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Spatial Analysis of Tunisian Governorate-Level Health Efficiency

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Abstract: We investigate the differences of efficiency in health system between Tunisian governorates over the period 2010-2015 and examine how socioeconomic factors influence the regional distribution of the efficiency scores. The parametric stochastic frontier approach with fixed effects is employed to cacultate Tunisian governorate-level health efficiency scores. Spatial analysis tools are used to determine the spatial pattern of the efficiency scores and spatial econometric model are used to examine the impact of the socioeconomic and demographic factors on health efficiency. Our results show that education affects positively the efficiency of health system not only in region itself but also its neighbouring regions .However, the effects of unemployement are negative.

Keywords: Spatial data, Spatial auto correlation, Health efficiency, Tunisia.

1.INTRODUCTION

Health care access equality and health equity between populations of different socio-economic classes are among the main objectives of policymakers and have been the subject of several debates in recent decades (Dahlgren & Whitehead, 2000).In fact, promoting health by helping people get timely, high-quality health care services, and reducing health inequalities at the national level.

Nevertheless, accessibility to health services aims to help individuals using appropriate health resources to maintain or improve their health. However, access to health and care may be still unequal, due to various factors, such as disparities in health infrastructure between different regions, and lack of resources or budget constraints. Some factors include shortages of doctors and medicines the distance of health facilities a limited number of doctors commuting long distances to obtain a healthcare assistance. All of these factors can contribute to the misuse of resources, which in turn leads to poor health outcomes (Evans et al., 2001).

Some empirical studies use a rural-urban divide of health care, that better health is , on average , joined by urban inhabitants than their rural counterparts (Quashie and Pothisiri,2019), but the benefits are usually greater for the rich than for the poor (Dye ,2008). Moreover, intra-urban differences in child malnutrition are larger than overall urban-rural differentials in child malnutrition (Fotso, 2006). Rural areas tend generally to face a dual problem of relatively high need for health services but low levels of access to them. Some of rural districts tend to have higher and more rapidly increasing mortality rates (Bentham, 1984). However, some studies found that higher population density was modestly related to increased mortality, independently of baseline socioeconomic position and health (Beenackersa et al., 2019).

The twin goals of improving health of everyone and reducing inequalities in health between different groups are seen to depend on addressing basic determinants of socioeconomic inequities (Graham, 2004).

On the other hand, for a long time, the relationships between the values observed in neighbouring territories have been a concern of geographers. Indeed, Waldo Tobler has synthesised this problem in a formula that is often referred to as the first law of geography: "Everything interacts with everything, but two objects close together are more likely to do so than two objects far apart". This is why we use spatial econometric techniques in our work on Tunisian regional data from 24 governorates over the period 2010-2015 to examine the determinants of efficiency in the delivery of health care services. The use of specialized data allows us to better take into account territorial interactions and externalities in the analysis of agents' economic decision-making.

The analysis of regional variation of health care outcomes and regional performance of health care systems has gained increasing interest in health economics and policy, especially for the case of developed countries (for a summary see Herwartz & Schley , 2018). Xiang & Song (2016) have used spatial analysis tools to determine the spatial patterns of China province-level perinatal mortality and used spatial econometric model to examine the impacts of health care resources and different socio-economic factors on perinatal mortality. Herwartz & Schley (2018) analyze how regional deprivation and diversity govern (in)efficiencies in the provision of health care services in German districts. They find that regional utilization patterns of health services as well as the access to health care influence the efficiency of health care provision.

There are only a few studies that analyse the effect of socio-economic environment i.e., income, unemployment, and the educational level, on health. (Herwartz&Schley 2018, Xiang & Song ,2016). The literature on heath indicated that studies focused on the effects of only one of these socio-economic factors.
The results of previous studies carried out for a panel of countries, or for a single country or province-level confirm the influence of income not only on health status by increasing health expenditure (Esmaeili A et al., 2011, Gerdthamet al., 1992; Leu, 1986; Newhouse, 1977) but also influences access to health care services (Dunlop et al., 2000) and on the reduction of mortality rates (Xiang & Song, 2016)
The literature suggests regardless of time period, and country being studied, a strong positive association emerges between education and health outcomes , as better educated people are more likely to follow a healthy lifestyle.So, high educational attainment improves health directly, and it improves health indirectly through work and economic conditions, social-psychological resources, and health lifestyle(Catherine et al., , 1995). Some studies (Herwartz& Schley, 2018) even suggest that educational achievement seems to lower inefficiencies in the provision of health care services. Moreover, positive health effects have been cited among the advantages of a further raising of the school-leaving age (Clarck et Heather ,2013). Specifically, individus with lower incomes and fewer years of schooling visit specialists at a lower rate than those with moderate or high incomes and higher levels of education attained (Dunlop S et al. ,2000).
Some empirical studies have established relationship between unemployment and health, that unemployment increases the risk of morbidity and mortality (Bambra & Eikemo, 2009). In particular, access to health care is influenced by employment status and unemployment duration. Unemployed individus were more likely to delay health care services due to cost, and were less likely to have access to health care than employed (Jennifer et al., 2011).Also, unemployed people reported higher rates of poor health than those in employment Bambra et Eikemo (2009) and Being unemployed for a long period has a negative effect on health satisfaction (Gordo, 2006). Moreover, the access barriers to the health care system for the unemployed and, hence, lower utilization increase the inefficiencies in the provision of health care services (Herwartz & Schley,2018).
The aims of the current paper are as follows: 1) construct and calculate the Tunisia governorate-level health system efficiency scores (EFFC), which reflects the efficiency of Health sector of Tunisia. 2) quantify the spatial distribution pattern of the EFFC and its changing trend with time from 2010 to 2015 using the spatial autocorrelation analysis method; 3) explore the impact of the socio-economic environment on health efficiency.
Section 2 describes the methods and data; The empirical results are discussed in Section 3. Section 4 concludes.

