authors find that cities with higher skills are growing because they are becoming more economically productive (compared to cities where there are less skills). They say their analysis implies that "city growth can be promoted with strategies that increase the level of local human capital." They assert that economic revitalization efforts should concentrate on "basic services, amenities, and quality public schools that will lure the most skilled," and on boosting the education level of local residents. Here, the share of students with a bachelor degree (HUM) is used as a measure of quality of education and as indicator of per capita income growth. The second goal indicator to be maximized is living standards (CONS) measured by consumption per capita. The third goal indicator to be maximized is the share of people who live in families with purchasing power parity (PPP) equal to $1 per day. The DEA variable to be maximized, POV, is thus defined as 100% minus extreme poverty rates. The fourth goal indicator to be maximized is the employability rate (EMP); hence, a DEA variable to be maximized, EMP, is defined as 100% minus TU; that is, the unemployment rate.

With respect to the inputs of the transformation relationship, a whole set of economic and social factors can act as resources that influence the previously identified goals. First, infrastructure—physical resources like roads and electricity infrastructures—is recognized as a key variable. It leads to a decrease in poverty and to a rise in living standards in addition tothe creation of employment by acting as incentive to investment. For the second resource components, the number of teachers and the number of secondary school buildings are used as inputs in order to detect the provision of education for every delegation. Furthermore, hospital beds per 1000 citizens (NHO) and the number of doctors per 1000 citizens (NDO) are used to detect the health care provision. Finally, to account for private capital formation the number of enterprises (ENTER)is used.

Table .1: Variables used to construct the DEA model

Inputs (minimize resource use or conditions):	
Education	-School buildings measured by the number of secondary school buildings - Number of teachers (TEACH)
Health	Number of doctors per 1000 citizens (NDO), Number of hospital beds per 1000 citizens (NHO),
Sanitation	Access to Safe Water (% of Population), (WATER)
Road infrastructure	Roads, paved (% of total roads) , (ROAD)
Electricity infrastructures	Rate of Access to electricity (% of Population), (ELEC)
for private capital formation inputs	Number of private enterprises (FIRM)
Outputs (maximize output or goal):	
Growth or Quality of education	students with a bachelor degree , (HUM)
Living standards	Consumptionper capita, (CONS)
Population above poverty line	100% minus extreme poverty rate (POV)
Employability rate	100% minus unemployment rate (EMP).

After calculating DEA, we ranked the delegation according to the efficiency score provided by DEAP based DEA. To conduct DEA, an output-oriented measure is used to quantify the necessary outputs' expansion keeping the inputs at a constant level.
The data were taken from the National Institute of Statistics.

B. *DEA results*

In this section the estimates of technical efficiency for the 252 delegations in Tunisia are presented.

Table 2 – DEA regions' efficiency results						
Region	N. of DMUs	N. of Efficient DMUs (delegation)	N. ofDMU With 0.7<score<0.9	N. ofDMU With score <0.7	Average efficiency scores	Minimum efficiency scores
Tunis	21	3	16	2	0.85	0.534(DjebelDjelloud)
Ariana	7	1	2	4	0.78	0.631(El Mnihla)
Ben Arous	12	0	10	2	0.8	0.603(Mohamedia)
Manouba	8	0	6	2	0.75	0.562(Tebourba)
Efficiency score of the Tunis District region: 0.8						
Nabeul	16	3	12	1	0.86	0,292 (Grombalia)
Zaghouan	6	0	2	4	0.65	0.451 (En-Nadhour)
Bizerte	14	1	9	4	0.77	0.156 (MenzelBourguiba)
Efficiency score of the North-East region: 0.8						
Béja	9	0	6	3	0.71	0,325(Goubellat)
Jendouba	9	1	3	5	0,68	0,525 (Fernana)
Le Kef	11	0	3	8	0,57	0,108 (KalâatKhasbah)
Siliana	11	2	3	6	0,77	0.526 (Gaâfour)
Efficiency score of the North-West region: 0.68						
Sousse	15	3	10	2	0,85	0,28 (M'saken)
Monastir	12	1	10	1	0,92	0,5 (Sahline)
Mahdia	11	2	9	0	0.88	0.72 (BouMerdès)
Sfax	16	2	11	3	0.8	0.4 (Ghraiba)
Efficiency score of the Middle-East :0,85						
Kairouan	9	1	6	2	0,83	0.69 (EL Ouslatia)
Kasserine	10	1	2	7	0,69	0.41 (KasserineSud)
SidiBouzid	11	0	7	4	0,73	0.69 (Jilma)
Efficiency score of theMiddle -West :0,75						
Gabes	6	0	5	1	0,71	0.5 (El Hamma)
Mednine	8		8	0	0,85	0,236 (Ben Guerdane)
TaTaouine	4	1	3	0	0,76	0,72 (Remada)
Efficiency score of the SouthE**st**: 0,79						
Tozeur	5	0	4	1	0,75	0.67 (Degach)
Kebili	6	0	6	0	0,77	0,726 (KebiliSud)
Efficiency score of the South**West**: 0,77						

