

Sébastien, Chantelot

**Conference Paper**

## French creative clusters: An exploratory spatial data analysis

50th Congress of the European Regional Science Association: "Sustainable Regional Growth and Development in the Creative Knowledge Economy", 19-23 August 2010, Jönköping, Sweden

**Provided in Cooperation with:**

European Regional Science Association (ERSA)

*Suggested Citation:* Sébastien, Chantelot (2010) : French creative clusters: An exploratory spatial data analysis, 50th Congress of the European Regional Science Association: "Sustainable Regional Growth and Development in the Creative Knowledge Economy", 19-23 August 2010, Jönköping, Sweden, European Regional Science Association (ERSA), Louvain-la-Neuve

This Version is available at:

<https://hdl.handle.net/10419/118875>

**Standard-Nutzungsbedingungen:**

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

**Terms of use:**

*Documents in EconStor may be saved and copied for your personal and scholarly purposes.*

*You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.*

*If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.*

# The geography of the French creative class:

## An exploratory spatial data analysis

*Very First Draft, please do not quote*

Sébastien Chantelot<sup>1</sup>

Stéphanie Pérès<sup>2</sup>

Stéphane Virol<sup>3</sup>

### Abstract

This paper analyses the geography of creative class in France in 2006. This geography is seen here through the lens of Explanatory Spatial Data Analysis (ESDA). This method brings originality to the question of creative people geography in addition with the spatial context, France, where this question hasn't yet been deepened. We adopt a methodology allowing the measurement of the degree of spatial agglomeration and the identification of location patterns of creative people. First, we compute the spatial Gini coefficient and Moran's I statistics of global spatial autocorrelation. We show that these measures provide an overview of the uneven spatial distribution of creative people among French districts and the existence of some hotspot regions with strong dynamic of creative people accumulation. Second, we use the tools of Exploratory Spatial Data Analysis. Moran scatterplots and LISA statistics allow us to identify creative clusters shaped by French districts. It leads the evidence of a non uniformity in the geographic distribution of creative people. Creative occupational clusters results from the spreading of the influence of big metropolitan cities.

### Keywords

Creative class, ESDA, location patterns, spatial autocorrelation, French districts.

### J.E.L. classification

C12, O18, R23

---

<sup>1</sup> Assistant Professor - ESC Bretagne Brest - 2 avenue de Provence - CS23812 - 29238 Brest cedex 3, France. [sebastien.chantelot@esc-bretagne-brest.com](mailto:sebastien.chantelot@esc-bretagne-brest.com)

<sup>2</sup> Research Assistant - USC INRA 2032 GAIA - Enita de Bordeaux - 1 cours du Général de Gaulle - 33175 Gradignan cedex, France. [s-peres@enitab.fr](mailto:s-peres@enitab.fr)

<sup>3</sup> Assistant Professor - GREThA UMR - CNRS 5113 Université Montesquieu-Bordeaux IV - Avenue Léon Duguit - 33608 Pessac cedex, France. [stephane.virol@u-bordeaux4.fr](mailto:stephane.virol@u-bordeaux4.fr)

## 1. Introduction

The creative class thesis introduced by Florida (2002b) took a fresh look at socio-economic determinants that underpin local and regional development. Creative skills are considered as crucial in a knowledge-based economy in order to intensively produce innovation. That's why a literature emerged in order to take into account economic influence, localization and mobility of creative people. Creative people are gathered into the "creative class". This particular class is shaped by individuals that own a creative occupation, i.e. an occupation that need creative skills to perform its productive tasks. Then, it gathers occupations such as artists, designers, architects, engineers, education professionals, scientists, etc. The creative class is particularly linked to territorial considerations because, according to Florida (2005b) and following Lucas (1988), regions and cities have to attract high skilled or creative human capital in order to reach high levels of economic growth. In order to do it, regions or cities have to offer a high-quality people's climate providing low entry barriers to new ideas and new comers and let high levels of freedom to the development of creative ideas. These new vision about regional development immediately entered the policy arena and a large number of North American cities have tried to implement such strategy. This spectacular diffusion has led to a large debate where the thesis have been widely criticized by both scientific and politics spheres.

However, the question of the geography of the creative class has been deepened around the world, particularly in North America and in Europe. Just like high skilled human capital, creative people have been raised as crucial resource for innovation and economic competitiveness. Therefore it appears important to identify location patterns of creative people. This paper proposes to fill a blank concerning France. Although several European countries, mainly in the framework of international research project, explored the geography of their national creative class, France still remains *terra incognita* in spite of some developments (Chantelot, 2008; INSEE, 2009). That's why the aim of the article is to put forward an exploratory analysis of the geography of creative people in France. In order to perform, tools of exploratory spatial data analysis are mobilized. It allows to measure concentration of creative people among local territorial units (French districts) spatial dependence between these units to finally detect and identify creative occupational clusters. This last point leads to take into consideration the spatial distribution of creative people and local hotspot of creativity in France.

Section 2 presents major contents of the creative class thesis and the geography of creative people. Section 3 introduces the research problem of the paper while section 4 outline database and method used. Section 5 contains main findings on explanatory analysis of the geography of French creative people.

## 2. Theoretical background

### 1.1 The creative class thesis

The creative class thesis (Florida, 2002b) emphasizes the key role of creativity on economic growth's mechanisms. By identifying three main embedded forms of creativity – technologic, economic and artistic - Florida (2002b, 33) postulates the existence of a « creative class » that gathers the whole individuals that own a creative profession. According to the author, cities or regions with high concentrations of creative class reach virtuous path of economic competitiveness because they produce more innovation (Knudsen et al., 2008), attract innovative firms and have high levels of entrepreneurship (Acs et al., 2004). The recent advent of a knowledge-based economy where innovation became a permanent economic activity (Foray, 2000) allows putting light on importance and on explosive growth of creative professions since the beginning of 1990s: « *The rise of the creative class charts the growth in people who are paid principally to do creative work for a living. These are scientists, engineers, artists, musicians, designers and knowledge based professionals, whom collectively I call "Creative Class"* » (Florida, 2002b, xii). Even if the notion of "class" seems to be questionable (Shearmur, 2005; Vivant, 2006)<sup>4</sup>, the creative class belongs to representative concepts such as *knowledge workers* (Drucker, 1969) or *symbolic analysts* (Reich, 1993) that both show the importance of knowledge production and use for the economic growth regime. Creative class looks like *change agents* (Carter, 1994) too whose productive role is entirely dedicated to stimulate and supervise the innovation. By moving the approach's entry of sources of innovation analysis from firms to individuals, this thesis echoes Veblen (1899) that pointed out that technological change is essentially a cultural process and that the capacity to perpetuate and institutionalize change belongs to a certain class of the society. The original aspect of such a class is to gather people at the roots of innovation, science and arts issues around a common trait called « creative ethos » born from the merging of values of « organization man » (Whyte, 1956) with more cultural and artistic ones of bohemian *avant-garde* (Brooks, 2000, 132). Creative class celebrates the union of discipline, strictness of professional ethics with alternatives values in terms of lifestyle, underground, fashion and original thinking. Then, a main point of the creative class thesis is that geography matters because first, according to Florida (2002b, 30) « *places have replaced companies as the key organizational units in our economy* », and second, because the geography of the creative class doesn't appear uniformly shaped. The thesis points out a second postulate: creative people are particularly attracted by places characterized by tolerant and open climate

---

<sup>4</sup> Shearmur (2005) and Vivant (2006) advance that using « class » notion could be wrong. As shown by Markusen (2006), creative occupations and preferences of creative people are heterogeneous to shape a « class » in a sociologic way.

to diversity, new ideas and new comers. Florida (2005b) notes that the ability of cities in attracting creative people in domains like arts or culture and in offering low entry barriers to individuals whatever their background, origin or lifestyle is now a comparative advantage in generating innovation and stimulating local economic growth. The author follows Jacobs (1969) or Hall (1998, 501) that promote the idea that the local level of innovation results from the joint product of creativity and economical, technological and social diversity levels that are present in city. However, Florida's thesis lies on considerations made by Lucas (1988) on the fact that cities have to attract, retain, organize and generate talent, highly skilled human capital in order to reach high levels of economic development. Associated with the presence of socialization places such as "Third places" (Oldenburg, 1991) like cultural services, pubs, restaurants, etc. urban climate that are open and tolerant to diversity shape a *people's climate* that complete mainstream *business climate* based on firms attraction through low taxes physical assets. Florida (2005b) advances that a high quality people's climate in terms of free expression and stimulation of individual and collective creativity is crucial to attract creative people. Creative people in turn will attract or create innovative firms. Then, creative class thesis reverse a causality link postulating that jobs follow people instead of mainstream people follow jobs. In that way under impulsion from its author, the thesis became a questionable tool of economic development policy (see Peck, 2005 for a complete survey of these different discussions).

