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INEQUALITY AND SPATIAL DISPARITIES IN TUNISIA

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Abstract

The purpose of the paper is to analyze spatial disparities between Tunisian's "*délégations*" by making up a Spatial Composite Index of Welfare (SCIW) according to a multidimensional perspective. The Exploratory Spatial Data Analysis (ESDA) enables an overview on regional disparities as regard to the main dimensions considered in the analysis. By using spatial econometrics models, we can see how variables related to regional development policies and economic openness can enhance or reduce the SCIW and assess, hence, their role in reducing spatial disparities. The results show that some "*délégations*" of the capital city Tunis, from cities of Sousse, Monastir and Sfax are significantly three favored areas. However, there are at least two areas (composed of "*délégations*" from the regions of Northeast and Center-West) which are clearly disadvantaged. The results of spatial econometric estimates show that economic liberalization and public policy of regional development have a positive impact on SCIW and enhance therefore the development of a set of "*délégations*" but reduce spatial inequalities in Tunisia only for coastal areas.

ملخص

الغرض من هذه الورقة هو تحليل الفوارق المكانية بين "الوفود" التونسية التي تشكل مؤشر مركب لرعاية المكانية (SCIW) وفقا لمنظور متعدد الأبعاد. ويتيح و التحليل الاستكشافي للبيانات المكانية (ESDA) لمحة عامة عن الفوارق الإقليمية وفيما يتعلق بالأبعاد الرئيسية. فباستخدام نماذج الاقتصاد القياسي المكاني، يمكننا أن نرى كيف ان المتغيرات المتعلقة بسياسات التنمية والانفتاح الاقتصادي الإقليمي يمكن أن تعزز أو تقلل من SCIW ، وبالتالي تقييم دورها في الحد من الفوارق المكانية. وأظهرت النتائج أن بعض "الوفود" في تونس العاصمة، في الفترة من مدن سوسة والمنستير وصفاقس هى الثلاث المناطق المفضلة. ومع ذلك ، هناك اثنين على الأقل من المناطق (التي تتألف من "وفود" من مناطق شمال وغرب) محرومة بشكل واضح. نتائج تقديرات الاقتصاد القياسي المكاني تبين أن تحرير الاقتصاد والسياسة العامة للتنمية الإقليمية يكون لها تأثير إيجابي على SCIW وبالتالي تعزيز وتطوير مجموعة من "الوفود" ولكن تحد من التفاوتات المكانية في تونس فقط للمناطق الساحلية.

1. Introduction

A simple analysis of the history of Tunisia shows that after the independence in 1956, the contrast is widening between capital city (Tunis) and other cities of the country as regard to concentration of population and activities. Tunis acquires at that time 70 to 75% of industrial jobs and nearly three quarters of industrial companies of more than fifty employees (Métral 2003). Different policies pursued since the 1960s (the creation and strengthening of development centers, industrialization through private initiative, etc.) have reduced this contrast which have been gradually replaced by a structural imbalance between coastal regions and regions of the interior. This is largely explained by factors related to the presence of a modern public infrastructure and a social and cultural infrastructure, size of regions, high regional population density, urbanization (Karray and Driss, 2006).

Because of this new configuration, some development policies have been adopted to reduce these regional development inequalities. For example, Tunisian authorities have adopted several measures such as classification of the less developed regions as regional development areas and priority development areas. This classification provides a number of advantages (grants, tax exemptions, etc.) to companies (both domestic and foreign) who locate their activities in these regions. Similarly, location of training centers (vocational, technical and learning) in deprived areas improves skills of local workforce, the attractiveness of industrial enterprises and therefore the development of the region.

Moreover, the open door policy in Tunisia (started since the early 1970s and stressed in the mid-1990s when becoming a member of the World Trade Organization (WTO) and signing free trade agreements with the European Union), whose main vector is the growth of trade and foreign direct investment (FDI), contributes to the development of a set of regions in Tunisia. The location of foreign firms (and their effects on job creation, technology transfer and regional development) may reduce or increase disparities between Tunisians' regions.

The analysis of spatial inequalities in Tunisia has been the subject of several research works (see for example El Bekri 2000; Lahga and El Ayadi 2006; Montacer 2004) but only at a regional level (i.e. spatial disparities between cities). However, this paper produces a new empirical analysis of spatial disparities at the "*délégations*" level (which is a unit of spatial analysis as a finer geographical level than a city)[1]. This work enables a clearer analysis of disparities between "*délégations*" of the same city and between "*délégations*" of different cities by computing a Spatial Composite Index of Welfare (SCIW). We will identify the sources of spatial disparities in terms of well-being. We then try to see how variables related to institutional factors (regional development policies) and economic openness can enhance or reduce the SCIW and assess, consequently, their role in the reduction of spatial disparities.

The recent economic literature focuses on the negative effects resulting from a significant spatial inequality. Indeed, the economic performance of a country is strongly related to levels of inequality and the distribution of wealth, population and economic activity (Persson and Tabbelini, 1991). A relatively high inequality may increase social tensions and generate an unstable socio-economic situation (Ayadi and El Lahga, 2006). Quality of institutions is thus very important as a key factor of regional development and reduction of spatial disparities between different regions of a country.

The debate on spatial inequality was initially focused on the economic dimensions. This shows the importance not only of variables related to income as an indicator of well-being but also the priority given to policies promoting economic growth. This debate has been then extended to the conceptualization of inequality, highlighting the role played by non-monetary

[1] We should note that in 2005, Tunisia count 6 regions, 24 cities and 263 "*délégations*" (as "delegation" is the principal spatial division within the city).

dimensions, such as those relating to basic health, education, access to basic needs (water, electricity, information technology and communication, etc.). These factors can be related quite closely to improvement of poorest households' well-being (United Nations 2005; Bourguignon et al. 2007 and Walker 2007).