Source: **Author's estimates**.

From Table 2 we notice that efficiency scores of Tunisian delegations range from 0.28 to 1. There are Twenty-four delegations efficient in the year 2010. The DEA results show also there are 118 delegations with efficiency scores which range between 0.7 and 0.9. This category of regions operates at an acceptable level of efficiency but needs improvements on the utilization of their economic sources.

The Great Tunis, North-East and Mid-East seem to be the most efficient regions regarding the utilization of resources. These regions host the highest share of efficient delegations. The high efficiency of these regions emanates from the favorable conditions such as the existence of effective infrastructures and good local governance.

It is possible to note by comparing the average of efficiency scores observed within regions, that the North-West, the Mid –west and the south-west regions have the lowest efficiency score. It is in average 0.73. Consequently it can be roughly be stated that deprived regions produce 27% less output than the efficient area for the same inputs. The low efficiency scores of these deprived regions reflect the rather fragile situation in these regions that comes along with low standing living, power level of education, high poverty.

II. Exploratory spatial data analysis of regional disparities

In order to further the understanding of regional disparities in terms efficiency we use exploratory spatial data analysis (ESDA) technique. Prior to the analysis of spatial autocorrelation for the efficiency

indicator, it was necessary to understand the regional distribution the main of socio-economic variables:
- Extreme poverty rate (POV)
- Population density (DENSITY)
- Urbanization rate (URB)
- Illiteracy rate (ANNL)
- Mortality rate (MORT)
- Unemployment rate (UNEMP).
- Graduate Unemployment rate (UNMPS).
- The number of secondary school buildings (LOC)
- Number of teachers (TEACH)
-Number of doctors per 1000 citizens (MED),
- Number of beds per 1000 citizens (BED),
- Access to Safe Water (% of Population), (WATER)
-Number of enterprises (FIRM)
-Roads, paved (% of total roads), (ROAD)

These variables were analyzed with spatial autocorrelation statistics, which enable the measurement of spatial clustering and identification of spatial clusters. The spatial analysis was carried out using two aspects of spatial clustering, namely, the 'global' spatial clustering and the 'local' patterns of distribution.
The global measure of Moran's I, which ranges from +1 indicating a strong positive spatial autocorrelation to –1 meaning a strong negative spatial autocorrelation, wherein 0 indicates a random pattern. The definition of Moran's I for spatial variable Y*i* at location *i* is given below:

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{i,j}(y_i - \bar{y})(y_j - \bar{y})}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{i,j}(y_i - \bar{y})^2}$$

where n is the number of units (in this case municipalities), xi stands for the value of the observed variable in i-th location, x represents its mean, and wijisan element of the weights matrix W.The spatial weights matrix W, indexing the relative position of all locations$i$ and j, is a key concept in spatial autocorrelation analysis. Several criteria might be applied to define W (i.e. "neighbouring"). The most common criteria are binary contiguity (i.e. common boundary) or distance bands from eachlocation (see Anselin 1988; Getis, Aldstadt 2004; Spurna 2008).
In addition to the classical Moran's I, whose single value for the entire study area can be interpreted as a global statistic of spatial autocorrelation, capturing the average characteristics of the studied area (Unwin 1996, Fotheringham1997, Fotheringham et al. 2000), its local equivalent, called LISA (local indicatorof spatial association), was also used (see Anselin 1995).
The local measure of Moran's I is as follows:

$$I = \frac{(x_i - \mu)}{\sum (x_i - \mu)^2} \sum_j w_{i,j}(x_j - \mu)$$

Where $x_{i,t}$ is the observation in a region i to the period t; μ_t is the average of the observations through the geographics spaces in the period t and, the sum j includes only the values of j neighbors.
We start by first considering the extent of global spatial association. Table 3 reports the results of The Moran's *I test* for the main socioeconomic variables of Tunisian governorates.