## **1.2 The geography of creative people**

Following these seminal works, creative people's location became a major topic in regional science. This topic was particularly deepened in North America and Europe (see Chantelot (2010b) for a survey). In Europe, these developments have been made in the framework of research projects (*Technology, Talent, Tolerance in European cities: A comparative analysis*, ACRE, CREATICITY) and they found their relevance through the importance of talent on local economic growth (Lucas, 1988; Simon, 1998; Glaeser and Saiz, 2004). Then, the measurement of creative people allows to produce human capital index, based on an occupational approach that differs than the one mainly use and based on educational approach, i.e. diploma level. More, some works tend to show that a creative human capital index outperforms educational measure of human capital in explaining local economic growth (Marlet and Van Woerkens, 2007; Fritsch, 2007; McGranahan and Wojan, 2007; Florida, Mellander and Stolarick, 2008; Chantelot, 2008). However, if all the creative people are not highly educated, almost are. That's why Glaeser (2004) notes that such a measurement doesn't bring anything new to human capital theory. But creative people, just like talent, is an essential element for local economic growth (McGranahan and Wojan, 2007; Marlet and Van Woerkens, 2007; Andersen and Lorenzen, 2009; Boschma and

Fristch, 2009). Location analysis of creative people is seen through several entries. First, it's about the question of the mobility of creative people: the strong mobility of creative people is a founding assumption of the creative class thesis, because creative people are seen as most mobile and most informed about economic opportunities than other occupational groups. But if this assumption can be true in the United States, it is not necessary proven in Europe. Hansen and Niedomysl (2009) note that Scandinavian creative people are not more mobile than other people while Martin-Brelot, Eckert and *al.* (2008) or Grossetti (2009) and the main findings of ACRE project (2010) show that mobility of European creative people is not a panacea. These different authors lie on a survey driven in 13 cities of 12 European countries gathering 1700 questionnaires made with European creative people. Results are that creative people are not so mobile in Europe because 70% of surveyed people was born or have studied in the city where they live. The other 30% were driven to move because of economic opportunities. These results follow Scott (2006) that tends to demonstrate that the importance of soft factors such as tolerance and openness to diversity or third places put forward by Florida (2005b) to postulate the existence of a people's climate are overestimated<sup>5</sup>. Marlet and Van Woerkens (2005) note that the highest proportions of creative people are located in Dutch cities that offers a huge pool of professional opportunities, low automobile congestion rate and real estate prices instead of people's climate. However, these findings contrast with « *Technology, Talent, Tolerance in European cities: A comparative analysis* » project's ones. This project examines the co-location of creative people and people's climate, through factors such as tolerance, openness and diversity (measured through the presence of artists or foreign-born people), urban amenities (third places, public sector presence) and economic opportunities (job density, past economic growth). Results show for 8 European countries that cities with higher levels of creative people are also those that offer a high-quality people climate. Particularly, the presence of creative people from technological and economical sphere is strikingly correlated with the presence of bohemians, i.e. individuals that own a creative occupation in domains such as arts, culture, design, fashion, etc. (Isaksen, 2005; Haisch et Klöpper, 2005; Andersen et Lorenzen, 2006; Fritsch, 2007; Hansen, 2008; Clifton, 2008; Boschma and Fritsch, 2009). The level of this statistical correlation appears to be very high in all the countries studied. More, Chantelot (2008) finds this same finding using French urban areas. If these European findings follow what Florida (2005b) found in North America, the question of the causality direction of the attraction still remains open: Andersen and Lorenzen (2009) bring some answer elements by analyzing the relation between urban hierarchy and high proportions of creative people in the framework of Scandinavian cities. The authors observe a population threshold where these proportions

---

<sup>5</sup> Scott (2006, 11) notes that: "*this argument neglects to take into consideration the complex synchronic and diachronic interrelationships that must be present before a dynamic creative environment is likely to emerge*".

strongly decrease. Several answers are given to the existence of such a threshold: First, the preference of creative people for large agglomeration lies on their high consumption propensity of artistic and cultural goods that big cities can offer. Second, the specificity and high-specialization of creative occupations, as shown by Julien (2002) in France, makes that they are occupations we can mainly find in large agglomeration. At last, another bias leading to the existence of this threshold can be found through the presence of university that irrigates the local labor market with high skilled human capital. However and even if these results participates to strengthen the analysis of factors that shape the geography of the creative people, no indication is given about relevance of local development policies founded on creative people attraction (Lang, 2005).

### 3. Research problem

Although the creative class thesis has been largely developed and adapted in Europe, it remains quite unexplored in France - if we except Chantelot (2008; 2010a,b) and the French part of ACRE project (Martin-Brelot, Eckert and *al.*, 2008; Grossetti, 2009) – particularly in regional science even if it tends to be present in some works (Vivant, 2006; Suire, 2006; Gaschet and Lacour, 2007; Lacour and Puissant, 2008) but without being a first-order question. As such, there is some relevance to raise the question of the localization of creative people in France: To what extent creative people are geographically concentrated? What can constitute their location patterns? To do so, a first discussion on identification of creative occupations appears to be necessary because as noted by McGranahan and Wojan (2007), the original composition of the American creative class shaped by Florida (2002b, 328) tends to be too exhaustive and uncertain in regards to their creative skills contents. Next, the geography of French creative people lies here on tools of exploratory spatial data analysis (ESDA). First, we analyze here the concentration of creative people through a spatial Gini index. Second, we analyze global location patterns of creative people by identifying spatial autocorrelation between territorial units. This last information is coupled with its statistical significance at local level through *Locational Indicator of Spatial Association* (LISA; Anselin, 1995). These different but complementary pieces of information allow us to produce cartography of creative occupational clusters in France, i.e. concentrations of contiguous territorial units sharing local labor markets with high levels of creative people.

## 4. Data and Method

### 4.1 Database and selection of creative occupations

Database used here come from first results of the 2006 French population decennial census driven by INSEE<sup>6</sup>. It informs about individuals that owns a creative occupation for each 36549 French towns and cities. The method of identification of creative occupations among French local labor market issued from Chantelot (2010a). The composition of the creative class raised a great dilemma: some authors deals with correspondence between American Standard Occupational Classification (SOC) and European International Standard Classification of Occupations (ISCO) to shape the creative class in several countries (Florida and Tinagli, 2004; Fristch, 2007; Clifton, 2008; Boschma and Fritsch, 2009) or between SOC and national classification of occupations (Isaksen, 2005; Andersen and Lorenzen, 2006; Marlet and Van Woerkens, 2008; Hansen, 2008). But the original composition shaped by Florida (2002b, 328) appears to be too exhaustive and too uncertain (McGranahan and Wojan, 2007; Marlet and Van Woerkens, 2007): First, because it lies on selection of occupational groups instead of occupations. Occupational groups mostly gather a large number of occupations and some of them are weakly or not creative. Second, there isn't any discriminatory measurement about creative contents of occupations. So the selection is mainly made through the title of occupations. That's why McGranahan and Wojan (2007) and Chantelot (2010a) identify creative occupations lying on occupations themselves – and not on aggregated groups of occupations – and by using a selection method that includes a measurement of occupational creativity. As such, Chantelot (2010a) shows that a close adaptation of the American creative class in France would lead in 1999 to a mean proportion of 25.7% of creative people on French labor market with 155 occupations market against 16.17% with 101 occupations with its identification method. This selection has been used by INSEE in the framework of the preliminary short exam of French creative class (INSEE, 2009). In the same order of ideas, Marlet and Van Woerkens (2007) note that only 19% of the Dutch labor market could be considered as shaped by creative occupations against 30% using Florida's definition. Following Chantelot (2010a), Table 1 contains descriptive statistics on creative people in France in 2006.

Insert Table 1. Descriptive statistics on creative people in France, 2006

---

<sup>6</sup> Institut National de la Statistique et des Etudes Economiques



This last table doesn't deal with evolution of creative people since the last 1999 French population decennial census: indeed, French classification of occupations (PROF) used by INSEE in 1999 was elaborated in 1982 and recasted in 2003 (PCS-2003) in order to fit with recent labor mutations. Yet these two classifications are not comparable because of changes in survey field. More, some occupations were merged because of their obsolescence and some were broken up to take into account of emergence of new occupations (mainly among ICT domains).

We focus here on local creative assets through the lens of districts as territorial units. Districts are mainly shaped with several towns or cities except in the case of metropolitan cities where only the core city is taking into account. There are 3644 districts in France (without Corse and islands of DOM-TOM). This territorial unit appears to be more relevant than towns and cities because of reduction of observed units. More, it allows reducing the uncertainty of data associated with very small towns while remaining contiguity of studied units in order to facilitate spatial analysis.

A localization quotient (LQ) of creative people is produced for each French district. It represents the local proportion of creative people among the local labor market related to the national proportion of creative people regarding national employment. Several LQ are produced too for each subgroup of creative people, creative core, creative professionals and bohemians. Then, LQ index  $>1$  indicates an overrepresentation of creative people in the district compared to national mean. Conversely, LQ index  $<1$  indicates an underrepresentation of creative people in the district.

#### **4.2 Method: Locational Gini index and ESDA**

The aim of this paper is to question about location patterns and spatial distribution of creative class in France. In that perspective, this work put the focus on the measure of agglomeration dynamics. It raises the question of the plethoric choice of estimation criteria of agglomeration process. Among the panel of choices and according to Guillain and Le Gallo (2008), we are convinced that agglomeration of people, just like economic activities, needs on a first hand to a measure of locational concentration and, on the other hand, a characterization of location patterns "where refers to the location of agglomeration process and how to refers to its form" (ibid., 5). Indeed agglomeration is a polymorphic process that needs to explore at the same time these two dimensions.