2. METHODS AND MATERIALS

2.1. Regional efficiency of health sector

a. The stochastic frontier model SFA

The techniques for measuring efficiency in general and efficiency in the health system in particular are classified theoretically into two methods: non-parametric and parametric. The non-parametric method seeks to estimate the proportional efficiency of one unit relative to others in the same sector. For this approach, the most commonly used methods are “Data Envelopment Analysis” and “Free Disposal Hull Analysis”. These methods have been used by some studies (Herrera & Pang, 2005 Afonson & Aubyn, 2005, Gupta & Verhoeven, 2001) to estimate efficiency scores in the health system at the macroeconomic level. The parametric approach is based on the development of the stochastic method of the production frontier (technical efficiency) and the cost of production (allocative efficiency). It has been the subject of some empirical studies (Greene 2005; Wang &Schmidt, 2002; Battese & Coelli, 1995). In all these models, inefficiency is assumed to be constant over time. However, the inability to separate inefficiency and individual heterogeneity is likely to limit their applicability in empirical studies. This point is clearly articulated in Greene (2005), who compares the effectiveness of health care services and argues that the efficiency effect and the country specific effect are different and need to be considered separately in the estimation (Chaffei & Plane 2013, page 107). The stochastic frontier method (SFA) estimates a frontier function that takes into account both the random error (symmetric error term) and the efficiency component (asymmetric error term) at the same time. In fact, Greene (2005) proposes to reconcile stochastic frontier models and panel models by proposing two models well known as "TrueFixed Effects" and "True Random Effects" to remedy the problem of heterogeneity in the analysis of panel data. The Hausman (1978) test is applied to choose between the two models.To estimate health efficiency in the Tunisian case, we use Greene's (2005) model and uses the SFA.

b. The SFA panel model

The calculation of efficiency scores for a sector requires the definition of an output and inputs. The mortality rate is used as an output of the health sector (referred to as mor). This indicator assesses the number of deaths in a year in relation to the total population in the same year. Three inputs are used. These are the number of doctors (referred to as doc), the number of hospitals including district, regional and university hospitals (referred to as hosp) and health expenditure measured by hospital operating budgets (referred to as spen). Output and inputs are expressed in logarithm.

Green's (2005) Specification for the health sector in a governorate i and year t is as follows:

$\log(\mathrm{mor}_{it}) = \alpha_0 + \alpha_1 \log(\mathrm{doc}_{it}) + \alpha_2 \log(\mathrm{hosp}_{it}) + \alpha_3 \log(\mathrm{spen}_{it}) + v_{it} + u_{it}$ (1)

$\log(\mathrm{mor}_{it}) = \alpha_0 + w_i + \alpha_1 \log(\mathrm{doc}_{it}) + \alpha_2 \log(\mathrm{hosp}_{it}) + \alpha_3 \log(\mathrm{spen}_{it}) + v_{it} + u_{it}$

$\mathrm{TE}_{it} = [\exp(-u_{it})]/\ \mathrm{mor, doc, hosp, spen\ avec}\ 0 \leq \mathrm{TE}_{it} \leq 1$ (2)

2.2: Spatial autocorrelation analysis

In our econometric study, the emphasis will be on the analysis of spatial autocorrelation for the variables, in other words the analysis of the presence of a relationship between different spatial observations. The existence of a spatial autocorrelation indicates that there is always a functional link between what happens at one point in space and what happens elsewhere; these spatial interactions are stronger when the locations are closer together.

a- Global spatial autocorrelation

Before specifying a spatial econometric model, it is necessary to check whether a spatial phenomenon is indeed to be taken into account. The first step is to characterise spatial autocorrelation using statistical tests. The most common statistic for spatial autocorrelation tests is that of Moran (1948).

Moran's global Moran I index comes from a paper by Pat Moran from 1950. However, it was his rewriting proposed by Cliff and Ord (1969) that made it possible to disseminate it, and it is in this new form that it is discovered. Indeed, Moran's index is an index that makes it possible to evaluate the level of spatial autocorrelation for a variable as well as its significance. It is equal to the ratio of covariance between contiguous units (defined by the weight matrix) and the overall variance of the sample.

This Moran index (1950) is formally written as follows:

$$I = \frac{N \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(y_i - \bar{y})(y_j - \bar{y})}{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(y_i - \bar{y})^2} \quad (3)$$

Where y_i and y are respectively the value of the variable in location I and j, ̄is the overall average, wij is the ithelement of the spatial weight matrix defined as contiguity, distances or common boundaries.