Table 3. Measures of regional inequality for the selected socioeconomic variables 2004-2010						
	VARIABLES	MORANI	E(I)	SD(I)	Z	p-value*
DEMOGRAPHIC	DENSITY04	0.226	-0.043	0.06	4.58	0.000
	DENSITY10	0.27	-0.043	0.07	4.4	0.000
	URB10	0.364	-0.043	0.127	3.211	0.000
EDUCATION	ANNL04	0.463	-0.043	0.127	3.971	0.000
	ANNAL10	0.49	-0.043	0.128	4.155	0.000
HEALTH	MORT10	0.385	-0.043	0.125	3.420	0.000
POVERTY	POVERTY10	0.270	-0.043	0.125	2.514	0.006
LABOUR FORCE	UNEM04	0.317	-0.043	0.126	2.852	0.002
	UNEM10	0.314	-0.043	0.121	2.951	0.002
	UNEMPG 10	0.453	-0.043	0.127	3.902	0.000
PRIVATE INVESTMENT	ENT04	0.142	-0.043	0.100	1.867	0.03
	ENT10	0.172	-0.043	0.101	2.127	0.017
SOCIOECONOMIC INFRASTRUCTURE	TEACH04	0.154	-0.043	0.124	1.587	0.056
	TEACH10	0.174	-0.043	0.125	1.744	0.041
	LOC04	0.112	-0.043	0.123	1.263	0.08
	LOC10	0.167	-0.043	0.124	1.703	0.044
	WATER04	0.454	-0.043	0.123	4.026	0.000
	WATER10	0.424	-0.043	0.125	3.746	0.000
	ROAD 10	0.430	-0.043	0.107	4.412	0.000

*All values of Moran's / are statistically significant at the 1 % significance level

As can be seen, the evidence suggests the presence of positive spatial autocorrelation, which appears to be statistically significant in all cases (see Table 3). Thus, at the global scale, as one would expect, socioeconomic outcomes appear clustered and/or positively associated in space. The result indicates that the regional socioeconomic indicators in Tunisian governorates possess a very conspicuous spatial concentration feature. This result suggests that governorates with relatively high/low values of socioeconomic outcomes are surrounded by governorates with relatively high/low values (they cluster).

Concerning efficiency index, the value of Moran's I statistic for is positive and significant with p = 0.01 (see Table 4). This result suggests that the delegations with relatively high/low values of efficiency index are surrounded by delegations with relatively high/low values (they cluster). This proves the thesis about relevance of geographical dimension in (effectiveness) inequality research.

Table 4: Moran's I					
Variables	I	E(I)	sd(I)	Z	p-value*
Effvrs	0.269	-0.004	0.043	6.432	0.000

*1-tail test

Moran's *I* is a global test that does not indicate where the clusters are located or what type of spatial autocorrelation is occurring (i.e. whether positive or negative)(Anselin 1995). The local indicator of spatial autocorrelation (LISA) is therefore applied to indicate local spatial associations.

The spatial distribution of LISA statistics (Fig. 1) uncovers further information. Using a significance level of 5%, at governorates level we detect clusters of low values in the interior part of Tunisia and clusters of high values in the coastal areas (Great Tunis and the Middle East).

Figure 1 . LISA maps of key socio-economic indicators

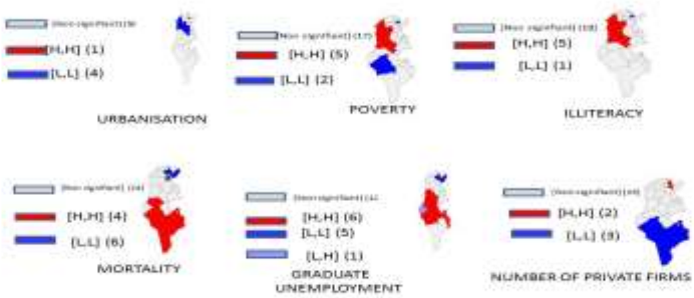

Figure 1 presents the geography of local spatial association through a number of LISA maps. The six rows correspond to the main socioeconomic indicators. The indicators analyzed include illiteracy, infantile mortality, poverty, graduate unemployment, and number of private firms. The indicators are chosen because they reflect various aspects of development correlated with efficiency.