Measurement of spatial concentration can be done through several global indexes: Hirshman-Herfindhal spatial index, locational Gini coefficient or Ellison-Glaeser concentration index (1997). Following Guillain and Le Gallo (2008), we use locational Gini index that allows to measure the relative structure of a random variable of a spatial unit in comparison to its value in

another spatial units. Then, weights of each spatial unit are taken into consideration through the index's calculation. Locational Gini index can be computed following:

$$G_m = \frac{\Delta}{4x_m}$$

$$\text{with } \Delta = \frac{1}{n(n-1)} \sum_{i=1}^n \sum_{j=1}^n |x_{i,m} - x_{j,m}|$$

Where  $n$  is the number of spatial units (French districts);  $x_{i,m}$  the creative workforce of the district  $i$ ,  $x_m$  mean workforce by districts. This index values 0 if the workforce of the variable  $m$  is equally distributed among districts and 0.5 if this workforce is entirely concentrated into one district. Information given by this index is then relative to the concentration level of a variable in a district. Moreover it allows comparisons between index's values of different variables. If we can appreciate the concentration of a population on a defined spatial area, we can't identify the spatial structure associated to this concentration. A same value of locational Gini index can be associated to a relative concentration of contiguous spatial units or several isolated spatial units among the study area. Relative position and distance between spatial units is not neutral regarding agglomeration measure. Now, these two aspects are not taken into account in location Gini index and other indexes quoted upper. It leads to a incorrect measure of agglomeration that do not take in consideration geographical spillover of agglomeration process. As Tobler (1979) noticed « Everything is related to everything else, but closer things more so ». Then, a measure of spatial clustering becomes essential to complete locational Gini index. It allows to correctly give an account of agglomeration process. To that purpose we use Exploratory Spatial Data Analysis (ESDA).

ESDA is a set of techniques that aims 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 patterns or other forms of spatial heterogeneity (Haining 1990; Bailey and Gatrell 1995; Anselin 1998a, 1998b). These methods provide measures of global and local spatial autocorrelation.

#### 4.2.1 Global spatial autocorrelation

Spatial autocorrelation can be defined as the coincidence of similar values with similar locations (Anselin, 2000). Therefore 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 dissimilar values. The measurement of global spatial autocorrelation is based on Moran's  $I$  statistic, which is the most widely known measure of spatial clustering (Cliff and Ord, 1973, 1981; Upton and Fingleton, 1985; Haining, 1990). This statistic is written in the following way:

$$I_t = \frac{\sum_i \sum_j w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum (x_i - \bar{x})^2}$$

Where  $x_i$  is an observation in district  $i$ ,  $\bar{x}$  is the mean of observations across spatial units,  $w_{ij}$  is an element of the spatial weight matrix  $W$ . This matrix contains information about the relative spatial dependence between spatial units  $i$ . Elements  $w_{ii}$  on the diagonal are set to zero, although elements  $w_{ij}$  indicate the way spatial unit  $i$  is spatially connected to the spatial unit  $j$ .

The spatial weight matrix we use in this study is based on the 5 nearest neighbors calculated from the great circle distance between region centroids. In France, districts have on average 5 to 6 contiguous neighbors. Guillaing and Le Gallo (2008) use such a determination process to shape the k-nearest neighbors matrix they used in their analysis. In order to normalize the outside influence upon each spatial unit, the spatial weight matrix is row-standardized such as elements in each row sum to 1. Larger values of  $I$  than the expected value  $E(I) = -1/(n-1)$  indicate positive spatial autocorrelation, while smaller values than those expected indicate negative spatial autocorrelation. Inference is based on a permutation approach, with 9,999 permutations. In this approach, it is assumed that, under the null hypothesis, each observed value could have occurred at all locations with equal likelihood. But instead of using the theoretical mean and standard deviation (given by Cliff and Ord, 1981), a reference distribution is empirically generated for  $I$ , from which the mean and standard deviation are computed. In practice, this is carried out by permuting the observed values over all locations and by re-computing  $I$  for each new sample. Then mean and standard deviation for  $I$  are the computed moments for the reference distribution for all permutations (Anselin, 1995).

#### 4.2.2 Local Spatial autocorrelation

Moran's  $I$  statistic is a global measure of autocorrelation: it does not enable us to appreciate the regional structure of spatial autocorrelation. However, one may wonder which spatial unit contributes more to the global spatial autocorrelation, when there are local spatial clusters of high or low values. Finally, to what extent does the global evaluation of spatial autocorrelation mask atypical localizations, i.e. districts or groups of contiguous districts which deviate from the global pattern of positive spatial autocorrelation. The analysis of local spatial autocorrelation is

carried out with two tools: first, the Moran scatterplot (Anselin 1996), which is used to visualize local spatial instability, and second, local indicators of spatial association *LISA* (Anselin, 1995), which are used to test the hypothesis of random distribution by comparing the values of each specific localization with those in neighboring localizations. Inspection of local spatial instability is carried out by the means of the Moran scatterplot (Anselin, 1996). Four different quadrants of the scatterplot correspond to the four types of local spatial association between a spatial unit and its neighbors:

- Quadrant HH: a spatial unit with a high value surrounded by spatial unit with high values (Quadrant in top on the right),
- Quadrant LL: a region with a low value surrounded by regions with low values (Quadrant in bottom on the left),

These quadrants refer to positive spatial autocorrelation indicating spatial clustering of similar values.

- Quadrant LH: a spatial unit a with low value surrounded by regions with high values (Quadrant in top on the left),
- Quadrant HL: a spatial unit with a high value surrounded by /regions with low values (Quadrant in bottom on the right).

These quadrants represent negative spatial autocorrelation indicating spatial clustering of dissimilar values. The Moran scatterplot may thus be used to visualize atypical localizations (HL or LH). Moreover, the use of standardized variables allows Moran scatterplots to be comparable across time. The detection of outliers and sites, which exert strong influence on Moran's  $I$ , is based on standard regression diagnostics: studentized residuals and leverage measures are used to detect outliers. However, let us note that the Moran scatterplot does not give any indications of significant spatial clustering and therefore, it cannot be considered as a Local Indicator of Spatial Association (*LISA*) in the sense defined by Anselin (1995).

#### **4.2.3 Local Indicator of Spatial Association LISA**

Anselin (1995) defines a local indicator of spatial association as any statistics satisfying 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 the Moran's  $I$  statistic for each region  $i$  can then be written as following:

$$I_i = \frac{(x_i - \bar{x})}{m_0} \sum_j w_{ij} (x_j - \bar{x}) \quad \text{with} \quad m_0 = \sum_i w_{ij} (x_j - \bar{x})^2 / N$$

A positive value for  $I_i$  indicates clustering of similar values (high or low) whereas a negative value indicates clustering of dissimilar values. Due to the presence of global spatial autocorrelation, inference must be based on the conditional permutation approach: the value  $x_i$  at location  $i$  is held fixed, while the remaining values are randomly permuted over all locations. Finally, using jointly the Moran scatterplot and LISA allow obtaining maps of Moran significance, which show that spatial units are sometimes associated with a significant LISA and indicate with a color-coded in which location pattern these spatial units belong (Anselin and Bao, 1997).

## 5. Main findings

### 5.1 Global measures of agglomeration and spatial autocorrelation

A main assumption of this paper lies on creative people location. It assumes that location process of creative people stand on a most important agglomeration process than employment or population. Table 2 contains results of locational Gini index regarding workforce, population, creative class and its subgroups.

Insert Table 2. Locational Gini index, 2006

Table 2 results obviously show that concentration of creative people is more important than employment and population. This first result is quite interesting, because it shows that factors that shape location process of creative people lies on particular mechanisms that leads to a more important agglomeration. However, these results do not bring any information about location patterns of this concentration. Spatial autocorrelation measure is a first step in analyzing spatial structure of agglomeration process. It can be obtained using Moran  $I$ . One of fundamental element of this index is the choice of the weight matrix that constraint the extent of spatial dependency. This choice appears to be crucial because it conditions on a first hand results and in a second hand analysis. It can be computed following several modalities: as we don't know *a priori* the extent of spatial autocorrelation phenomenon on which lies location process of creative people, determinant of weight matrix can be exogenously fixed. We test several

possibilities: matrix based on queen and rook contiguity<sup>7</sup>, and  $k$ -nearest neighbors matrix. Matrix based on threshold distance doesn't allow to have better results in our case and are subject to high variability regarding neighbors number. It can raise important methodological problem. That's why we do not include these results in the following table 3 that show Moran  $I$ 's values for creative class LQ index and its subgroups LQs index according to different weight matrix and for our 3644 French districts sample in 2006.

Insert Table 3. Moran  $I$ , creative class LQ index, French districts, 2006

Results in table 2 lead to several comments: first of all and as expected, we can notice a strong positive spatial autocorrelation. Geographical distribution of creative people does not randomly occur in France. *Au contraire*, spatial structure of creative class location is characterized by clusters of same values of LQ index. Next, in order to catch spatial interactions between districts on the best way, *i.e.* that maximizes spatial autocorrelation, we choose here the matrix associated with larger Moran  $I$ 's value. That's why  $k$ -nearest neighbors with  $k=5$  is the best alternative. The choice to keep the matrix that maximizes Moran  $I$ 's value is generally recommended in literature (Le Gallo, 2002; Le Gallo and *al.*, 2003). However, different values of Moran  $I$  drive to same conclusions about sign and significance of global spatial autocorrelation. It put light on robustness of these results whatever spatial weight matrix used. Also, whatever the sample of creative individuals, 5-nearest neighbors is the best spatial weight matrix in catching global spatial autocorrelation.

Locational Gini index and Moran  $I$  are tools measuring global concentration. If Moran  $I$  allows to identify global location patterns, it does not allow to appreciate its local structure. The next step in characterizing spatial structure of creative class agglomeration process lies on local measure of spatial autocorrelation through Moran scatterplot and Local Indicators of spatial Association (LISA). If Moran scatterplot allows to detect clusters, to analyze local instability or atypical location, it does not give any information about significance of different location patterns obtained. These two tools provide complementary information to characterize location patterns of creative class in France.