In this paper, we assume that spatial disparities are multidimensional and are related to three kinds of determinants. First, spatial disparities and the unevenness of growth within countries reflect market forces associated with economies of scale and movements of goods and factors. There is an increasing density of economic activity and populations associated with urbanization as firms and workers move closer to areas with greater market potential. Concentration of economic activity (stressing the balance between agglomeration economies and congestion costs) seems to be source of economic growth and at the same time source of spatial disparities and poverty (Ravi and Venables 2004). Second, regional disparities are closer related to stylized facts on various aspects of the rural-urban transformation, and how they are related with economic growth, poverty, and disparities in living standards, such as access to basic services (Milanovic 2005). There are identifiable relationships among sectoral shifts, changes in density, and urbanization rates; and urban-rural disparities vary systematically at different stages of urbanization. Third, spatial disparities are also related to monetary indicators. There is a robust positive relationship between per capita incomes and urbanization rates (Henderson 2005).

This work presents two main specific features as regard to existing studies on spatial disparities. On the one hand, we examine spatial disparities in Tunisia at disaggregate geographic level, i.e. the "delegation" unit. The "delegation" is a lower geographical level than city and enables to make more precised study of regional disparities. We consider both spatial disparities between "*délégations*" of the same city and spatial disparities between "*délégations*" of different cities. On the other hand, we consider a multidimensional measure of inequality at the spatial level as it is now recognized that human development goes beyond economic growth and is a multidimensional phenomenon covering all aspects of well-being (monetary and non-monetary attributes of inequality). To our knowledge, nobody has studied the determinants of spatial disparities considering a multidimensional level of inequality at a very detailed geographical level for developing countries of MENA, and more precisely for Tunisia. Our main objective is to provide more detailed study of the effects of economic activity agglomeration, socio demographic and monetary indicators on spatial disparities.

The paper is organized as follows. The next section presents specification of data, method of construction of the SCIW and the exploratory spatial data analysis (ESDA). This will enable us to analyze the determinants of spatial disparity between Tunisian "*délégations*". In the third section, spatial econometrics models offer the opportunity to assess the extent to which variables related to markets liberalization and regional development policy explain the SCIW and reduce spatial inequalities.

2. Computation of the SCIW and Spatial Disparities Analysis

We proceed in this section in two stages. In the first, we apply a Principal Component Analysis (PCA) method on attributes of "*délégations*" to make up a synthetic index (SCIW)[2] of spatial multidimensional inequalities between "*délégations*" in Tunisia. This index is intended to summarize multivariate information for spatial inequality and its origins demographic, social and economic but also non-monetary and monetary. In the second stage, an exploratory spatial data analysis (ESDA) of this index (SCIW) and its determinants enables identification of any spatial autocorrelation positive or negative and therefore

[2] We consider the ICBE developed among others by Ayadi and El Lahga (2006) to introduce a spatial index (SCIW).

specification of spatial inequality in Tunisia (concentrated or dispersed). The data used in this section relating to different attributes of "*délégations*" are extracted from the CGDR-INS (2005) database.

2.1 Construction of the Spatial Composite Index of Welfare (SCIW)

Indicators of inequality between "*délégations*" are numerous and varied. These attributes, used separately, provide an unstable picture of the state of the correlation and spatial heterogeneity of inequalities between "*délégations*". The purpose of this work is to introduce a SCIW by considering multidimensional attributes of inequality, and in which it is possible to assess the contribution of each attribute (dimension). The application of ESDA on this index will make it possible subsequently to describe spatial heterogeneity and thus to detect spatial clusters of favored or disadvantaged "*délégations*" on the basis of a set of attributes simultaneously.

Factorial analysis is a set of descriptive multivariate statistical methods to simultaneously describe a set of variables. These methods offer a synthesis analysis which is to define new composite variables (main factors) from the original variables (attributes/dimensions). Each factor is a linear combination of attributes. Each attribute contributes more or less strongly to the construction of the factor. Moreover, once built, the factor will be associated with a major component; it is a vector that defines factorial score for each individual (delegation) of the population, a single measure that summarizes all of its attributes original.

The quantitative data used justifies the use of Principal Component Analysis (PCA). We therefore seek to define the best factor that would explain the most important part of information. This factor, which summarizes all attributes of "*délégations*", is a spatial synthetic index of welfare at the "*délégations*" level (SCIW). It gives each "*délégation*" a measure (score) reflecting the overall conditions available in the "*délégation*" (a score of unequal opportunities for individuals living in different "*délégations*"). We will then measure the importance of contribution of each attributes in the construction of the index.

The database CGDR-INS-2005[3] provides a number of attributes for the 263 Tunisian "*délégations*"[4]. These variables provide valuable information on the attributes of "*délégations*" and thus enable to compare and identify possible inequalities between them. However, these variables are numerous and very heterogeneous and refer to different concepts. Thus, some variables describe access to basic needs such as the rate of connection to the fixed telephone network (tel_fixe), the mobile phone (tel_mob), the percentage of households owning a computer (computers), the connection to the sewerage network (ONAS)[5] and access to tap water (water_tap). Other variables are demographic, such as the number of housing (house), the number of households (numb_households), or refer to levels of education such as the share in the population of individuals with the level of secondary education (educ_secondary) and above (educ_sup) and the illiteracy rate. Finally, another set of variables are economic; monetary, such as expenditure per capita (EPC) or non-monetary such as active population (pop_act) and the stock of employment (employment).

Given the high number of attributes and their heterogeneity, it would be very difficult to describe precisely the form of spatial inequalities in Tunisia. Hence, using the PCA provides a single measure (SCIW) describing the spatial inequality in Tunisia. The results of the PCA show that the first principal component explains over than 65% of the initial information represented by 13 attributes observed for 254 "*délégations*". All these variables have good

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[3] Unfortunately, the database is available only for 2005. If we had the same database for previous years, we can study the dynamic aspect of spatial disparities in Tunisia.

[4] Our study concerns only 254 "*délégations*" because of missing values for nine "*délégations*".

[5] Office National d'Assainissement.

representation and contribution to SCIW according to order shown in table 1 (see more detailed results in appendix 1).

After computing the index, it is appropriate to make an exploratory spatial data analysis (ESDA) to study the spatial heterogeneity of "*délégations*" based on a single measurement namely SCIW. This provides a robust representation of spatial clusters of "*délégations*" based on the nature of the inequalities connections.