We notice on the maps the presence of positive spatial autocorrelation, which appears to be statistically significant in all cases. Thus, at the global scale, as one would expect, socioeconomic outcomes appear clustered and/or positively associated in space.

The LISA maps show that patterns of spatial association remain dominated by clustering High-High and Low-Low types. This means the governorates with relatively high economic development level are surrounded by the governorates with relatively high economic development level, and it is the hot spot for economic development. The interior areas are mainly the distribution areas of governorates with relatively low economic development level, presenting "L-L" concentration and belonging to low-low collapsed area, which means the governorates with relatively low economic development level are surrounded by the governorates with relatively low economic development level.

The location of coastal areas is the political, economic and cultural center, as well as the traffic hub. Conversely in the interior regions, the topography is rugged, with scarce resources, lack of infrastructure; it is distant from central city, and the economic development level of bordered areas in every direction is not high. Therefore these regions cannot be affected by the spillovers of regions with developed economy.

Across all measures, as expected, some strong spatial patterns of clustering are observed. A high-concentration cluster of poverty, infantile mortality and illiteracy is located in the western and northern periphery of the country. The same areas are largely areas of low activity and high graduate unemployment. In contrast, a strong high-urbanization cluster is located north of . As should be expected, private investment is a high-value cluster around the capital and a low-value cluster in the northwest.

The presence of strong spatial autocorrelation for socioeconomic indicators suggests that geographic location and the spatial interactions should play an important role for explaining the efficiency of regions.

The LISA map (Figure 1) demonstrates that spatial clustering of efficiency index clearly exists in Tunisia. Delegations geographically close to each other tend to share similar effectiveness index. The Lisa map reveals significant spatial associations in terms of spatial efficiency index distributions (HH or LL) which represent nearly 80% of all associations: 37% of HH region and 43% of LL region. Negative associations are about 10% for HL and around 8.4% of LH. This spatial pattern seems to confirm the global spatial association made earlier.

It should be also noted a clear regional disparity between the coastal areas and the interior areas. Thus, 27 delegations of coastal region are of type (HH) and have high values of efficiency index. In contrast, most of the delegations that are clustering as LL, are located in Middle-West and in South-west regions.

IV Explaining delegations' efficiency: logistic regression and spatial dependence

A. Methodologies

- **Logistic regression**

Logistic regression (Hosmer and Lemeshow 1989, Allison 1999) is typically used for describing and testing hypotheses about relationships between a categorical outcome variable and one or more categorical or continuous predictor variables. Binary Lr was selected because DEA efficiency is a categorical dependent variable (efficient = 0, inefficient = 1) and because the assumptions undergirding Lr impose no requirements about the distribution of the predictor variables .

In this second part of the study, Logistic (log odds) analysis is used in order to explain the efficiency differences among delegations for the year 2010. The censored DEA efficiency score lie between 0 and 1 with some values achieving the highest value of 1.

Logistic (log odds) regression model can be defined as

$$\text{Log}(\vartheta_i / 1 - \vartheta_i) = \text{Logg}(\text{Odd}_{EFF}) = X_i \beta + \mu_i \quad (1)$$

In (1) the dependent variable is logarithm of the odds of being inefficient. This model can be applied as none of the I*i* is zero or 1, rather all regional inefficiency scores are in the (0,1) interval. We estimate the parameter vector β by OLS.

Above, X*i* is a vector of explanatory variables, i refers to region and β is a vector of parameters to be estimated. ϑ_i * is a latent variable which can be viewed as a threshold beyond which the explanatory variables must affect in order for ϑ_i to "jump" from 0 (here being efficient) to some positive value (being inefficient in various degrees).

As for the explanatory variables in Logistic regression model, we use the following variables. **Population density** of the region (AGGL) is aimed to catch agglomeration effects. It is calculated as the (log) ratio between regional population and size (square kilometers).

The state of knowledge or education level is measured by the percentage of people graduating from university (HT). This measure is associated with "talents" or the creative class. As a measure of

concentration of private sector economic activity, we use regional Herfindahl index measure(SPEC). It is calculated in terms of the city's number of firms per sector in a city. Its high values indicate specialisation and low values are related to diversified structure.