The assumptions of this test are as follows:

- H0: if I= 0, absence of spatial autocorrelation

- H1: if I $\neq 0$, presence of spatial autocorrelation: In this case :

If -1 <I : There is negative spatial autocorrelation: the non-similar values of the studied variable are clustered geographically: close locations are more different than distant locations

If I >1: There is a positive spatial autocorrelation: similar values of the variable studied are clustered geographically.

b- Local Indicator of Spatial Association

After the evaluation of the global spatial autocorrelation, the local spatial autocorrelation for each unit of the space is analyzed in a second step. This is an evaluation of the significance and intensity of the existing local dependency between the value of a variable in one geographical unit and the values of the same variable in neighbouring geographical units using the local Moran Index. The Local Indicator of Spatial Association LISA (Anselin, 1996) indicates the contribution of this region in the global spatial autocorrelation evaluated in all n regions.

The Local Moran Index evaluated at location i is defined as follows:

$I_i = Z_i \sum_j W_{ij} Z_j$; $\sum_i I_i = \sum_i Z_i \sum_j w_{ij} Z_j$ and $\sum_i I_i = \gamma I$ (4)

Then $\gamma = S_0 m_2$ and $m_2 = \sum_i Z^2{}_i / n$

The observation of that spatial structur is possible on Moran's diagram. The last shows the types of local spacial autocorrelation for a spatial unit and the neighbouring units. Moran's I scatter plot will be employed to examine the spatial distribution of the efficiency scores for the period 2010-2015 among Tunisia governorates.

2.3. Spatial Regression Analysis Models

a. spatial autoregressive models / spatial error models

The most commonly used models for spatial regression analysis are spatial autoregressive models (SAR) that contain spatial lag variable and spatial error models (SEM) for processing error terms. The SAR model is expressed by Equation (5) as follows:

$y_{it} = \alpha_i + \rho \sum_j^n w_{ij} y_{jt} + x_{it}\beta + u_{it}$ with $i \neq j$ (5)

Where i and t design respectively region and year, y it is the dependent variable, w ij is the weight matrix with dimension (N,N), α is the intercept term. Wy is the spatial lag variable, β is the regression coefficients vector, x is the independent regression variables vector and u is the error term vector.

ρ is the spatial autoregressive coefficient. Subsequently, whether or not the variable ρ equals to 0 (ρ≠ 0) is evaluated to determine if spatial autocorrelation exists in the SAR model.

Spatial Error Models (SEMs) speculate that spatial autocorrelation is present in the error terms. These latter are typically calculated by multiplying the spatial error coefficient with the spatial weight matrix. The model is expressed in Equation (6)

$y_{it} = \alpha_i + x_{it}\beta + u_{it}$, with $u_{it} = \lambda \sum_j^n w_{ij} u_{jt} + \varepsilon_{it}$ (6)

where α is the intercept term, β is the regression coefficient, x is the independent variables vector , u is the error term vector, λ is the spatial error coefficient, W is the spatial weight matrix and ε is the modified error term. Whether or not the spatial error coefficient λ has statistical significance and equals 0 ($\lambda \neq 0$) are evaluated to determine if spatial autocorrelation exists in the SEM.

b. Comparison of the Spatial regression analysis Models

To determine which type of model is more appropriate, firstly we adopted several spatial panel models for investigation: SAR fixed effects, SAR random effects, SEM fixed effects, and SEM random effects. In a fixed-effect model, individual heterogeneity is modelled taking into account individual specific effects that are invariant over time, and in the random-effect model, individual heterogeneity is modelled taking into account individual specific random effects that are invariant over time. Secondly, When spatial autocorrelation is evident , the Akaike information criterion (AIC) is adopted to test whether the SAR model or the SEM is more applicable for the data. A smaller AIC value denotes a stronger goodness-of-fit.Thirdly, the Hausman test (1978) is applied.

c. spatial regression analysis models for health efficiency

In the spacial models, the dependent variable is measured by the health sector efficiency scores that will be estimated by using the SFA (referred to as EFFC). The explanatory variables are three socio-economic variables, namely the unemployment rate, higher education and household income, and a demographic variable, namely population density. The latter is integrated to express the urbanisation of the area in the production function.

Specifically, the unemployment rate variable (referred to as UNEM) is measured by the percentage of the labour force that is unemployed. The number of higher education graduates per km² measures the higher education variable designated by SCO. In our study, the level of consumption of individuals is used as a proxy variable for household income (referred to as CONS). The number of inhabitants per km² measures the population density variable (referred to as DENS). All explanatory variables are expressed in logarithmic form in order to stabilize the variance.