2.2. Exploratory spatial data analysis on the SCIW

The empirical literature offers several methods and techniques for detecting spatial inequalities. Generally, these methods use spatial and economic data to construct indices of inequality and poverty in order to study the spatial pattern of inequality in an area. Each center is formed by one or more contiguous "*délégations*" where the indicator is different from that of neighboring areas. Two cases are possible: first, the core has a higher index value than its neighbors; it would be associated with assigned positive and correspond to a favored area. Otherwise, the area would be disadvantaged (periphery). This type of analysis assumes that the methods of detection of centers take into account the spatial data, namely spatial autocorrelation and spatial heterogeneity which are unavoidable features.

According to Anselin and Bera (1998), spatial autocorrelation reflects the idea that the values taken by a random variable in a geographical region are not arranged at random, but are often close to two neighboring spatial observations (Jayet, 1993). More specifically, *spatial autocorrelation* can be defined as the coincidence of value similarity with location similarity (Anselin, 2001). In other words, there is positive spatial autocorrelation when high or low values of a random variable tend to cluster in space and there is negative spatial autocorrelation when geographical areas tend to be surrounded by neighbors with very dissimilar values. The absence of autocorrelation leads to a random spatial distribution of the values of the variable (Vasiliev, 1996). *Spatial heterogeneity* means in turn that economic behavior is not stable across space and may generate characteristic spatial patterns of economic development under the form of spatial regimes. This instability is often observed. Thus, the economic phenomena differ between the city center and its suburbs, between rural and urban space.

Exploratory Spatial Data Analysis (*ESDA*) is a set of techniques aimed at describing and visualizing spatial distributions, at identifying atypical localizations or spatial outliers, at detecting patterns of spatial association, clusters or hot spots, and at suggesting spatial regimes or others forms of spatial heterogeneity (Haining 1990; Baily and Gatrell 1995; Anselin 1998a,b). In order to properly account for spatial interactions, these methods take into account the relative positions of data through the inclusion of spatial weight matrices. Thus, the comparison of a spatial observation and its neighbors is taken into account directly and no longer later. In addition, these methods provide measures of global and local spatial autocorrelation (Guillain, Le Gallo and Boiteux-Orain 2004).

As a first step, we look at the global spatial autocorrelation. The most used and best known statistic for measuring the global spatial autocorrelation is Moran's ***I*** statistic (Cliff and Ord 1981), which is written as follows:

$$I = \frac{N}{A} \frac{\sum_i \sum_j w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_i (x_i - \bar{x})^2}$$

where x_i is the observation in the area i, $\bar{x}$ is the average value for all areas considered, N is the number of areas and w_{ij} is the element of the weight matrix, A is the sum of all elements of the weight matrix. The term of the numerator is the covariance between adjacent observations. Each contiguity is assigned by a weight equal to w_{ij} / A. It is normalized by the term in the denominator which is the total variance observed. Values of I larger (respectively smaller) than the expected value $E(I) = -1/(N-1)$ indicate positive (respectively negative) spatial autocorrelation.

The Moran's index I may also be written in the following matrix form:

$$I = \frac{N}{A}\frac{Y'WY}{Y'Y}$$

where Y is the vector of N observations in deviation from the mean $\bar{x}$. W is the spatial weight matrix. For standardized matrix, this formula is simplified as $A = N$.

Moran's I statistic is a global statistic and does not allow to assess the regional structure of spatial autocorrelation. However, it may be asked whether there are local spatial clusters of high or low values, which regions contribute more to the global spatial autocorrelation, and to what extent the global evaluation of spatial autocorrelation masks atypical localizations or "pockets of local nonstationarity". In this respect, local spatial autocorrelation is analyzed with other tools (Le Gallo and Ertur 2003). In this perspective, we use the Moran map, whose goal is to see the local spatial instability and extreme observations, and the local Moran still called the Local Indicators of Spatial Association (LISA) to test the hypothesis of random distribution by comparing the values of each specific location with the values of nearby locations.

Let Y a random variable and W a weight matrix. The variable shifted to N areas is defined by the vector of dimension (N, 1): WY. When Y is a standardized matrix, the i^{th} element of the spatial lagged variable contains the weighted average of observations adjacent to the area i. However, as we saw earlier, if the matrix W is standardized, the Moran's $\boldsymbol{I}$ statistic can be written in the matrix form as $I = \frac{Y'WY}{Y'Y}$. In this case, the Moran's I statistic can be considered as the slope coefficient of a linear regression of WY on Y using a row-standardized weight matrix. Local spatial instability is studied by means of the Moran scatterplot (Anselin, 1996), which plots the spatial lag WY against the original values Y. The four different quadrants of the scatterplot correspond to the four types of local spatial association between a region and its neighbors: HH a region with a high value surrounded by regions with high values, LH a region with low value surrounded by regions with high values, etc. Quadrants HH and LL (respectively LH and HL) refer to positive (respectively negative) spatial autocorrelation indicating spatial clustering of similar (respectively dissimilar) values. The Moran scatterplot may thus be used to visualize atypical localizations, i.e. regions in quadrant LH or HL. Moreover, the use of standardized variables makes the Moran scatterplot comparable across time. However, Moran scatterplot does not give any indications of significant spatial clustering and cannot therefore be considered as a LISA in the sense defined by Anselin (1995).

Anselin (1995) defines a *Local Indicator of Spatial Association* (*LISA*) as any statistic that satisfies two criteria: First, the LISA for each observation gives an indication of significant spatial clustering of similar values around that observation, second, the sum of the *LISA* for all observations is proportional to a global indicator of spatial association. The local version of Moran's $\boldsymbol{I}$ statistic for each "*délégation*" i is written as follows:

$$I_i = \frac{(x_i - \bar{x})}{m_0} \sum_j w_{ij} (x_j - \bar{x})$$

with

$$m_0 = \sum (x_i - \bar{x})^2 / N$$

where x_i is the observation in the "*délégation*" i; $\bar{x}$ is the means of the observations across regions and where the summation over j is such that only neighboring values of j are included. A positive value for I_i indicates spatial clustering of similar values (low or high), whereas a negative value indicates a spatial clustering of dissimilar values between a "*délégation*" and its neighbors.