- **Spatial dependence**

The study was enriched by testing for spatial interactions. As revealed in Table 4 the Moran statistic rejected the hypothesis of absence of spatial autocorrelation and shows a slightly positive spatial autocorrelation among the scores of technical efficiency in the Tunisian delegations. In the light of such results, while employing logistic regression to model regional efficiency, the spatial heterogeneity of spatial data should be considered. Spatial statistics like spatial dependence and spatial sampling also have to be considered in logistic regression to remove spatial autocorrelation. Otherwise, unreliable parameter estimation or inefficient estimates and false conclusions regarding hypothesis test will result.

In spatial econometrics, there are two basic specifications in order to model the existence of spatial autocorrelation: spatial lag model and spatial error model.

In the spatial lag model, named by Anselin (1988) as mixed regressive spatial autoregressive model, a spatially lagged dependent variable is included as explanatory. The model is formulated as follows:

$$y = \rho Wy + X\beta + \varepsilon \quad (2)$$

whereρ is the spatial autoregressive parameter, that, if different from zero, implies that the computed efficiency score of a given delegation is directly affected by the scores of its neighbors. W is the spatial weight matrix, X is the matrix of exogenous variables and β is the coefficient vector.

The second option consists in the specification of a spatial process for the disturbance terms. This is the most common specification:

$$y = X\beta + \varepsilon \,,$$

$$\varepsilon = \lambda W\varepsilon + \xi \quad (3)$$

where λ is the spatial autoregressive coefficient for the error lag $W\varepsilon$ and ε is an error term uncorrelated. In this case, the dependent variable is censured and this type of model is characterized by heterocedasticity. If this type of model is estimated based on the assumption of homoscedasticity, in the presence of heteroscedastic disturbances are inconsistent. To overcome such problems, Lesage (2000) proposes Bayesian estimation.

B. Results from logistic regression model

In Table 5, we compare both the model without spatial interactions (a-spatial model) with the model that accounts for spatial interaction**.**

Table 5: Parameter estimates of Logistic model explaining efficiency of delegations for 2010

	OLS	**SAR**	**SEM**
LAGGL	.122 (0.05)	.086 (0.283)	.13 (0.144)
HSU	.062 (0.00)	.056 (0.050)	.048 (0.110)
SPEC	1.16 (0.10)	1.03 (0.073)	1.22 (0.037)
Constant	.37 (0.22)	.67 (0.16)	.48 (0.302)
Rho		.012 (0.498)	
Lamda			.03 (0.140) **
Root MSE	1.88	1.88	1.87
LR p-value		-468.8	-467.98
G. Moran- p-value		0.0940 (0.0153)	0.0938 (0.0156)
LM-err p-value		6.87 (0.008)	6.02 (0.014)
LM-lag p-value		0.40 (0.52)	0.0001 (0.99)
LM*-err p-value		38.62 (0.000)	21.64 (0.0000)
LM*-lag p-value		32.15 (0.0000)	15.60 (0.0000)
Number of observatio ns	246	246	246

According to table 5, in the a-spatial model, regression coefficients of the density, the education and specialization are all significant.

The population density (AGGL) coefficient had an expected positive sign, and was found to be significant at the 1% level. This indicates the presence of agglomeration economies and suggests that densely populated cities often providing a larger home market, rich physical and institutional infrastructure in addition to a large number of financial, legal and social services may be advantageous for efficiency of resources and investment. According to Krugman (1991b), manufacturing firms tend to locate in regions with larger market demand to realize scale economies and minimize transaction costs.

The tertiary education had a positive and significant impact on regions 'efficiency, indicating that higher education institutions have an important role to play in regional development. They achieve this through a number of mechanisms such as providing high-level skills in the workforce so that they attract high-technology industries generating high income in the region. Secondly, higher education institutions contributing to the development of a knowledge-based economy improve access and use of technology and improve the competitive advantage of the region. Finally, these institutions promoting entrepreneurship can be used to provide employment.

The specialization variable had a positive sign and was found to be significant at the 1% level. The more specialized a region is the higher efficiency tends to be. Our results suggest that externalities of Marshall Type affect the efficiency of the regions. This confirms previous results by Paci and Usai (1999, 2000b) and Van der Panne (2004).