## 5.2 Local spatial autocorrelation and creative clusters identification

The analysis of spatial autocorrelation at local level by using Moran scatterplot and LISA allows to identify spatial patterns of creative occupational clusters and their statistic significance. Significance means that a value associated with a district  $i$  is significantly influenced by value of

---

<sup>7</sup> Queen and Rook refer to move modalities of this chess pieces. Rook owns horizontal and vertical movement while Queen is able to move in all directions.

neighboring districts, as defined in spatial weight matrix. Reciprocity can be also true. Moran scatterplot allows us to identify location patterns of creative people among French districts. All these location patterns are mapped in map 1<sup>8</sup>. It enables to qualify dependence relations between spatial units regarding creative people. Then, map 2 indicates some significant LISA areas where district LQ's value is dependent on surrounding district's values. This is particularly obvious with NUTS 2 region like Ile-de-France, Rhône-Alpes, PACA, Midi-Pyrénées and Languedoc-Roussillon<sup>9</sup>. Creative occupational clusters are mapped with HH districts: these districts show high values of creative people's LQ and are surrounded by districts with high values of creative people's LQ. Moreover HL districts are isolated pole with high values of LQ surrounded by low LQ districts. HH and HL districts are mapped in red and pink on the map 1. The location patterns (HH, HL, LH and LL) of districts in each NUTS 2 region are displayed in table A2 in appendix. As we study creative clusters, LH and LL districts are not detailed here.

Insert Map 1: Moran scatterplot, Creative class LQ index, French districts, 2006.

Insert Map 2: LISA, Creative class LQ index, French districts, 2006.

In order to produce a compared analysis of French hotspots of creativity, we detail location patterns at a NUTS 2 level. This aggregate level allows to identify creative clusters. In addition to maps 1 & 2, graphic 1 shows the number of HH and HL districts in each French NUTS 2. Moreover, this table contains the number of significant LISA districts. Then, we group here French NUTS 2 following their spatial structure issued from Moran scatterplot in terms of number of HH and HL districts. We can shape 5 groups of regions:

- Group 1: Ile-de-France;
- Group 2 : Rhône-Alpes, PACA, Midi-Pyrénées, Languedoc-Roussillon *with large number of HH and HL districts*;

These two first groups account for 56% of total French creative districts.

- Group 3 A : Aquitaine, Centre, Alsace, Bretagne, Pays de la Loire *where HH districts > HL districts*;

---

<sup>8</sup> Map A2, A3, A4, A5, A6 and A7 in appendix gives cartography of location patterns for Bohemians, Creative core and Creative professionals LQ index among French districts.

<sup>9</sup> Map A1 in appendix gives cartography of French NUTS 2 regions and main metropolitan areas quoted here. Table A1 gives descriptive statistics for each NUTS 2 regions.

- Group 3 B : Nord-Pas-de-Calais, Bourgogne, Lorraine, Franche-Comté, Poitou Charente, Picardie *where HL districts > HH districts*;
- Group 4: Haute Normandie, Basse-Normandie, Auvergne, Champagne-Ardenne, Limousin *with weak number of HH and HL districts*.

Group 1 only includes Ile-de-France NUTS 2 region. France is a centralized country and its capital city, Paris, is the biggest city in Europe with London. Ile-de-France concentrates 19% of French population and 22% of national employment. French political and economical affairs are mainly located in Paris. As a consequence, Paris and its surrounding is a major hotspot of creative activities and Ile-de-France districts amount for 17% of total French creative districts. We can see that 96% of Ile-de-France districts can be considered as creative. These HH districts share a large spatial dependence because 82% of them are significant when looking at Moran significance map (LISA, map 2). Then, there is a strong location dynamic of creative people in and around Paris. This region is an exception among French regions.

Group 2 is shaped with 4 French NUTS 2 regions sharing a similar profile with a large number of HH districts. Rhône-Alpes is the biggest region in terms of districts number (311) while including the second largest number of creative districts. The region counts several metropolitan pole such as Lyon, Grenoble and Annecy that are important (for the two first) or secondary economic pole (for the last). Then, Rhône-Alpes is widely shaped with HH districts but HL districts are very numerous (33 districts). HH and HL districts structure the region to a 58% level of total regional district number. Only the two main economic poles (Lyon and Grenoble) are LISA significant testifying of a strong spatial dependence between these core cities and their surrounding districts. However, Provence-Alpes-Côte-d'Azur region (PACA) is the second region in terms of HH districts number (148) after Ile-de-France. 81% of PACA districts can be estimated as creative. Most of them are significantly spatially correlated particularly around two main poles that are Aix-en-Provence-Marseille-Avignon and the French Riviera. As seen in Rhône-Alpes region, agglomeration spreads here significantly around major cities of the region (Marseille and Nice). A different case can be understood with Midi-Pyrénées region. Fourth creative region in terms of number of HH districts, this region differs from the last because of its monocentric spatial structure. Toulouse is the only metropolitan area of the region. Then, Midi-Pyrénées concentrates a large amount of isolated poles (43 HL districts) but not significantly spatially autocorrelated. A wide but limited pocket of HH districts can be identified around Toulouse. Interestingly, we can find here a confirmation of the core/periphery regional structure and a real shadow effect due to the disparity between Toulouse metropolitan area and other cities in the region. The region is shaped with 31% of HH districts and 15% of HL



districts. We can note here that most of districts that shape Toulouse creative cluster are significantly spatially autocorrelated. Moreover Midi-Pyrénées is the second region in terms of bohemians clustering (after Ile-de-France). The creative clustering is widely driven by creative professionals too. Although Languedoc-Roussillon ranks at the 5<sup>th</sup> position in terms of creative districts number, it ranks 4<sup>th</sup> in terms of HH districts number in France. This region counts 1 major city (Montpellier) and 2 secondary cities (Nîmes and Perpignan). 68% of the total number of districts can be considered as creative but only districts surrounding Montpellier metropolitan area are significantly spatially autocorrelated. Regions in Group 2, in addition to Group 1, can be seen as leaders in terms of creative people accumulation in France. Except Montpellier (15<sup>th</sup> urban area in term of population), we notice that this ranking follows French urban hierarchy.

Group 3 is shaped with 11 regions but it has been divided in two subgroups in order to follow specificities of their spatial structure regarding creative clusters. A first subgroup 3A gathers 5 regions with a number of HH districts > HL districts, i.e. with more creative clustering than isolated pole of creative people. Subgroup 3B owns an inverse structure, with 6 regions gathering more isolated pole than a real creative clustering effect.

We can notice two particular regions in subgroup 3A, Alsace and Aquitaine. Creative spatial structure of Alsace is shaped with a weak number of districts (64). However, 73% of them are HH or HL districts including 63% of HH districts. In proportion of creative district, Alsace is the third French region after Ile-de-France and PACA. The region structured around two cities (Strasbourg and Mulhouse) but only districts of Strasbourg metropolitan area can be significantly seen as spatially autocorrelated. Aquitaine gathers a quite important number of creative districts (91) but largely structured with HL districts (39). Districts of the region don't show an important significance regarding spatial dependence in spite of 3 major regional poles (Bordeaux, Pau and Bayonne-Anglet-Biarritz). Nearby these two regions, Centre, Bretagne and Pays de la Loire NUTS 2 share a spatial structure shaped with a large number of LL districts (more than 65% for the two first and 79% for the last). Centre gathers a weak amount of creative districts (26%) that don't show any statistical significance although a bipolar spatial structure (Tours and Orleans). Bretagne counts 25 and 20 HH and HL districts. Creative districts concentrate around two major but geographically opposite poles (Brest and Rennes) without being significantly spatially autocorrelated. Between these two east-west opposite poles, the region gathers a large amount of LL districts. At the difference, Pays de la Loire NUTS 2 gathers a significant creative cluster (Nantes) but creative districts only amount for 18% of regional total number of districts. In proportion, this region is the 4<sup>th</sup> weaker.

Region belonging to subgroup 3B share a common spatial structure where number of HL districts > HH districts. They are mainly shaped with isolated creative districts. Then, Nord-Pas-

de-Calais counts 51 creative districts with dominant HL district type. One large cluster can be identified, Lille-Villeneuve d'Ascq-Roubaix. This cluster gathers the totality of regional HH districts. Bourgogne and Lorraine NUTS 2 exactly share the same spatial configuration shaped with one third of HH district and two third of HL district. Above all, these regions gather a large number of significant LL districts. Dijon in Bourgogne and Nancy in Lorraine constitute the largest regional creative cluster. Particularly in Lorraine, Nancy metropolitan area gathers the half of regional creative districts number that is significantly spatially autocorrelated. Bourgogne, suffering from Paris shadow effect, shows a great lag in creative people accumulation. Although 34% of Franche-Comté districts can be seen as creative (HH and HL), this quite small NUTS 2 region doesn't exhibit any creative cluster. Moreover, no one of HH or HL districts can be estimated as significantly spatially dependant from its neighborhood. The absence of large city doesn't allow to engage a dynamic of accumulation of creative people. Same conclusion can be drawn about Poitou-Charente NUTS 2, while the great proximity of Picardie with Paris doesn't allow the region to concentrate major creative activities. Globally, regions in subgroup 3B can be seen as laggards in terms of creative clustering development.

At last, the last group 4 is shaped with NUTS 2 region that are losing the race to creative development. More than 75% of districts are LL-type in each of these regions (Haute-Normandie, Champagne-Ardenne, Basse-Normandie, Auvergne, Limousin). The proximity with Paris (two first regions) or the importance of rural spaces (three last regions) doesn't allow this region to be competitive and attractive to creative people. The lag in creative development appears to be here very important.