Anselin (1995) gives two interpretations of LISA. They can be used first as indicators of significant local spatial clusters and second as diagnostics for local instability (atypical localizations), significant outliers, and spatial regimes. This second interpretation is similar to the use of a Moran scatterplot to identify outliers and leverage points for Moran's *I*: since there is a link between the local indicators and the global statistic, LISA outliers will be associated with the regimes which exert the most influence on Moran's *I*. Finally, combining the information in a Moran scatterplot and the significance of LISA yields the so called "Moran significance map", showing the regions with significant LISA and indicating by a color code the quadrants in the Moran scatterplot to which these regions belong.

2.3 Global Spatial Autocorrelation

Table 2 displays the value of the Moran's *I* statistic for the SCIW[6]. We should note that all subsequent analyses are conditional upon the choice of the spatial weight matrix. We used the spatial weight matrix of contiguity of level 1[7] to take into account the spatial correlations. If the computations lead to a positive and high value of the index (greater than its expected value), this indicates the presence of global and strong spatial autocorrelation of inequalities between the "*délégations*" in Tunisia. This positive relationship is a spatial configuration of inequality characterized by a tendency towards spatial clustering of low values of SCIW on one side and high values of the same index on the other side. The results of appendix 2 confirm this trend. The Moran's *I* calculated on all attributes presents positive and significant values at the threshold of 1%. The hypothesis of a positive spatial autocorrelation of inequality is confirmed and that whatever the nature of the monetary or non-monetary dimensions.

2.4 Local Spatial Autocorrelation:

To view the different kinds of spatial association between the "*délégations*", we use Moran map (Anselin, 1995). The Moran map as regard to the SCIW 2005 (Figure 1) shows important positive associations in terms of spatial inequality which represent nearly 80% of all associations: 34% are HH and 46% are LL. Negative associations are about 13% as HL and around 7% as LH. These local spatial associations confirm the global spatial association found previously.

It should be noted that Moran maps do not guarantee the statistical significance of associations detected. To overcome this shortcoming, we used the significance of Moran and

[6] We have also calculated the Moran's *I* for all attributes, see results in appendix 2.

[7] We have tested several kinds of weight matrices, those based on the nearest neighbors from the great circle distance between region centroids up to level 5. The results show that the most significant autocorrelation are those with contiguity matrix.

LISA statistics (see Figure 1)[8]. In short, only two spatial regimes are significant (40 "*délégations*" of HH type and 34 "*délégations*" of LL type) and refer to positive associations. Thus, 29 "*délégations*" of capital city (Tunis), five "*délégations*" in Sousse and Monastir and six "*délégations*" in Sfax are significantly advantaged areas (HH) and have high values of SCIW. The Moran significance map shows clearly three clusters of type HH. On the other hand, there are at least two clear areas which are disadvantaged and thus constitute poverty traps. A first area is located in the North-West region and formed by two "*délégations*" of LL type, and the second area is located at the Center-West of the country and composed of 32 "*délégations*" of LL type with low and spatially correlated values of the SCIW[9].

This overall trend has split the country into two zones: a Sahel and capital city (Tunis) favored on one side, and a North and Central-West disadvantaged on the other side. This is confirmed by the ESDA we have done on most dimensions (attributes), despite the significance differences (Appendix 3). Thus, whatever the variable, the spatial autocorrelation is positive and significant and the spatial distribution of inequalities in Tunisia follows a process in which "*délégations*" of HH type are clustered and others such as LL are also spatially concentrated.

Regarding the variables most strongly correlated with SCIW, the Moran significance maps show the following configurations: Access to tap water, the ONAS, the expenditure per capita, share of population with secondary education, access to fixed and mobile phones have the same configuration as the SCIW, with an additional group of "*délégations*" of HH type in the South-East for the phone and a group of LL type also in the South for the ONAS. The composition of groups in terms of significant "*délégations*", is not always the same, however the distribution of inequality has the same structure as that of the SCIW.

Other variables show differences compared to the SCIW, it is the case of employment variables, number of houses and number of households where only the favored areas of the Sahel and the capital city are significant. For against, variables such as the rate of illiteracy and unemployment are only significant for "*délégations*" of the Center-West and North-West with associations of LL type. This result confirms the difficulties of these regions to be more developed areas. Finally, the variable on the level of higher education is significant for the capital city (Tunis) with positive associations of HH type.

3. Determinants of Spatial Disparity

As we have now a clear illustration of the spatial inequality in Tunisia, the purpose of this section is to examine the extent to which variables related both to public policy of regional development and to markets liberalization policy, explain spatial inequalities in Tunisia. On the one hand, we examine the effectiveness of public measures of regional development adopted to reduce disparities. On the other hand, the expected effect of variables related to economic openness is ambiguous[10]. Indeed, the location of foreign companies in Tunisia (FDI is considered as the major vector of liberalization) may benefits relatively to disadvantaged areas (classified as area of regional development or priority development) through tax incentives and in this case the effect will be positive. However, foreign companies may choose to settle in developed areas (in order to benefit from agglomeration effects) and then increase inequalities between the "*délégations*".

[8] Moran maps related to each attribute of "*délégations*" are in appendix 3.

[9] These "*délégations*" are located at cities of Sidi Bouzid, Gafsa an Kasserine from where the Tunisian revolution flame has been launched in December 2010. In this region, the index for every "*délégation*" has very low values and these "*délégations*" are surrounded by similar "*délégations*". They have also the most important values of unemployment (see appendix 3).

[10] For a survey on the impact of economic openness on spatial disparities, see Catin and Van Huffel (2004b).

Thus, spatial econometrics model allow assessment of the impact of these two dimensions on spatial inequality in Tunisia. Variables related to regional development policies are: the number of training center by "*délégation*" and the classification of each delegation. This last variable takes the values 1, 2 or 3 if the "*délégation*" is classified respectively as an area to be developed of 1st group, of 2nd group or priority development area. It takes the value 0 if the "*délégation*" is not classified, i.e. has no advantage associated to development. Regarding the variables related to economic liberalization, we selected three measures[11]: the number of companies with foreign capital participation, the number of jobs created by them and the stock of FDI[12]. Data on these variables are extracted from the FIPA *(Foreign Investment Promotion Agency)* database, while data for the first four variables are extracted from the API ("*Agence de Promotion de l'Industrie*") database. All variables related both to regional development and to open door policies are considered with two-year lag in order to have a better assessment of the impact of these measures on the spatial index of inequality.