According to the Table 5, by accounting for spatial interactions, the last two columns show the estimated value of the spatial coefficients, for the effect of the autoregressive model and for the effect of the error model.

The presence of spatial autocorrelation in the residuals of OLS regression is tested using Moran's I test. The results in Table 5 indicate that the Moran's I null hypothesis of no global spatial autocorrelation in the residuals of OLS regression is overwhelmingly rejected. This finding suggests that the OLS estimates are invalid. The OLS result ignores spatial variation and produces biased estimates .Moran's I test shows that the efficiency in the selected delegations is spatially correlated. That is, neighborhood interactions are significant in explaining regions' efficiency.

Once the spatial autocorrelation is detected, the Lagrange Multiplier (LM) tests developed by Anselin et al. (1996) are applied to select between a spatial lag and a spatial error alternative (Anselin, 2003a). There are two major types of the LM test. The $LMlag$ statistic tests the null hypothesis of no spatial autocorrelation in the dependent variable; the $LMerror$ statistic, on the other hand, tests the null hypothesis of no significant spatial autocorrelation in the error terms.

The superiority of the spatial Logistic model over the standard Logistic model is further confirmed by the significant spatial error coefficient (value = 0.03; standard error= 0.14).

In addition, the statistic of $LMerror$ is greater compared to the result in $LMlag$ indicating that the null hypothesis of partial lag could be rejected in favor of homoscedastic or uncorrelated errors as the best alternative hypothesis. The robust LM tests consistently show the same results, with rejection of both hypotheses at a 1% significance level. This implies that OLS is rejected in favor of SEM models. Indeed, regional econometric in the models using cross-sectional data often the error terms are not completely independent but exhibit a spatial autocorrelation. It can be caused according to Anselin (1988), by a variety of measurement problems such as arbitrary characterization of spatial units of observation, problems of spatial aggregation, the presence of spatial externalities and spillover effects. In these case while there is residuals autocorrelation, the ordinary least squares estimator is inefficient, the estimator of the residual variance is biased and the inference procedures are invalid (Anselin and Griffith (1988)).This result strongly suggests that the ordinary least squares estimator is inefficient and it is necessary to correct for the case the presence of spatial autocorrelation.

V. Conclusion

In this paper efficiency differences between 252 Tunisian delegations in 2010 were examined by using Data Envelopment Analysis (DEA) and Logistic analysis.

Regional efficiency scores were first estimated with a DEA model, ranging from a basic four outputs–six inputs case. Outputs included regional quality of education, living standards, population above poverty line, employability rate from inputs covering the number of secondary school buildings, the number of teachers, the number of doctors per 1000 citizens, the number of hospital beds per 1000 citizens, access to safe water (% of Population), paved roads (% of total roads), rate of access to electricity (% of Population)and the number of enterprises.

According to the DEA estimates regional differences in efficiency proved to be considerable. There are in 2010 only twenty nine delegations located on the analytical production frontier , 108 delegations with acceptable level of efficiency and 115 inefficient. The most efficient delegations are found in the Great Tunis, North-East and Mid -East region of Tunisia, while the most inefficient delegations are located predominantly in the North-west, Mid-west and the south.

In the second part of the study, Spatial Logistic analysis was used in order to explore the impact of spatial dependence on efficiency results. For the year 2010, empirical results reveal that regional interdependencies do matter in order to explain efficiency differentials across regions. Our results suggest the pertinence of the neighborhood effect in the spatial distribution of the efficiency scores. The LM tests applied to the estimates at both spatial scales indicated spatial error specification to be the appropriate model. Spatial models, justified by the significant lambda in the regression. Misspecification of non spatial models results in bias.

Moreover, we find , urbanization, human capital and specialization are also significant in explaining regional efficiency. The delegations with high population density were significantly more efficient. Efficiency increases with education and knowledge. The increase of percentage of high-school graduates strengthens efficiency. Additionally, the existence of a significant effect of Marshall externalities.

References

[1]Anselin, L. (1988), Spatial Econometrics: Methods and Models. Dordrecht (the Netherlands):Kluwer Academic Publishers.

[2]Anselin, L. (2001) Spatial Econometrics, in *A Companion to Theoretical Econometrics*, ed. by B. H. Baltagi. Massachusetts: Blackwell Publishers, 310-330.