The specification of the SAR fixed-effects model is as follows:

$\mathrm{EFFC}_{it} = \alpha_i + \rho \sum_j^n w_{ij}\mathrm{EFFC}_{jt} + \beta_1\mathrm{SCO}_{it} + \beta_2\mathrm{DEN}_{it} + \beta_3\mathrm{CONS} + \beta_4\mathrm{UNEM} + \mathrm{U}_{it}$ (6.a)

The random effects SAR model is as follows:

$\mathrm{EFFC}_{it} = \rho \sum_j^n w_{ij}\, \mathrm{EFFC}_{jt} + \beta_1\mathrm{SCO}_{it} + \beta_2\mathrm{DEN}_{it} + \beta_3\mathrm{CONS} + \beta_4\mathrm{UNEM} + \mathrm{U}_{it}$ (6.b)

With $\mathrm{U}_{it} = \alpha_i + \varepsilon_{it}$

The specification of the SEM fixed-effects model is as follows:

$\mathrm{EFFC}_{IT} = \alpha_i + \rho \sum_{j=1}^n w_{ij}\, \mathrm{U}_{jt} + \beta_1\mathrm{SCO}_{it} + \beta_2\mathrm{DEN}_{it} + \beta_3\mathrm{CONS} + \beta_4\mathrm{UNEM} + \mathrm{U}_{it}$(7.a)

The specification of the SEM random effects model is as follows:

$\mathrm{EFFC}_{IT} = \beta_1\mathrm{SCO}_{it} + \beta_2\mathrm{DEN}_{it} + \beta_3\mathrm{CONS} + \beta_4\mathrm{UNEM} + \mathrm{U}_{it}$ (7.b)

With $\mathrm{U}_{it} = \alpha_i + \rho \sum_{j=1}^n w_{ij}\mathrm{U}_{jt} + \varepsilon_{it}$

2.4.Data resources

The data are collected for the 24 Tunisian governorates and for the period 2010-2015. They are based on two databases, namely the National Institute of Statistics and the health map (Tunisian Republic, Ministry of Public Health).

3. RESULTS

3.1: Health system efficiency scores

Tables a and b in Appendix A present the descriptive statistics of the variables of the SFA model and the partial correlation coefficients between them. They indicate that the average of the mortality rate indicator is of the order of 5.32% with a standard deviation of 1.29. The maximum value of this rate is 10.9%. It is recorded in the governorate of Tunis for the year 2014, and the minimum of its value is 3.2%. The correlation matrix indicates low coefficients of partial correlation between the different inputs.

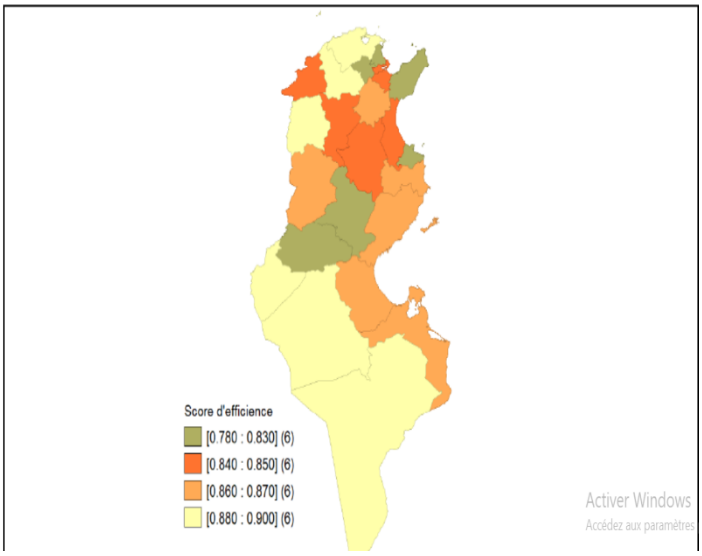
The two specifications of Green's (2005) model, the fixed effects model and the random effects model were estimated for our sample of Tunisia governorates. The estimation results are presented in **Table 1**. The probability of the Hausman test shown in the **table1** is less than 1%. Thus, the fixed effects model is retained as the most adequate specification. The results also show that the estimated parameters are valid, indicating a reliability of the efficiency estimates obtained.

Table 1 : Stochastic Frontier Regression

Determinants	**Green Model (2005)** Dependant variable :mortality rate (2010-2015)	
	True fixed-effects model	True random-effects model
Intercept		0,0115** (0.047)
doc	-0.0122** (0.048)	0.0021 (0.449)
hosp	-0.0108 (0.641)	-0.0083** (0.011)
Spen	-0.00551** (0.038)	-0.0077*** (0.002)
Observations	144	
Hausman test specification Chi(2)	15.3	
Prob > chi(2)	0.0018***	

Note: All variables are measured as natural logs. Standards errors are in parentheses.
* Denotes P<0.1. ** De-notes P<0.5. *** Denotes P< 0.01.

The estimation results shown in column 1 of the table 1 indicate that an increase in health expenditure has the effect of reducing mortality rates. This implies that governorates with higher health expenditure tend to have a more efficient health system. Similarly, the variable number of doctors has a negative and significant effect on mortality. Thus, increasing the number of doctors by 5% can contribute to reducing the mortality rate by 1%. On the other hand, the results reveal a non-significant effect of the number of hospitals on the mortality rate. In sum, the calculation of health system efficiency scores for our sample of 24 governorates. These scores fluctuate between 0.78 and 0.89. In addition, the estimation results indicate a disparity in efficiency scores between the Tunisian regions.



Map 1: illustrates the distribution of these health system efficiency scores in all regions of Tunisia.