3.1 Elements of spatial econometrics models

The weight matrix allows the construction of specific variables, called lagged variables, an observation that connects to its neighbors. We will use spatial econometric methods to take into account spatial autocorrelation by using several specifications leading to different interpretations of the coefficients associated with geographic spillovers. Thus, in the spatial autoregressive model *(SAR model),* spatial autocorrelation concerns the explained variable (Anselin, 1980, 1988):

$$ICBES = \rho W \; ICBES + X \beta + \varepsilon$$

where W is the spatial weight matrix whose element w_{ij} measures the degree of dependence between the "*délégation*" i and its neighbor "*délégation*" j, ρ is the spatial lag parameter, X is the matrix of explanatory variables and β the vector of parameters to estimate.

In the model with spatial autocorrelation of errors *(SEM model),* geographic spillover effects may be indirectly associated with different variables in regression (Anselin, 1980, 1988):

$$ICBES = X \beta + \varepsilon$$

as $\varepsilon = \lambda W \varepsilon + u$

where λ is the parameter of spatial autocorrelation of error terms. Estimators obtained using the method of Ordinary Least Squares (OLS) are not converging and/or are inefficient if there are spatial autocorrelation. We will adopt the method of maximum likelihood and we will use tests of statistical inference to determine the most appropriate specification for spatial autocorrelation.

3.2 Estimation and interpretation

We first estimated the function of spatial inequalities by OLS method (Table 3). The set of tests we conducted indicate the presence of spatial autocorrelation problem at the level of OLS residues. The Lagrange test of errors autocorrelation is significant to the threshold 10% and in the same sense Moran test is significant to the threshold 1%. These results indicate therefore the presence of spatial autocorrelation of errors and the inequality function must be estimated by the SEM model that allows autocorrelation modeling. Moreover, the Lagrange test of the lagged endogenous variable rejects this hypothesis. This result is confirmed by estimating the SAR model which provided a not significant estimated Rho (shift parameter).

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[11] Data related to exports and imports at the "*délégation*" level are not available.

[12] Data related to FDI stocks are available only at the level of the city and not at the "*délégation*" level. So, we consider the interaction between this variable and the jobs creation.

Finally, the SEM model provides efficient estimators for unknown parameters of the model and will be considered for interpretation.

In general, the explanatory capacity of the model is quite satisfactory as the values of the R^2 are ranging from 0.53 (OLS and SAR models) to 0.64 (SEM model). The estimate of the SEM model by the maximum likelihood (ML) method shows first, the absence of spatial lag of the endogenous variable as evidenced by the value of the LM-lag[13] test and second demonstrates a good quality of adequacy. The estimated lambda parameter has also a significant coefficient at the threshold 1% justifying thus the presence of spatial autocorrelation of errors which is taken into account by the SEM model.

Estimation of parameters suggests generally that variables related to economic liberalization have a positive impact on SCIW and increase thus, ceteris paribus, the level of welfare in "*délégations*"[14]. In all estimated models coefficients associated to the number of foreign companies and the stock of FDI per job created by them, exert significant and positive effects on the value of SCIW. This shows that economic openness approximated through the presence of foreign firms, FDI and created jobs contribute to the development of host "*délégations*". The more a "*délégation*" hosts foreign firms, the higher its rate of development is important and it will be classified as favored area. This result, fully consistent with that of Catin and Van Huffel (2004a) which examines the case of Chinese regions, provides an explanation to the results of the previous section that coastal "*délégations*" (mainly in the North-East and Center-East) hosting the majority of foreign companies are considered themselves as advantaged areas.

Furthermore, the variable related to the number of training center has a positive and significant coefficient at the threshold 1%. The more a "*délégation*" would be given vocational training centers, the more its value of SCIW will be high and least it will be disadvantaged. This justifies the policy of setting up training centers in areas initially disadvantaged, which enables local workforce to be more skilled and thus gives these areas an attractiveness factor to attract foreign companies considered as source of employment and economic growth. Thus, the "*délégation*" may catch up on regional development in relation to neighboring areas. Classification of "*délégation*" as area to be developed has a negative and significant coefficient at the threshold 1%. Indeed, it is an ordinal variable where the highest value corresponds to areas of priority development, those who benefit from the most important advantages in stimulating investment. Thus, public authorities apply the most expensive measures of regional development in the most disadvantaged "*délégations*", those with the lowest values of the SCIW.

Thus, significant effects associated with variables related to public policy of regional development suggest some effectiveness of the role played by Tunisian authorities in reducing spatial inequalities between "*délégations*". In addition to the public policy of development of basic infrastructure, basic services (education, health, etc) and improving access to basic needs, the Tunisian authorities use other measures (such as setting up of training centers and classification of regional development zones) to reduce inequalities in development between "*délégations*" and between different regions. However, these measures are clearly insufficient and inefficient as there is a big cluster of "*délégation*" with LL type at the East region of the country. These "*délégations*" suffer from social tensions and inequity allocation of wealth and growth.

[13] This test is done on the residues of the SEM model.

[14] We have applied an ESDA on explaining variables of the model (see appendix 4). The results show that variables related to economic openness present clustering of HH type at the coastal "*délégations*". However, training centers seems to be equally disturbed whereas regions classified as development areas present a great clustering of HH type in the interior of the country.

A second specification was chosen and estimated, in which we have introduced two additional variables, namely the rate of unemployment in order to control the economic heterogeneity between "*délégations*" and the size of population which represents a demographic differentiation. The tests show the presence of spatial autocorrelation of error term. We therefore considered a SEM model[15] that takes into account this correlation. The parameter lambda is significant at the threshold 1%, i.e. we have corrected the problem of autocorrelation. Furthermore, the value of the LM-lag test demonstrates the absence of spatial lag of the endogenous variable.

The estimation of this specification confirms the results of the first equation with respect to variables of economic openness and regional development policy. Then, the size population variable has a positive and significant coefficient at the threshold 1%. Thus, the most populous "*délégations*" would be less disadvantaged; this is a strong demographic effect. Similarly, the coefficient associated to unemployment rate is negative and significant at the threshold 1%. The higher is the unemployment rate in a delegation; the more the spatial index of inequality would be low.