## 6. Conclusion

The aim of this paper was to specify the geography of the French creative people. First, it wonders about the concentration of creative people among French district using spatial Gini index. Creative people appear to be very concentrated, particularly in and around Paris. Creative people appear to be more concentrated than employment and population. Among the different groups of creative people, bohemians are particularly concentrated. Second, Moran statistics allows to put forward spatial dependence between French districts regarding creative people LQ. Then, creative occupational clusters gathering several contiguous districts have been identified and each French NUTS 2 has been characterized by the number of districts that own high value of creative people LQ. The geographic distribution of hotspots of creative people takes the shape of an anchor including Paris, east/south east-regions and middle south-east regions. This distribution follows the hierarchy of French metropolitan regions following a

major trend in Europe (Andersen and Lorenzen, 2009). It confirms that creative people location patterns occur essentially in urban environment. Moreover, tests of LISA significance show that big French cities own an influence sphere: creative occupational clusters results from the spreading of the influence of these big cities. It leads the evidence of a non uniformity in the geographic distribution of creative people. It drives the conclusion that regions are leaders in creative people accumulation while some really loose the race to creativity.

The originality of this paper lies on two new considerations: first, it reveals the particular geography of creative people in France. This question still remained open in spite of large developments in other European countries. Second, it proposes to include ESDA tools in the analysis of creative people distribution. If some authors takes this statistical techniques in consideration (Marlet and Van Woerkens, 2007; Boschma and Fritsch, 2009), the well-known link between creativity and space (Andersson, 1985; Hall, 1998; Tornqvist, 2004) implies to use spatial data analysis in order to really catch the whole extent of this phenomenon. This paper constitutes a first attempt in including ESDA tools to analyze creative people geography to date. However, future improvements have to take into account the territorial specificity of France: indeed Paris represents one of the European largest cities and may bias ESDA results that lie on mean deviation calculation. Then we face here a dilemma: make the analysis without Paris leads to quite different results in size or location of creative occupational clusters. However, main findings exposed here are not deeply modified. This paper sticks up to keep Paris because it aims to reveals a real phenomenon. It can be seen here through the shadow effect of Paris on its contiguous neighbors regions: these regions appear to concentrate very low level of creative people. An interesting opening to this work could be to proceed on the same exam only in Paris region. It could allow detecting at micro level what drives the core of French economy regarding creativity. This exam could be the subject of further research.

## Bibliographie

- Acs Z., R. Florida et S.Y. Lee, 2004. Creativity and entrepreneurship: a regional analysis of new firm formation. *Regional Studies*, 38(8), 879-891.
- Andersen and Lorenzen, 2006. The Geography of the Danish creative class. *Report*, CBS, Danemark.
- Andersson, Å.E., 1985. "Creativity and Regional Development", *Papers of the Regional Science Association*, 56, 5-20.
- Anselin L. and S. Bao, 1997. Explanatory Spatial Data Analysis Linking Spacestat and Arcview, in Fisher M., Getis A. (eds.), *Recent Developments in Spatial Analysis*, Springer Verlag, Berlin.

- Anselin L., 1995. Local Indicators of Spatial Association-Lisa, *Geographical Analysis*, 27(2), 93-115.
- Anselin L., 1996. The Moran Scatterplot as an Esda Tool to Assess Local Instability in Spatial Association , in Fisher M., Scholten H.J., Unwin D. (eds.), *Spatial Analytical Perspectives on GIS*, Taylor and Francis, London, pp.111-125.
- Anselin L., 1998a. GIS research infrastructure for spatial analysis of real estate markets. *Journal of Housing Research*, 9, 113-33.
- Anselin L., 1998b. *SpaceStat Version 1.90.*, <http://www.spacestat.com>.
- Anselin L., 2000. Computing environments for spatial data analysis. *Journal of Geographical Systems*, 2, 201-225.
- Bailey T.C. and A.C. Gatrell, 1995. *Interactive Spatial Data Analysis*, Second Edition: Longman.
- Boschma R. et M. Fritsch, 2009. Creative class and regional growth. Empirical evidence from seven European countries. *Economic Geography*, 85(4), 391-423.
- Brooks D., 2000. *Bobos in Paradise: the new upper class and how they got there*. Simon & Schuster, New York.
- Carter A.P., 1994. Change as economic activity. *Working Paper*, 333, Brandeis University, Waltham, MA.
- Chantelot S., 2008. Le rôle de la créativité sur le développement local: de l'influence économique à la géographie de la classe créative française 1990-99. *Thèse de doctorat de sciences économiques*, Université Toulouse I Capitole.
- Chantelot S., 2010a. Vers une mesure de la créativité : la construction de la classe créative française. *Revue d'Economie Régionale et Urbaine*, 3, 5-33.
- Chantelot S., 2010b. La thèse de la "classe créative" : entre limites et développements *Géographie, Économie, Société*, 11, 315-334.
- Cliff, A.D. and J.K. Ord. 1973. *Spatial Autocorrelation*. Pion, London.
- Cliff, A.D. and J.K. Ord. 1981. *Spatial Processes : Models as Applications*, Pion, London.
- Clifton, N., 2008. The "creative class" in the UK: an initial analysis. *Geogr. Ann. B*, 90(1), 63-82.
- Drucker P., 1969. *The Age of Discontinuity: Guidelines to Our Changing Society*. Harper & Row, New York.
- Florida R. et I. Tinagli, 2004. Europe in the creative age. *Report*, Carnegie Mellon Software Industry Center, Pittsburgh.
- Florida R., 2002b. *The Rise of the Creative Class*. Basic Books, New York.
- Florida R., 2005b. *Cities and the Creative Class*. Routledge, London.
- Florida R., C. Mellander et K. Stolarick, 2008. Inside the black box of regional development: Human capital, the creative class and tolerance. *Journal of Economic Geography*, 8(5), 615-649.
- Foray D., 2000. *L'économie de la connaissance*. Repères, La Découverte, Paris

- Fritsch M., 2007. The geography and the effect of creative people in Germany. *Jena Economic Research Papers 001-2007*, Max Planck Institute of Economics, Iena.
- Gaschet, F. et C. Lacour C., 2007. Les systèmes productifs urbains : des clusters aux « clusties ». *Revue d'économie régionale et urbaine*, 4, 707-728.
- Glaeser E.L. et A. Saiz, 2004. The Rise of the Skilled City. *Brookings-Wharton Papers on Urban Affairs*, 47-94.
- Glaeser E.L., 2004. Book Review of Richard Florida's The Rise of the Creative Class. [http://post.economics.harvard.edu/faculty/glaeser/papers/Review\\_Florida.pdf](http://post.economics.harvard.edu/faculty/glaeser/papers/Review_Florida.pdf)
- Grossetti M., 2009. La mobilité spatiale de la classe créative européenne : une enquête empirique sur 11 villes. *6e Journées de la Proximité*, Poitiers, 14-16 octobre.
- Guillain R. and J. Le Gallo, 2008. Identifier la localisation des activités économiques : une approche par les outils de l'analyse exploratoire des données spatiales, *Economie Appliquée*, 3, 5-34.
- Haining R., 1990. *Spatial data analysis in the social and environmental sciences*, Cambridge University Press, Cambridge, 409p.
- Haisch, T. et C. Klöpper, 2005. Investigating the environment for creative human capital: Structures and determinants for creativity in Switzerland. *Nordic Geographers Meeting*, Lund, 10-14 mai.
- Hall P., 1998. *Cities in Civilization*. Phoenix Giant, London.
- Hansen H. et Nedomysl T., 2009. Migration of the creative class: Evidence from Sweden. *Journal of Economic Geography*, 9(2), 191-206.
- Hansen H., 2008. *The Urban Turn*. Lund University.
- INSEE, 2009. La créativité, clé de l'économie fondée sur la connaissance, *Économie Lorraine*, n°199-200, Décembre.
- Isaksen A., 2005. Den kreative klassen og regional næringsutvikling i Norge. *Arbeidsnotat 22/2005*, NIFU STEP, Oslo.
- Jacobs J., 1969. *The Economy of Cities*. Random House, New York.
- Julien, P., 2002, Onze fonctions pour qualifier les grandes villes, *Insee Première*, n°840, Mars.
- Knudsen B., R. Florida, K. Stolarick et G. Gates, 2008. Density and Creativity in U.S. Regions. *Annals of the Association of American Geographers*, 98(2), 461-78.
- Krugman P., 1996. *The self-Organizing Economy*, Blackwell Publishers Ltd.
- Lacour C. et S. Puissant, 2008. Medium sized cities and the dynamics of creative services. *Cahiers du Gretha*, 2008-08, Université Montesquieu-Bordeaux 4.
- Lang R.E., 2005. Review roundtable: Cities and the creative class. *Journal of the American Planning Association*, 71(2), 203-20.