3.2: Spatial-temporal pattern of health system efficiency

3.2.1: Global Moran's index

First, the spatial autocorrelation of efficiency scores was examined. The Global Moran's I index is used to test whether the spatial autocorrelation exists. If this condition is confirmed, it is possible to apply the spatial models. The Global Moran's I index of Tunisia governorate-level efficiency scores and its P-valve in period from 2010 to 2015 are displayed in **table 2**.It can be seen that the null hypothesis of the non-existence of spatial dependence is rejected and the values of all Moran's I of selected years are positive, which indicates a positive spatial correlation in Tunisia governorate-level health efficiency scores. However, the Moran's I values differed each year indicating the different clustering tendency of health system efficiency in selected governorates.

Table 2: Moran's I index of Tunisia governorate-level health system efficiency scores

Variable	Moran's I index	**p-value**
Effc2010	0.446	0.000
Effc2011	0.367	0.000
Effc2012	0.458	0.000
Effc2013	0.388	0.000
Effc2014	0.489	0.000
Effc2015	0.525	0.000

3.2.2: Local spatial autocorrelation LISA

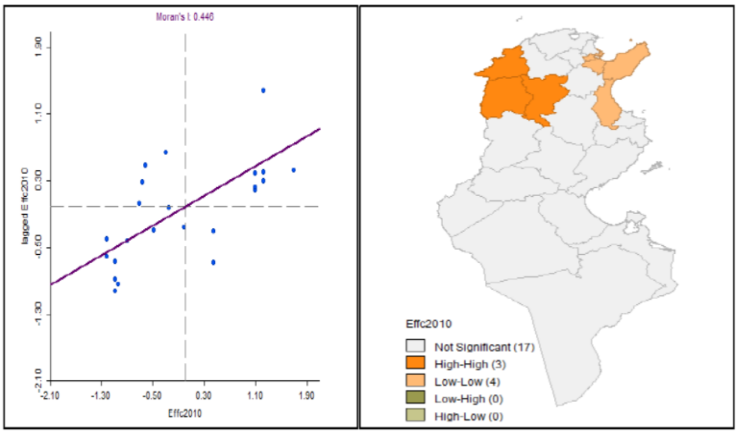
As illustrated in panels (a)-(d) of Figure 2,the scatter plot for every year has four quadrants based on the degree of spatial clustering, specifically, High-High, Low-High, Low-Low and High-Low,The résults defined by LISA are the following :

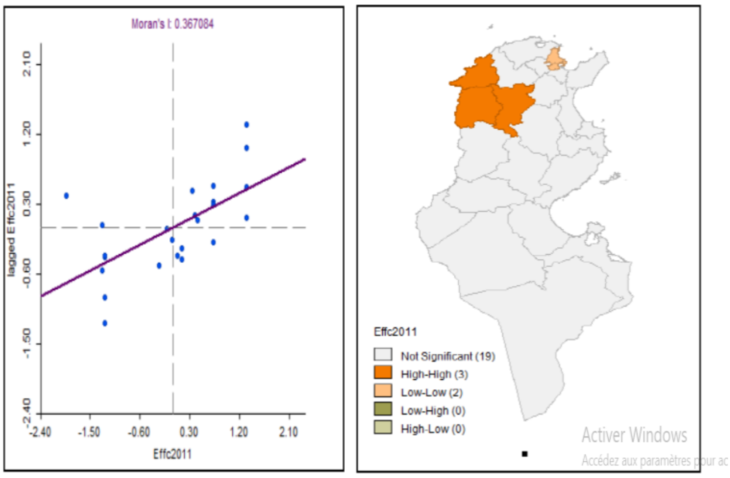
1. Quadrant High-High: HH clustering, it denotes spacial units with high scores are associated with neighboring units with high scores. These governorates demonstrate similar characteristics of spatial autocorrelation (positive spacial autocorrelation).
2. Quadrant Low-High: LH clustering, it denotes governorates with low scores are associated with neighboring regions with high scores. These regions have different characteristics of spatial autocorrelation, (negative spacial autocorrelation).
3. Quadrant Low-Low : LL clustering, it denotes governorates with low scores are associated with neighboring governorates with low scores. These governorates have similar characteristics of spatial autocorrelation (positive spacial autocorrelation).
4. Quadrant High-Low: HL clustering, it denotes governorates with high scores are associated with neighboring governorates with low scores. These regions have different characteristics of spatial autocorrelation, (negative spacial autocorrelation).

3.2. 3: The spatial clustering map and Significance map

Panels (a)–(f) of **Figure 2** allow visualization of the four types of local spatial associations between a governerate and its neighbours, each located in a quadrant of scatterplot. The significance of the identified local clusters are also provided by the LISA significance map.

They show that the LL governerates were mainly distributed in the North –East sub-region of Tunisia in all the years (2010-2015). However, the HH governates were locacated in the North –west sub-region in all years except in the year 2014 on wich the concentration of values is in the South sub-region of the country. The two quadrants LH and HL displayed no obvious spatial centralized distribution.