4. Conclusion

The main objective of this study was to analyze sources of spatial disparities between Tunisian's "délégations" by making up a spatial composite index of welfare (SCIW). The Exploratory Spatial Data Analysis (ESDA) on the SCIW and its determinants allowed us to describe the spatial heterogeneity and thus to detect clustering of favored or disadvantaged "délégations". The results show that 29 "délégations" of capital city (Tunis), five "délégations" of Sousse and Monastir and six "délégations" of Sfax are significantly advantaged areas and have high values of SCIW. At the opposite, there are at least two clearly disadvantaged areas: a first one (composed of two "délégations") is located in the North West region and a second area is located in the Center-West (composed of 32 "délégations") with weak and spatially correlated values of SCIW.

Spatial econometrics models have enabled us to analyze the impact of certain variables related to economic openness and regional development public policy on spatial disparities in Tunisia. The results show that economic openness, whose main vector is related to the presence of foreign companies (FDI) and their effects on jobs created as well, makes a specific contribution to the development of certain "délégations" of Tunisia. However, this effect benefits only to coastal areas and therefore increases the gap between advantaged areas at the littoral and lagged areas at the interior. In addition, measures relating to public policy for regional development seem to play an effective role in the process of regional development and reduction of spatial disparities for less favored "délégations" but are still insufficient.

This work enables us to suggest policies to shape regional transformations in Tunisia, to take advantage of the spatial concentration of economic activity without accentuating the gap between leading and lagging regions. Specific policies of territorial development (which aims to reduce regional divergence, i.e. to attend the convergence between leading and lagging areas) should differ depending on the stage of urbanization and the socio-political context. In order to improve regional convergence, public authorities should make up not only fiscal incentives measures specific to lagging regions, but also improve infrastructures and living services in these regions in order to avoid the delocalization of firms from lagging areas to leading ones when the period of fiscal incentives comes to end.

[15] Results of this estimation are presented in the last column of table 3.

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Figure 1: Map of Moran, Moran Significance Map and the LISA Map of SCIW

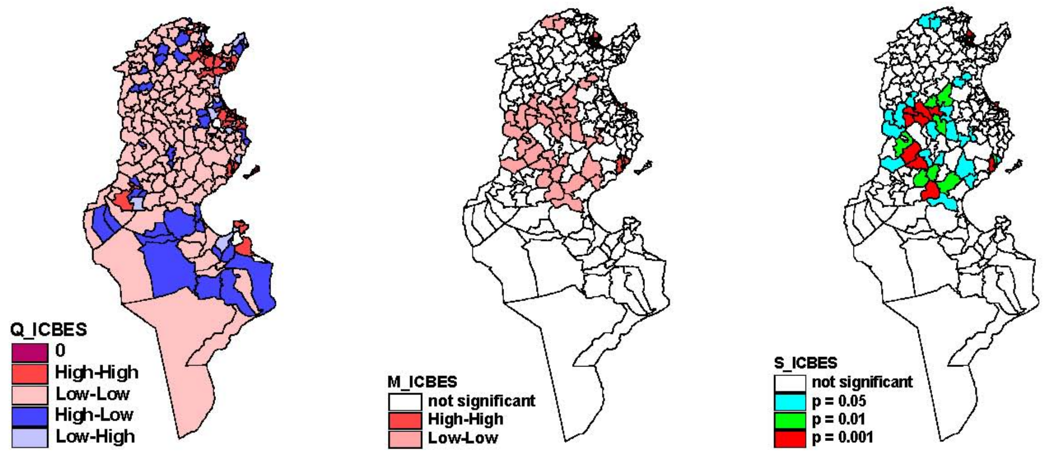


Table 1: Results of PCA

	Matrix components	
	Dimension 1	**Dimension 2**
Tel_Mob	0,891	- 0,249
Illiteracy rate	- 0,890	0,328
Tel_Fixe	0,879	- 0,260
educ_secondary	0,874	- 0,334
Computers	0,830	- 0,205
educ_sup	0,823	- 0,150
EPC	0,814	- 0,235
ONAS	0,810	- 0,205
Water_tap	0,773	- 0,344
employment	0,752	0,642
Pop_Act	0,741	0,661
House	0,725	0,670
numb_households	0,718	0,686
% of total variance	**65,868**	**18,443**

Table 2: Global Spatial Autocorrelation: Moran's *I* Statistic

	Matrix of contiguity of level 1	
	Moran's *I*	**p-value**
SCIW	0.645454	0.000000

Notes: The expected value of Moran's *I* statistic is -0,004 (0.040135)

Table 3: Estimation of Spatial Inequality Determinants

Variables	Dependant Variable: SCIW			
	OLS	**SAR**	**SEM**	
Constant	0.210744**	0.138946	0.256672***	-0.166561
	(0.0870063)	(0.105778)	(0.0863072)	(0.137591)
Number of training center	0.336285***	0.33746***	0.335243***	0.185114***
	(0.0502368)	(0.0495776)	(0.0488382)	(0.0444334)
Classification as development areas	-0.373107***	-0.331976***	-0.38672***	-0.279757***
	(0.0369105)	(0.0478083)	(0.0475294)	(0.044396)
Number of companies with foreign capital participation	0.0167272**	0.0147668**	0.0166883***	0.0100601*
	(0.00648413)	(0.00658243)	(0.0064879)	(0.00557441)
FDI per job created by foreign companies	0.0127659**	0.0112589*	0.0108411*	0.00994208**
	(0.00647836)	(0.00646932)	(0.00638643)	(0.00545064)
Population size	--	--	--	1.74147E-005***
				(1.90378E-006)
Unemployment	--	--	--	-0.0173975***
				(0.00676713)
Rho	--	-0.532026	--	--
		(0.354419)		
Lambda	--	--	-2.04396***	-2.25747***
			(0.333891)	(0.192293)
R^2	0.5304	0.5328	0.5487	0.6459
Fisher	70.3054***	--	--	--
p-value	0.00090815			
LR	--	1.566616	7.183008***	14.530260***
p-value		0.210699	0.007360	0.000138
LM-err	3.283675*	3.898491**	--	--
p-value	0,069972	0.048330		
Moran-err	-4.438930***	--	--	--
p-value	0.000009			
LM-lag	1.215142	--	1.231126	2.264385
p-value	0.270316		0.267188	0.132379
Number of observations	254	254	254	254

Notes: *** Significant to the threshold 1 % ; ** Significant to the threshold 5 % ; * Significant to the threshold 10 %. Values between parentheses are estimated standard deviation.