- Le Gallo J., Ertur C. and C. Baumont, 2003. A Spatial Econometric Analysis of Convergence across European Regions, 1980-1995, in Fingelton B. (éd.), *European Regional Growth*, Springer-Verlag, Berlin.
- Le Gallo J., 2002. Économétrie spatiale : l'autocorrélation spatiale dans les modèles de régression linéaire, *Economie et prévision*, 155(4), 139-158.
- Lorenzen M. and K.V. Andersen, 2009. Centrality and Creativity: Does Richard Florida's Creative Class Offer New Insights Into Urban Hierarchy? *Economic Geography*, 85(4), 363-390.
- Lucas R.E., 1988. On the Mechanics of Economic Development. *Journal of Monetary Economics*, 22, 3-42.
- Markusen A., 2006. Urban development and the politics of a creative class. *Environment and Planning*, 38(10), 1921-40.
- Marlet, G. et C. van Woerkens, 2005. Tolerance, aesthetics, amenities, or jobs? Dutch city attraction to the creative class. *Discussion Paper Series*, 05-33, T.C. Koopmans Research Institute, Utrecht.
- Marlet, G. et C. van Woerkens, 2007. The Dutch Creative Class and How It Fosters Urban Employment Growth. *Urban Studies*, 44(13), 2605-26.
- Martin-Brelot, H., M. Grossetti, E. Peyroux, D. Eckert et C. Thouzellier, 2008. Career trajectories and residential satisfaction in Toulouse. Understanding the attractiveness of the metropolitan region for creative knowledge workers. *ACRE report WP5.11*, AMIDSt., Amsterdam
- McGranahan D. et Wojan T., 2007. Recasting the creative class to examine growth processes in rural and urban counties. *Regional Studies*, 41(2), 197-216.
- Oldenburg R., 1991. *The Great Good Place*. Marlowe & Company, New York.
- Peck J., 2005. Struggling with the creative class. *International Journal of urban and regional Research*, 29(4), 740-70.
- Reich R., 1993. *L'économie mondialisée*. Dunod, Paris
- Scott A.J., 2006. Creative Cities: Conceptual Issues and Policy Questions. *Journal of Urban Affairs*, 28(1), 1-17.
- Shearmur R., 2005. L'aristocratie mobile du savoir et son tapis rouge. Quelques réflexions sur les thèses de Richard Florida. *working paper*, INRS, Université du Québec, Montréal.
- Simon C., 1998. Human capital and metropolitan employment growth. *Journal of Urban Economics*, 43, 223-43.
- Suire R., 2006. Creative cluster and relational proximity. *Canadian Journal of Regional Science*, 28, 124-38.
- Tornqvist G., 2004. Creativity in time and space, *Geografiska Annaler*, vol. 86, series B, n°4, pp. 227-243.

- Upton G.J.G. and B. Fingleton, 1985. *Spatial Data Analysis by Example*, vol. 1, John Wiley, New York.
- Veblen T.B., 1899. *The theory of the leisure class: An economic study of institutions*. MacMillan, New York.
- Vivant E., 2006. La classe créative existe-t-elle ? *Les Annales de la Recherche Urbaine*. 101, 155-61.
- Whyte W.H., 1956. *The organization man*. Doubleday, New York.

## Graphics, Tables and Maps

Graphic 1: Number and significance of HH and HL districts by French NUTS 2, 2006

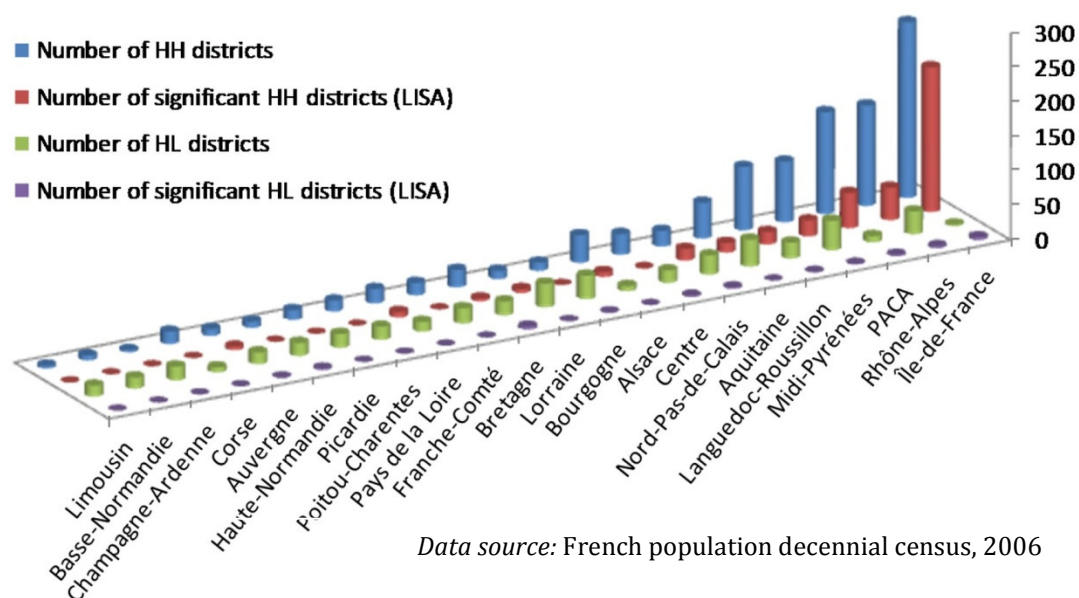


Table 1. Descriptive statistics, creative class, 2006, France

Group	National Workforce	National Labor Market Proportion
Creative class	3,689,365	16.2%
Bohemians	320,415	1.4%
Creative Core	1,622,218	7.1%
Creative Professionals	1,746,732	7.7%

Data source: French population decennial census, 2006



Table 2. Locational Gini index, 2006

Variable	Locational Gini index
Employment	0,303
Population	0,251
Creative class	0,353
Creative Core	0,359
Creative Professionals	0,347
Bohemians	0,370

*Data source: French population decennial census, 2006, INSEE*

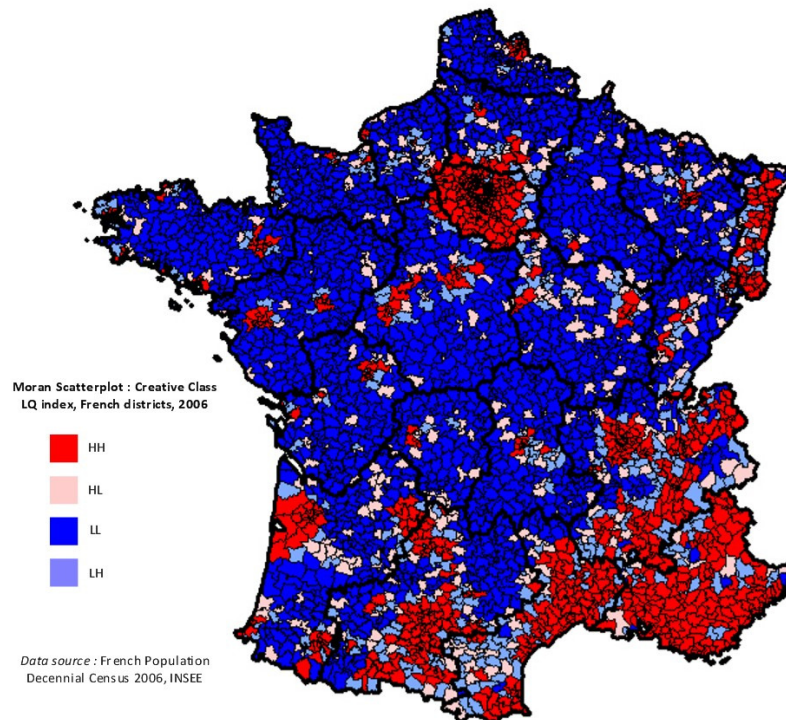
Table 3. Moran  $I$ , creative class LQ index, French districts, 2006

Groupe	Matrix	Moran's $I$	p-value
Creative Class	<b>5-k-nearest neighbors</b>	<b>0.6441</b>	0.0001
	6-k-nearest neighbors	0.6369	0.0001
	10-k-nearest neighbors	0.6181	0.0001
	15-k-nearest neighbors	0.5913	0.0001
	Rook contiguity	0.6358	0.0001
	Queen contiguity	0.6360	0.0001
Bohemians	<b>5-k-nearest neighbors</b>	<b>0.3254</b>	0.0001
	6-k-nearest neighbors	0.3044	0.0001
	10-k-nearest neighbors	0.2896	0.0001
	15-k-nearest neighbors	0.2757	0.0001
	Rook contiguity	0.3117	0.0001
	Queen contiguity	0.3119	0.0001
Creative core	<b>5-k-nearest neighbors</b>	<b>0.4775</b>	0.0001
	6-k-nearest neighbors	0.4711	0.0001
	10-k-nearest neighbors	0.4540	0.0001
	15-k-nearest neighbors	0.4272	0.0001
	Rook contiguity	0.4641	0.0001
	Queen contiguity	0.4641	0.0001
Creative Professionals	<b>5-k-nearest neighbors</b>	<b>0.4747</b>	0.0001
	6-k-nearest neighbors	0.4706	0.0001
	10-k-nearest neighbors	0.4491	0.0001
	15-k-nearest neighbors	0.4303	0.0001
	Rook contiguity	0.4711	0.0001
	Queen contiguity	0.4714	0.0001

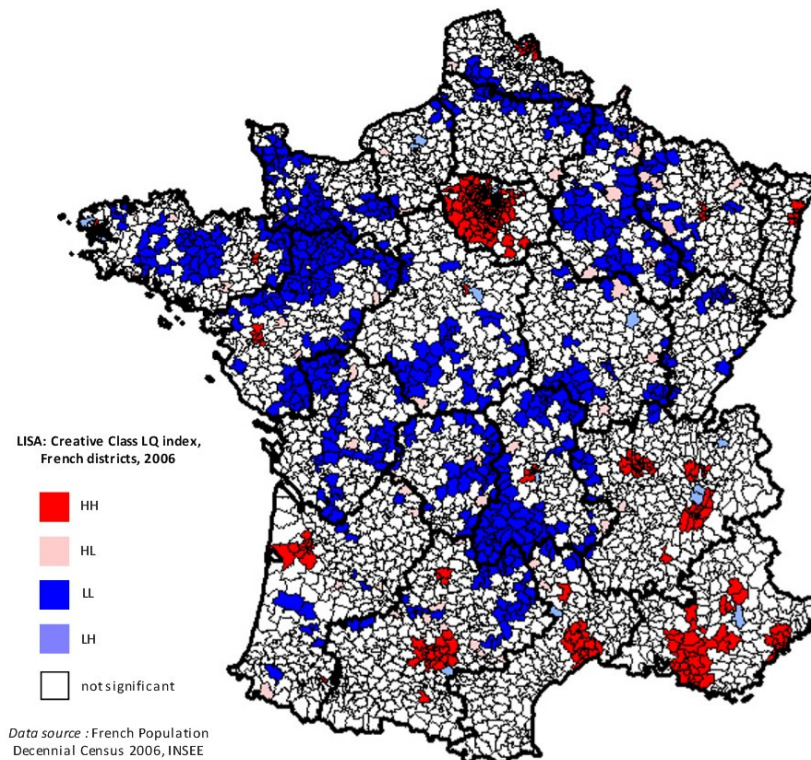
Notes :  $E(I) = -0.0003$ ; Moran  $I$ 's Statistical inference is based on a conditional permutation approach with 9,999 permutations

*Data source: French population decennial census, 2006, INSEE*

Map 1: Moran scatterplot, Creative class LQ index, French districts, 2006.