Moran's I: 0.367084
lagged Effc2011
Effc2011
Effc2011
Not Significant (19)
High-High (3)
Low-Low (2)
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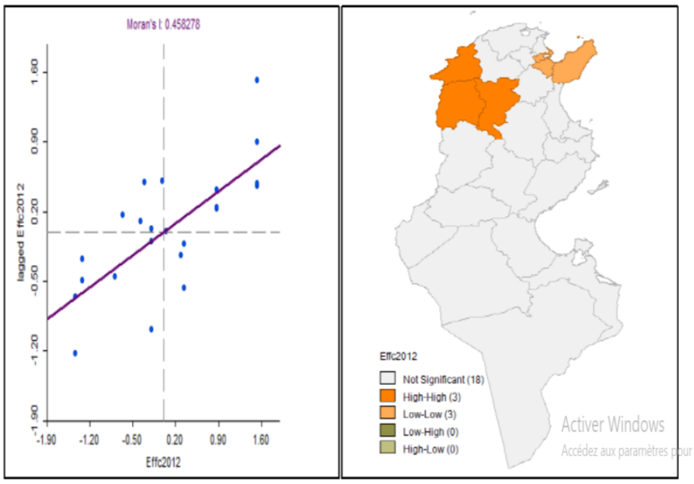
Moran's I: 0.458278
lagged Effc2012
Effc2012
Effc2012
Not Significant (18)
High-High (3)
Low-Low (3)
Low-High (0)
High-Low (0)
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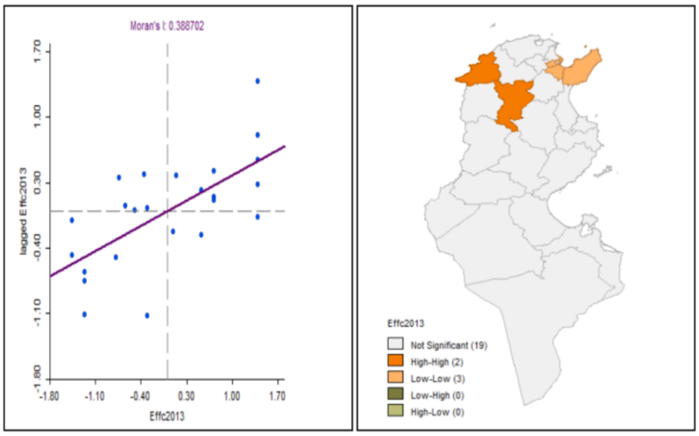
Moran's I: 0.388702
lagged Effc2013
Effc2013
Effc2013
Not Significant (19)
High-High (2)
Low-Low (3)
Low-High (0)
High-Low (0)

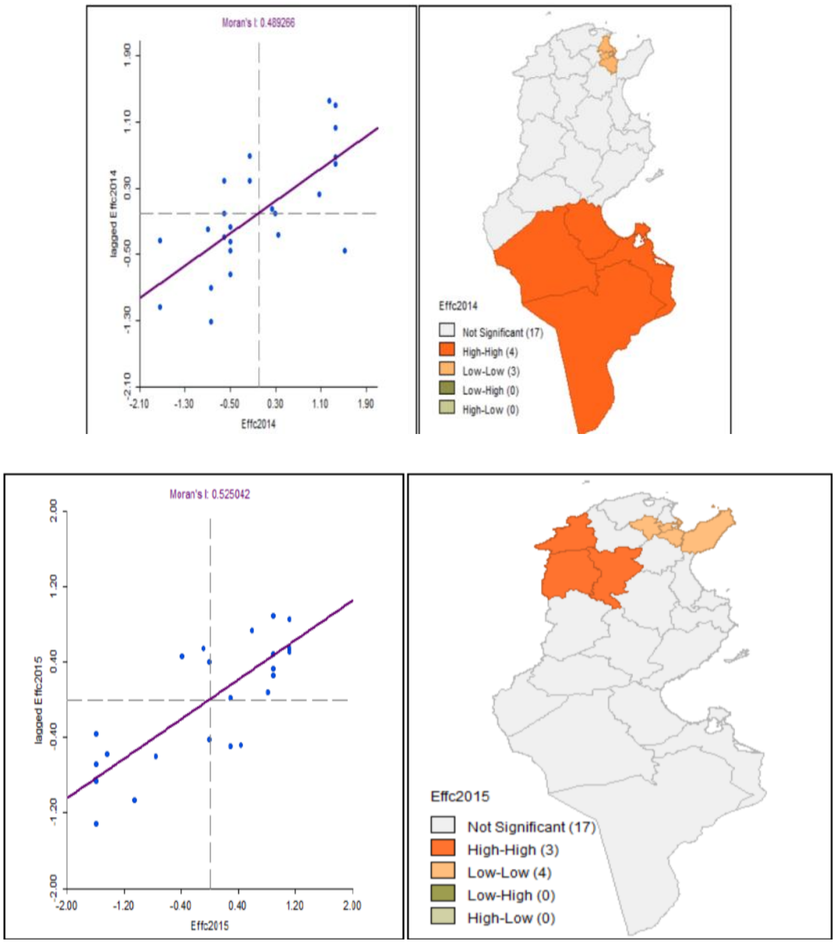

Fig. 2 :Spatial distribution of efficiency scores 2010–2015. (a)-(f)

Table 3 summarizes the locations of the clusters according to the results obtained from the geographical distribution of efficiency scores of local spatial association in the period 2010-2015.