Appendix 1: Results of Principal Component Analysis (PCA)

Statistiques descriptives

	Moyenne	Ecart-type	n analyse
TEL_FIXE	30.0071	17.72388	254
TEL_MOB	42.3354	13.94889	254
ORDINAT	5.2866	6.24255	254
NIV_SC	30.625591	7.5851643	254
NIV_SUP	6.526378	5.5332746	254
POP_ACT	10833.28	7165.708	254
EAU_ROB	78.706299	22.82531	254
ONAS	42.979921	35.45038	254
TX_ANALP	25.331496	9.9982386	254
DPA	1280.633	355.9817	254
EMPLOI	9366.0157	6542.801	254
LOG	9551.2677	6211.242	254
MG	8340.71	5252.572	254

Qualité de représentation

	Initial	Extraction
TEL_FIXE	1.000	.840
TEL_MOB	1.000	.856
ORDINAT	1.000	.731
NIV_SC	1.000	.875
NIV_SUP	1.000	.699
POP_ACT	1.000	.986
EAU_ROB	1.000	.716
ONAS	1.000	.699
TX_ANALP	1.000	.899
DPA	1.000	.718
EMPLOI	1.000	.978
LOG	1.000	.975
MG	1.000	.986

Méthode d'extraction : Analyse en composantes principales

Variance totale expliquée

	Valeurs propres initiales			Extraction Sommes des carrés des facteurs retenus		
Composante	Total	% de la variance ==	% cumulés	Total	% de la variance ==	% cumulés
1	8.563	65.868	65.868	8.563	65.868	65.868
2	2.398	18.443	84.312	2.398	18.443	84.312
3	.778	5.983	90.295			
4	.430	3.311	93.606			
5	.264	2.029	95.635			
6	.192	1.479	97.113			
7	.158	1.218	98.331			
8	7.193E-02	.553	98.885			
9	6.135E-02	.472	99.357			
10	4.470E-02	.344	99.701			
11	3.010E-02	.232	99.932			
12	7.828E-03	6.021E-02	99.992			
13	1.008E-03	7.752E-03	100.000			

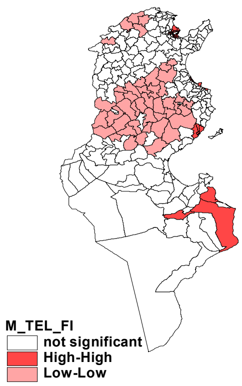
Méthode d'extraction : Analyse en composantes principales.

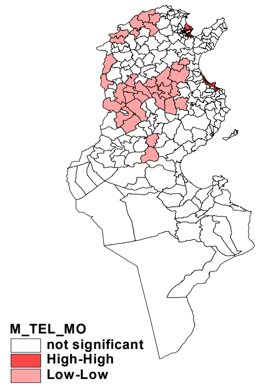
Appendix 2: Global Spatial Autocorrelation: Moran's I Statistic

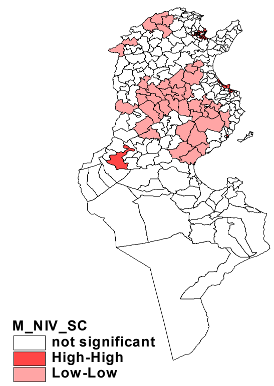
	Contiguity Matrix of level 1	
	Moran's *I*	**p-value**
Fixed phone network	0.6158507	0.000000
Mobile phone network	0.6551264	0.000000
Computers	0.5841219	0.000000
educ_secondary	0.6158507	0.000000
educ_sup	0.5891490	0.000000
Pop_act	0.3298830	0.000000
Water_tap	0.6351555	0.000000
ONAS	0.6455516	0.000000
Balance migratory	0.0904716	0.018638
Tx_elect	0.2855055	0.000000
Illiteracy rate	0.7095174	0.000000
Expenditure per capita	0.8207860	0.000000
Masculinity rate	0.3697279	0.000000
Houses	0.2939093	0.000000
Number of households	0.3034858	0.000000
Employment	0.3515915	0.000000
Number of training centers	- 0.0503110	0.248059
Number of foreign companies	0.4155325	0.000000
Number of job creation by foreign companies	0.3242503	0.000000
Stock of FDI	0.8280699	0.000000
Areas classification as development area	0.9067056	0.000000
SCIW	0.6454540	0.000000

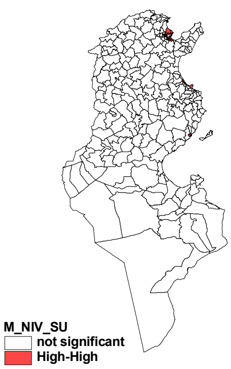
The expected value of Moran's *I* statistic is -0,004 (0.040135)

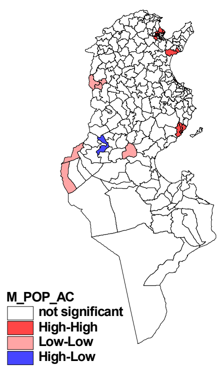
Appendix 3: Moran Significance Map for Attributes