Map 2: LISA, Creative class LQ index, French districts, 2006.



## Appendix

Table A1: Descriptive statistics, French NUTS 2 regions, 2006

Pop Rank	NUTS Region	Demography		Creative people demography			
		Population	Employment	Creative Class	Bohemians	Creative Core	Creative Professionals
1	Île-de-France	11 008 136	5 041 995	25,8%	3,0%	9,9%	12,9%
2	Rhône-Alpes	5 591 146	2 265 001	15,6%	1,2%	7,2%	7,3%
3	PACA	4 506 151	1 576 808	16,6%	1,3%	7,2%	8,0%
4	Nord-Pas-de-Calais	3 996 588	1 344 313	13,2%	0,7%	6,4%	6,1%
5	Pays de la Loire	3 222 061	1 276 353	12,0%	0,9%	5,7%	5,5%
6	Aquitaine	2 908 359	1 106 620	13,7%	1,0%	6,1%	6,5%
7	Bretagne	2 906 197	1 115 252	12,5%	0,9%	6,1%	5,5%
8	Midi-Pyrénées	2 551 687	980 079	15,8%	1,1%	7,9%	6,8%
9	Centre	2 440 329	940 473	12,3%	0,9%	6,0%	5,4%
10	Lorraine	2 310 376	816 387	12,2%	0,7%	6,0%	5,5%
11	Languedoc-Roussillon	2 295 648	755 345	15,1%	1,4%	6,6%	7,1%
12	Picardie	1 857 481	645 631	11,8%	0,7%	5,7%	5,3%
13	Haute-Normandie	1 780 192	664 092	12,5%	0,7%	6,3%	5,4%
14	Alsace	1 734 145	687 767	14,5%	1,0%	6,6%	6,9%
15	Poitou-Charentes	1 640 068	617 282	11,6%	0,9%	5,3%	5,4%
16	Bourgogne	1 610 067	619 049	11,6%	0,8%	5,4%	5,4%
17	Basse-Normandie	1 422 193	539 870	11,0%	0,7%	5,4%	4,8%
18	Champagne-Ardenne	1 342 363	518 371	11,1%	0,7%	5,3%	5,2%
19	Auvergne	1 308 878	502 095	11,4%	0,7%	5,5%	5,2%
20	Franche-Comté	1 117 059	430 446	11,9%	0,8%	6,2%	4,9%
21	Limousin	710 939	271 832	11,5%	0,9%	5,4%	5,3%

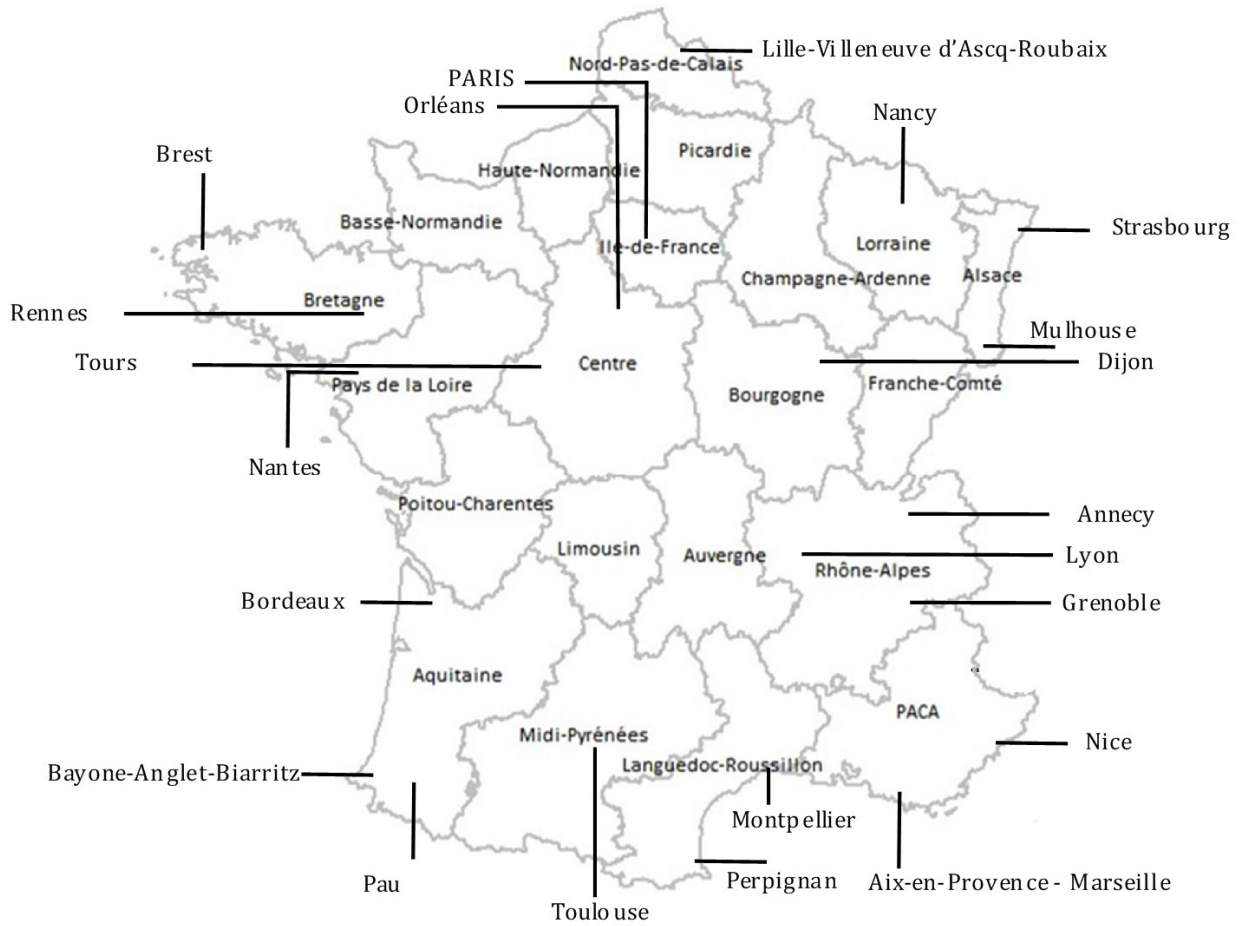
*Data source* : French population decennial census, 2006, INSEE

Table A2: Moran scatterplot and LISA, creative class LQ index, French districts, 2006

Descriptive statistics French NUTS 2 regions				Moran scatterplot Creative class LQ index, 2006 (in number of districts)				LISA Creative class LQ index, 2006 (in number of districts)				
Rank	NUTS 2 region	Nb of districts	Creative districts	HH	HL	LH	LL	HH	HL	LH	LL	Not sig.
1	Île-de-France	267	257	255	2	9	1	210	0	4	0	53
2	Rhône-Alpes	311	179	146	33	55	77	47	1	3	9	251
3	PACA	193	157	148	9	30	6	51	0	2	0	140
4	Midi-Pyrénées	286	131	88	43	43	112	23	8	1	33	221
5	Languedoc-Roussillon	170	115	92	23	41	14	18	2	1	5	144
6	Aquitaine	231	91	52	39	22	118	14	5	0	11	201
7	Nord-Pas-de-Calais	170	51	23	28	11	108	17	3	2	17	131
8	Centre	185	48	30	18	17	120	1	2	2	32	148
9	Alsace	64	47	40	7	11	6	7	0	0	0	57
10	Bourgogne	177	46	12	34	18	113	0	4	1	24	148
11	Lorraine	156	46	12	34	10	100	6	6	0	22	122
12	Bretagne	187	45	25	20	18	124	4	4	4	47	128
13	Franche-Comté	116	40	18	22	15	61	0	2	0	16	98
14	Pays de la Loire	192	35	21	14	5	152	8	5	0	75	104
15	Poitou-Charentes	158	35	16	19	13	110	0	3	0	41	114
16	Picardie	133	34	14	20	16	83	0	1	0	22	110
17	Haute-Normandie	103	28	9	19	15	60	0	2	2	4	95
18	Auvergne	156	27	10	17	12	117	5	3	1	55	92
19	Corse	43	25	18	7	14	4	0	0	0	1	42
20	Champagne-Ardenne	146	23	3	20	7	116	0	9	0	54	83
21	Basse-Normandie	147	23	7	16	14	110	0	2	0	58	87
22	Limousin	96	20	4	16	4	72	0	3	0	28	65