Table 3: Geographical distribution of efficiency scores of local spatial association in the period 2010-2015 on Tunisian sub-regions

		2010	2011	2012	2013	2014	2015
Quadrant HH	Sub-region	the North-West	the North-West	the North-West	the North-West	the Sourth	the North-West
	Governorates	3	3	3	2	4	3
Quadrant LL	Sub-region	the North-East	the North-East	the North-East	the North-East	the North-East	the North-East
	Governorates	4	2	3	3	3	4
Quadrant HL	Sub-region	-	-	-	-	-	-
	Governorates	0	0	0	0	0	0
Quadrant LH	Sub-region	-	-	-	-	-	-
	Governorates	0	0	0	0	0	0

3.3: The impact of the socio-economic environment on health efficiency

Descriptive statistics including the mean, maximum, minimum and standard deviation for each of the variables are presented in Table c in the Appendix B. The table shows that the unemployment rate varies between

governorates, ranging from a minimum of 4.9% to a maximum of 6.93%. With regard to higher education, the governorate of Tataouine records the minimum value in 2010, which is equal to 1.2 graduates/km^2, and the governorate of Tunis records the maximum value, which is equal to 196.8 graduates/km2 in 2015. The variables, which record a maximum variation, are the level of consumption and the population density.
Table 4 shows the estimation results of spatial panel models (SEM , SAR). Columns 1-4 represent the different specifications we used: fixed effects and random effcts, respectively.

Table 4 : The Analysis Results by the spatial error model (SEM) and the spatial spatial autoregressive modell (SAR)

Spatial Model / Variables	SEM		SAR	
	True fixed-effects model	True random-effects model	True fixed-effects model	True random-effects model
Intercept		0.8070*** (0.000)		0.2974* (0.051)
SCO	0.4389*** (0.000)	0.2604*** (0.000)	0.5125*** (0.000)	0.3324*** (0.000)
DEN	-0.1046 (0.579)	-0.0872* (0.066)	-0.1012 (0.565)	-0.1311** (0.013)
CONS	-0.0078 (0.892)	0.0160 (0.777)	0.0009 (0.985)	0.0429 (0.414)
UNEM	-0.0859 (0.320)	-0.1133 (0.155)	-0.1303** (0.028)	-0.0815 (0.171)
Rho (ρ)			0.5467*** (0.000)	0.5154*** (0.000)
Lambda (λ)	0.5561*** (0.000)	0.5961*** (0.000)		
AIC	-512.4267	-400.8855	-522.9987	-401.003
observations	144		144	
Hausman test specification Chi(2) Prob > chi(2)	3.52 0.6207		16.39*** 0.0058	

Note: All variables are measured as natural logs. Standards errors are in parentheses.
* Denotes P<0.1. ** De-notes P<0.5. *** Denotes P< 0.01.

The results displayed in the table 4 show that the hypothesis of no spatial autocorrelation for the dependent variable is rejected [H0: Rho(ρ) =0] . For the spatial autocorrelation error test [H0: Lambda (λ)=0], the results indicate that the null hypothesis is also rejected. This implies that the econometric model to be estimated is a spatial model.
Based on the Akaike Information Criterion (AIC Akaike Information Criterion), the valuesAICs for the fixed-effect and random-effect models of the SAR model are lower than those of the SEM model. The SAR model then appears to be more appropriate. The result of the Hausman test indicates that the SAR model with fixed effects is the most suitable (probability < 1%).
According to the results of the SAR fixed-effects model obtained in the column of Table No. the relationship between higher education enrolment and health system efficiency is significant and positive at the 1% threshold. An increase in university graduates of 1% leads to an increase in efficiency in the Tunisian health system of 0.51%. More educated individuals have a better understanding of medical treatment. Moreover, generally having a good social position and a relatively higher purchasing power, higher education graduates have the means to resort to preventive care, which can contribute to improving the efficiency of health care.
The results indicate that the efficiency of the health care system in Tunisia is negatively influenced by unemployment. The estimated efficiency decreases by 0.13% following the 1% increase in the unemployment

rate. This result is explained by the fact that the unemployed do not have the means to access health care. Moreover, unemployment is related to the economic difficulties of a country, which probably results not only in a decrease in personal health expenditure but also in an increase in the burden of illness for the unemployed.
With regard to the two variables household income and population density, the results indicate that their effects on the efficiency of the health system are not significant in the case of Tunisia.

3.4: Direct, indirect and total effects of socio-economic variables on the efficiency of the health system

Our empirical analysis now consists in estimating the direct and indirect spatial effects of socio-economic variables on the efficiency of the health system in Tunisia over the period from 2010 to 2015, using the SAR spatial model on the specification of the fixed effects model.Therefore, we used the direct and indirect effects to investigate the spatial spillover. Table 5 shows all these effects.