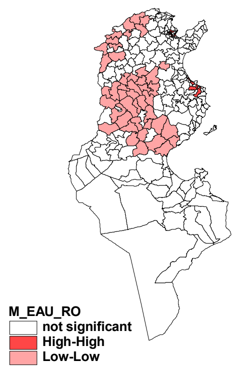


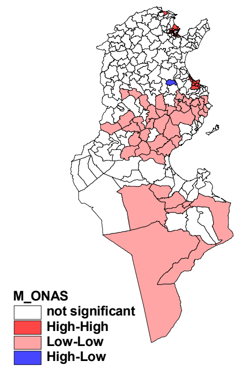


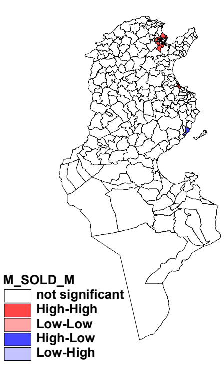


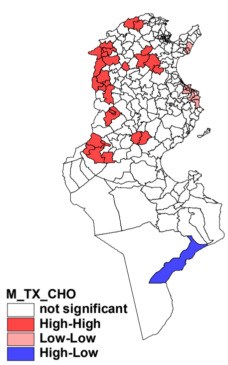


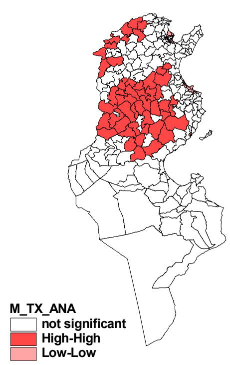


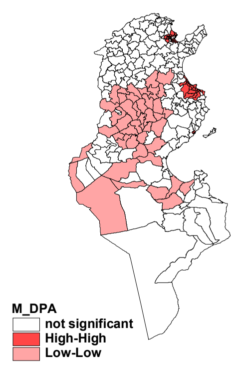


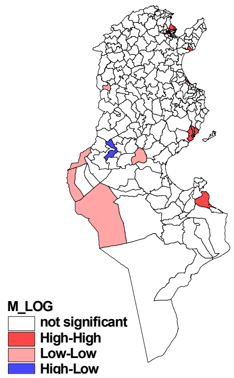


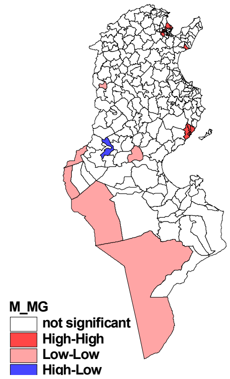


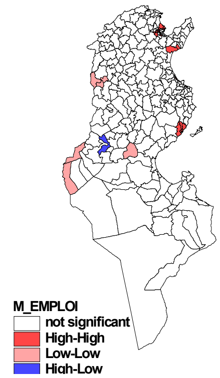




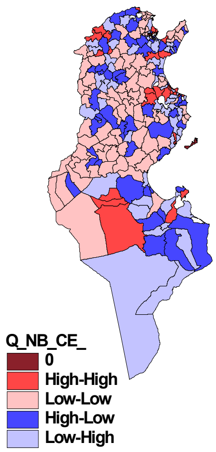


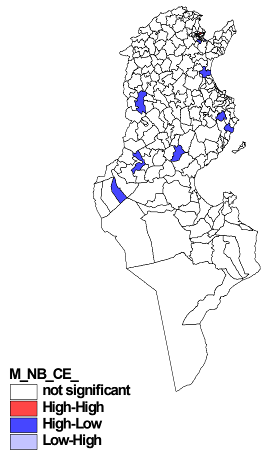

M_LOG
not significant
High-High
Low-Low
High-Low

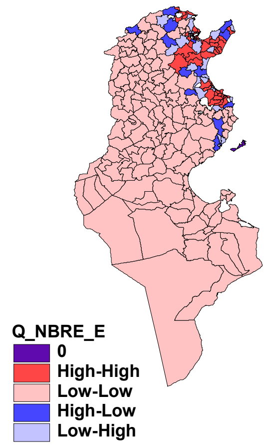

M_MG
not significant
High-High
Low-Low
High-Low

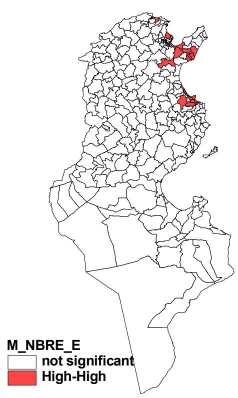

M_EMPLOI
not significant
High-High
Low-Low
High-Low

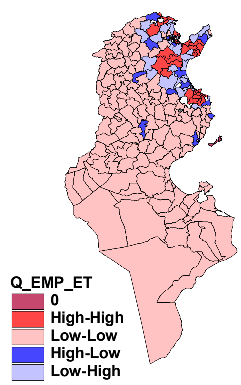
Appendix 4: Moran Maps Related to Variables of Regional Development Politics and Economic Openness

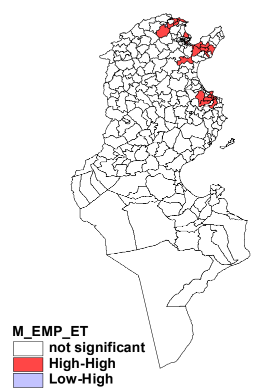


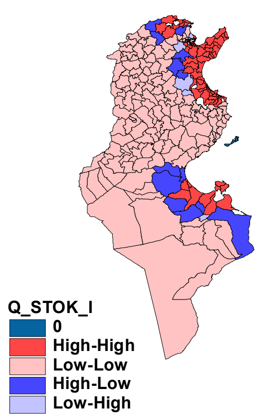


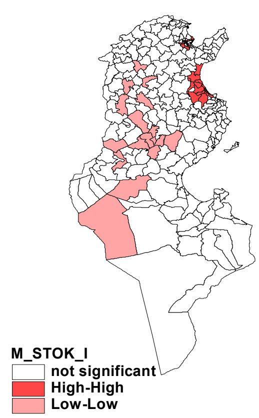


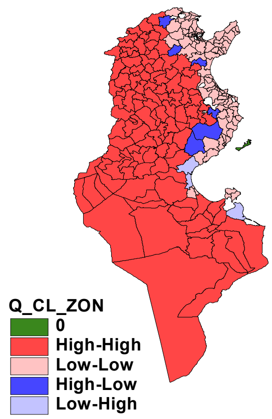


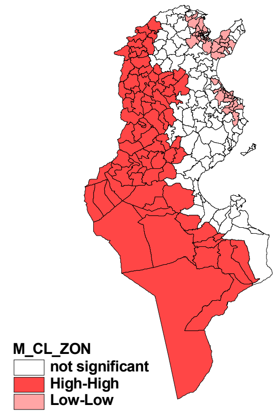









Q_CL_ZON
0
High-High
Low-Low
High-Low
Low-High


M_CL_ZON
not significant
High-High
Low-Low