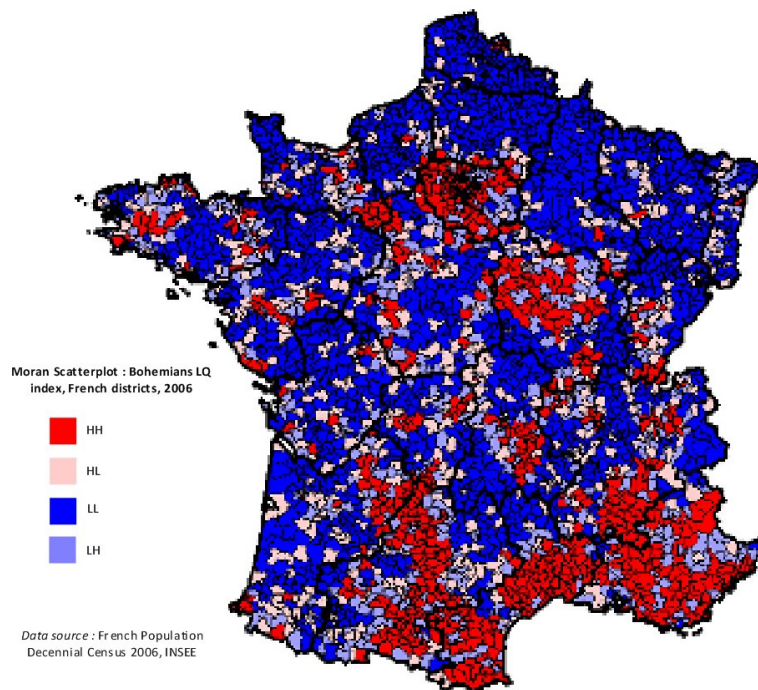
Data source : French population decennial census, 2006, INSEE

Map A1: French NUTS 2 regions and main metropolitan areas.

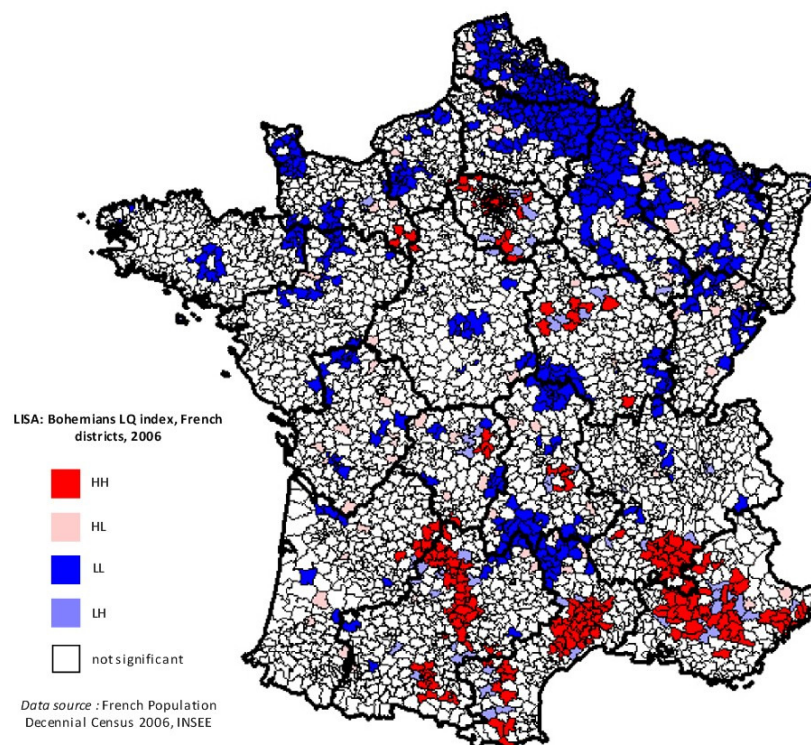




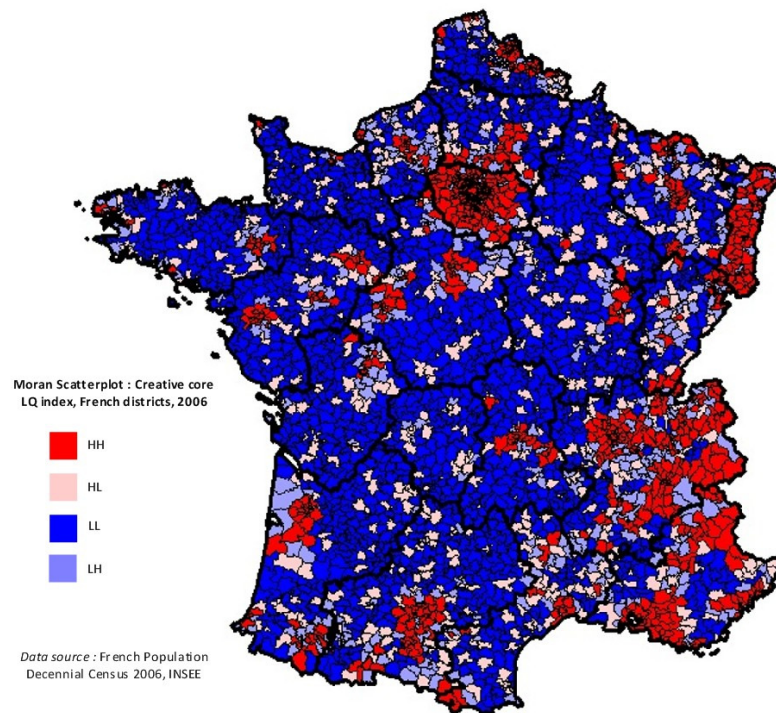
Map A2: Moran scatterplot, Bohemians LQ index, French districts, 2006.



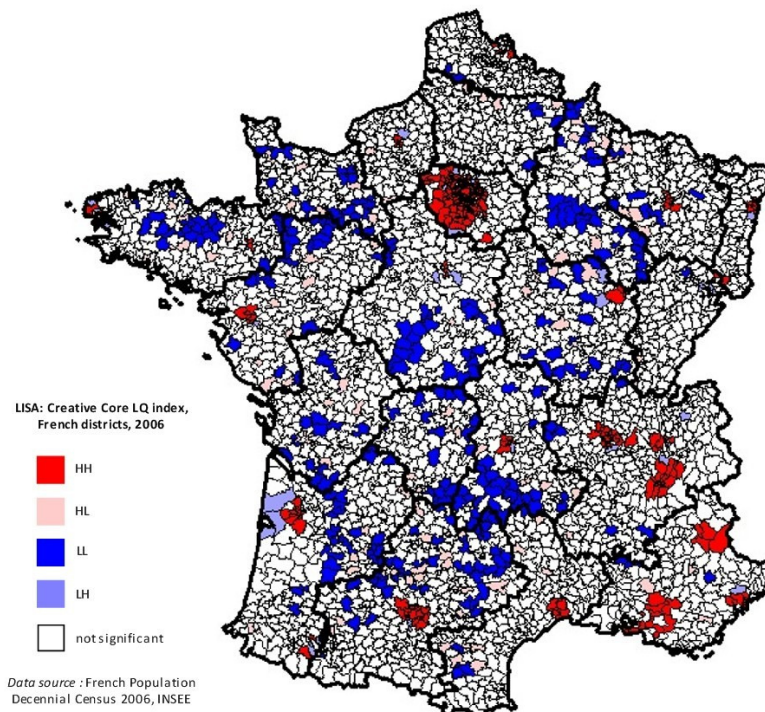
Map A3: LISA, Bohemians LQ index, French districts, 2006.



Map A4: Moran scatterplot, Creative core LQ index, French districts, 2006.

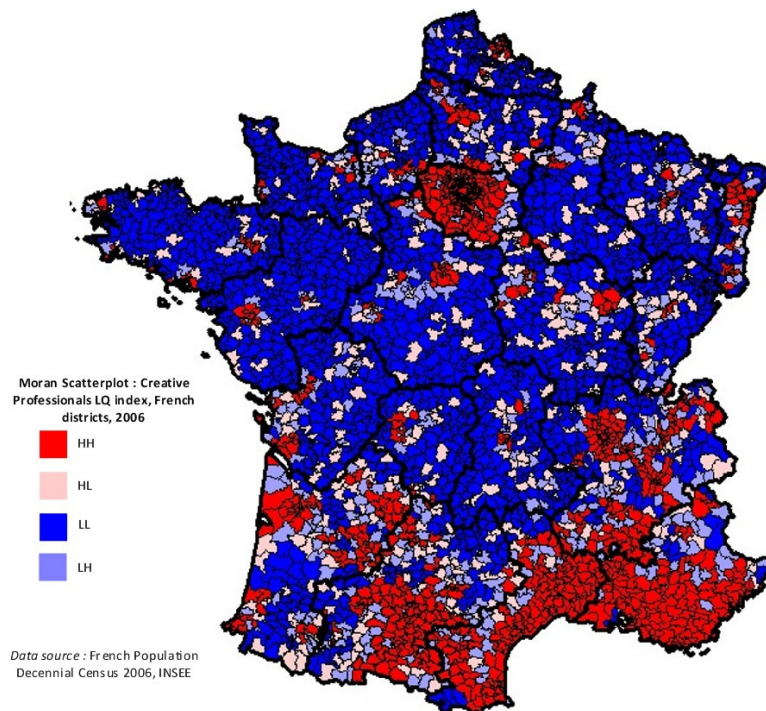


Map A5: LISA, Creative core LQ index, French districts, 2006.





Map A6: Moran scatterplot, Creative professionals LQ index, French districts, 2006.



Map A7: LISA, Creative professionals LQ index, French districts, 2006.