Table 5 : The analysis results by the spatial autoregressive model: direct and indirect effects

SAR-True fixed-effects model			
Determinants	Dependant Variable (Effc)		
	Direct effects	Indirect effects	Total effects
SCO	0.5711*** (0.000)	0.5877*** (0.002)	1.1589*** (0.000)
DEN	-0.1211 (0.523)	-0.1231 (0.551)	-0.2442 (0.534)
CONS	0.0058 (0.915)	0.0039 (0.946)	0.0097 (0.930)
UNEM	-0.1465** (0.025)	-0.1540* (0.075)	-0.3006** (0.042)

Standards errors are in parentheses. * Denotes P<0.1. ** De-notes P<0.5. *** Denotes P< 0.01

The direct and indirect effects of higher education on the efficiency of the Tunisian health system are positive and statistically significant at the 1% threshold. Estimation results indicate that a 1% increase in the number of university graduates from region i will improve efficiency in the health sector for this same region by 0.5% as well as for its neighbouring regions. The existence of a positive spillover effect emanating from the increase in higher education can be explained by the displacement of university graduates from their home governorate and their settlement in neighbouring regions in search of employment and/or internships.
Concerning the unemployment rate, the estimated coefficients of this variable indicate that it exerts a negative and statistically significant direct effect at the 5% threshold and a negative and significant indirect effect at the 10% threshold. An increase in the unemployment rate in region i of 10% leads to a decrease in the efficiency of the health system in neighbouring regions of 0.15%. The negative "spillover" effects generated by an increase in unemployment in a region can be explained by the fact that the unemployed person decides to immigrate to neighbouring governorates to maximise their chances of working.
The two variables household income and population density have no direct or indirect effect on the efficiency of the health system.

CONCLUSION

This paper presents a spatial analysis of health efficiency in Tunisia. It investigates efficiency differences between Tunisian governorates on the period 2010-2015 and examines the impact of the socio-economic and demographic factors on health efficiency. The Tunisian health sector is subject to strong financial pressures in the provision of health care. In particular, an inequitable distribution of medical services between regions of the country can lead to a less efficient health system. Therefore, a better understanding of the factors that determine inefficiencies in health care delivery is likely to promote a good spatial distribution of medical infrastructure between regions that may lead to inefficiencies in health care delivery. We measured health efficiency scores for a sample of 24 governorates observed over the period 2010 to 2015, using the stochastic frontier method by employing a parametric stochastic frontier approach with fixed effects (Green's model, 1995). This approach has the advantage of requiring a precise specification of the relationship between input and output and that the error term has two components, one representing technical efficiency and the other representing random error. The results showed that the average efficiency scores for health care delivery ranged from 0.78 to 0.89, with higher efficiencies in urban settings and lower efficiencies in rural settings. By using spatial analysis, we have examined whether the spatial autocorrelation exists in Tunisian governorate-level health efficiency scores. The results of the Moran test confirm the positive spatial autocorrelation in Tunisia governorate-level health efficiency scores. However, the Moran's I values differed each year, which in turn indicates a different

clustering tendency of health efficiency in selected governorates. Besides, by using Moran's I scatter plot, we find that Tunisia has significant clustering of health efficiency scores in North
East sub-region and significant clustering of health efficiency in the North -West sub-region.
The spatial econometric models analyses confirm the existence of a spatial autocorrelation, which is negative, and the existence of a link between health efficiency scores and socioeconomic factors. In the present study, the spatial lag models (SAR) that contain spatial lag (endogenous) variables was used. AIC test has indicated that this type of model is more appropriate than spatial error model. According to Hausman test, the SAR model random effectsis rejected in favour of the SAR model fixed effects.
The estimation of spatial effects by this model showed that education positively affects the efficiency in the health system of region i as well as the efficiency of neighbouring regions.
Similarly, unemployment negatively affects the health efficiency of region i and its neighbouring regions. Whereas income and population density have no direct or indirect effect on the efficiency of health care use, the Spatial Model regression results suggest that the increase of unemployment in one region directly decreases the health efficiency system in this region and indirectly reduces the health system efficiency of its neighbouring regions. The increase on education in one region will lead to an increase in its health efficiency system and an increase in the health efficiency system of its neighbouring regions. Income and the population density have no significant effects on the efficiency healthsystem.
Based on the findings of this study, we made two following recommendations: First, higher infrastructure investments in education are likely to improve efficiency of the health system in Tunisia . Second, since unemployment also affects health efficiency, there are creation of new jobs and reduction in the rate of unemployment that can help improvement on individual income earning and improve the efficiency of the health system in Tunisia.

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Appendix A. The stochastic frontier model SFA

Table a: Descriptive Statistics

Variable	Mean	Standard deviation	Minimum	Maximum
Mor	5.320139	1.288713	3.2	10.9
Spen	29162.62	62747.15	3885	329670
Doc	577.9583	771.557	77	3900
Hosp	6.951389	3.052753	2	14

Table b: Correlation Matrix

	mor	Spen	Doc	Hosp
mor	1.0000			
Spen	-0.5863	1.0000		
Doc	-0.4334	0.9092	1.0000	
Hosp	-0.5047	0.4325	0.3291	1.0000

Appendix B. The impact of the socio-economic environment on health efficiency

Table c: Descriptive Statistics

Variable	Mean	Standard deviation	Minimum	Maximum
EFFC	0.85	0.94	0.72	0.43
SCO	47.50	196.8	1.2	41.06
DEN	325.76	3727.9	3.8	688.31
UNEM	17.12	51.7	4.9	6.93
CONS	803.19	2104.69	259.94	378.37