[3]Anselin, L. (2002) Under the Hood. Issues in the Specification and Interpretation of Spatial Regression Models, Agricultural Economics, 27 247-267.

[4]Anselin, L. (2003) Spatial Externalities, *International Regional Science Review*, 26 (2), 147-152.

[5]Anselin, L. and Bera, A. K. (1998) Spatial Dependence in Linear Regression Models with an Introduction to Spatial Econometrics, in *Handbook of Applied Economic Statistics*, ed. by A. Ullah and D. Giles. New York: Marcel Dekker, 237-289.

[6]Anselin, L., Bera, A. K., Florax, R. J. G. M. and Yoon, M. J. (1996) Simple Diagnostic Tests for Spatial Dependence, *Regional Science and Urban Economics*, 26 77-104.

[7]Anselin, L. and Cho, W. K. T. (2002) Spatial Effects and Ecological Inference, *Political Analysis*, 10 (3), 276-297.

[8]Axel Schaffer, Léopold. S &Jan.R, 2010. "Decomposing regional efficiency," Working Paper Series in Economics 10, Karlsruhe Institute of Technology (KIT), Department of Economics and Business Engineering.

[9]Bernard, J. Cantner, U. (1997). French Regional Performance and Variety. A Non-Parametric Frontier Approach. Paper Presented at the 37th Congress of the European Regional Science Association, Rome

[10]Charnes, A. Cooper, W. and Li, S. (1989) Using Data Envelopment Analysis to Evaluate Efficiency in the Economic Performance of Chinese Cities. Socio-Economic Planning Sciences, Vol. 23, No. 6, pp. 325-344.

[11]Charnes, A., Cooper, W. W. and Rhodes, E. (1978).Measuring the efficiency of decision makingunits.European Journal of Operational Research, Vol. 2, pp. 429-444.

[12]Cliff, A. D. and J. K. Ord. (1973). Spatial autocorrelation. London: Pion

[13]Danijela Rabar (2013), "assessment of regional efficiency in croatia using data envelopment analysis ", Croatian Operational Research Review (CRORR), Vol. 4,

[14]Giedrė Dzemydaitė, Birutė Galinienė (2013), "evaluation of regional efficiency disparities by efficient frontier analysis". ISSN 1392-1258.EKONOMIKA Vol. 92(4)

[15]Heikki A. Loikkanen (2002), « An evaluation of economic efficiency of Finnish Regions by Dea and tobit models ", 42st Congress of the European Regional Science Association, Dortmund, Germany, 27. – 31.8.

[16]Ho Soo Nah, Hong YulJeong (2010), " The Comparative Study on Efficiency of the Large-sized Cities in Korea and China", the journal of the korean economy, Vol. 11, No. 1, 31-53

[17]Glaeser, Edward Ludwig &Kallal, H.D. &Scheinkman, Jose A. &Shleifer, Andrei (1992), "Growth in Cities," Scholarly Articles 3451309, Harvard University Department of Economics.

[18]Glaeser Edward L. &Saiz Albert,(2003). "The Rise of the Skilled City," NBER Working Papers 10191, National Bureau of Economic Research, Inc.

[19]Maudos, J., Pastor, J. and Serrano, L. (2000).Efficiency and Productive Specialisation: An Application to the Spanish Regions. Regional Studies Vol. 34, No. 9, pp. 829-842

[20]Mokaddem L (2014), **"** Evaluation of Tunisian regions' efficiency using Dea and tobit models ", Working paper ERF n 862.

[21]National Institute of Statistics (2012)," Measuring Poverty, Inequalities and Polarization in Tunisia 2000-2010". Copyright © National Institute of Statistics, November 2012. Serafeim Polyzos, Spyros

[22]Niavis,Triantafyllos Pnevmatikos (2012), « Longitudinal Evaluation of Greek Regional Policies Using Window Data Envelopment Analysis" *Polyzos-Niavis-Pnevmatikos, 305-317*

[23]Susiluoto, I. - Loikkanen H. (2001 a), " The Economic Efficiency of Finnish Regions 1988-1999, an Application of the DEA Method". Paper presented at the 41st Congress of the European Regional Science Association, Zagreb, Croatia, 29.8. - 1.9.2001