The geography of French creative class: An exploratory spatial data analysis

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Les clusters créatifs français : Une approche par l'analyse exploratoire de données spatiales

Résumé

Les travaux séminaux de Florida (2002b) ont mis en évidence l'importance de la créativité pour le régime de croissance économique. La relation entre une « classe créative », composée d'individus hautement créatifs dans le cadre de leurs professions, et la ville a dès lors été approfondie à travers l'examen d'une gamme de facteurs structurant la géographie de ces individus. En dépit de corrélations statistiques fortes entre la vitalité artistique, culturelle, les troisièmes places, la diversité et la présence de constellations importantes de créatifs au sein des villes, il apparaît que la taille urbaine et les opportunités économiques soient les vrais moteurs de l'attraction des créatifs. Cependant, si un nombre conséquent de travaux ont été produits en Europe du Nord sur ces questions, la géographie française des créatifs reste relativement inexplorée. Le papier propose donc ici une approche originale de l'examen de la localisation des créatifs en France en 2006 en s'appuyant sur les outils de l'analyse exploratoire de données spatiales. Cette technique permet de renseigner le degré de concentration des créatifs au sein des cantons français, tout en détectant les schémas de localisation des créatifs. L'analyse met en évidence l'existence de clusters de cantons français comprenant des proportions importantes d'individus créatifs et la structuration des différentes composantes de la « classe créative » (creative core, creative professionals, bohemians) au sein de ces clusters.

Mots-clés : Classe créative, clusters, analyse exploratoire de données spatiales

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Abstract

This paper analyses the creative class geography 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 to the spatial context, France, where this question hasn't been deepened yet. Methodology allows measurement of spatial agglomeration degree and identification of creative people location patterns. First, by computing locational Gini index and Moran's I statistic of global spatial autocorrelation. These measures provide an overview of the spatial distribution of creative people among French districts and the existence of some hotspot regions with strong dynamic of creative people accumulation. Second, Exploratory Spatial Data Analysis (ESDA) tools, such as Moran scatterplot and LISA statistics, allow to identify district clusters of creative people. It leads to evidence that creative people are unevenly geographically distributed across French districts. District clusters of creative occupations result from spreading of French largest cities influence.

Keywords: Creative class, ESDA, location patterns, spatial autocorrelation, French districts

JEL : C12, O18, R23

1. Introduction

The creative class approach (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" (Florida, 2002b). This particular class is shaped by individuals that own a creative occupation, i.e. an occupation that needs 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 to supply 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 a strategy. This spectacular diffusion has led to a large debate where the approach has been widely criticized by both scientific and politic communities.

However, the geography analysis of the creative class has been investigated 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 projects, 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. Tools of exploratory spatial data analysis (ESDA) are mobilized. It allows to measure concentration of creative people among local territorial units (French districts) and spatial dependence between these units to finally detect and identify creative occupational clusters. This last point leads to take into consideration location patterns of creative people in France.

Section 2 presents major contents of the creative class approach and main works about creative people geography. Section 3 introduces the research problem while section 4 outlines database and methods used. Section 5 contains main findings on exploratory analysis of the French creative people geography.

2. Theoretical background

2.1 The creative class approach

The creative class approach (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 occupation. 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 and *al.*, 2008), attract innovative firms and have high levels of entrepreneurship (Acs and *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 1990's: « *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)[1], 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. In the same way, creative class looks like *change agents* (Carter, 1994) whose productive role is entirely dedicated to stimulate and to supervise innovation. By moving the approach's entry of sources of innovation from firms to individuals, this approach echoes Veblen (1899) that pointed out that technological change is essentially a cultural process. Then, the capacity to perpetuate and institutionalize change belongs to a certain class of the society. The creative class is divided in three groups: First, the "creative core" group gathers individuals directly involved in creative occupations such as Architects, engineers, scientists, education and training professionals, etc. Next, the "creative professionals" groups is shape with occupations that enhance or foster innovation and creativity such as Management, business, financial, legal, healthcare, high-end sales occupations. At last, "bohemians" group gathers individuals involved in artistic and cultural occupations. These three groups shape the creative class. They own different role in regards to creativity and innovation, particularly through their respective use of synthetic, analytic and symbolic knowledge bases (Asheim and Hansen, 2009).The original aspect of such a class is to gather people at the roots of innovation, science and art productions around a common trait called « creative ethos » born from the merging of « organization man » values (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 alternative values in terms of lifestyle, underground, fashion and original thinking. Then, a main point of the creative class approach is that geography matters. First, according to Florida (2002b, 30), « *places have replaced companies as the key organizational units in our economy* ». Second, the creative class geography doesn't appear uniformly shaped. This approach points out a second postulate: creative people are particularly attracted by places characterized by tolerant and open climate to diversity, new ideas and new comers.

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[1] 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 sociological sense.

Cities that manage to attract creative people in domains like arts or culture as well as to provide low entry barriers to individuals whatever their background, origin or lifestyle own a comparative advantage in fostering innovation and stimulating local economic growth (Florida, 2005b). This view follows Jacobs (1969) or Hall (1998, 501) that promote local level of innovation results from the joint product of creativity and economical, technological and social diversity levels of a city. As for Lucas (1988), Florida (2005b) considers that cities have to attract, retain, organize and generate creative people in order to reach high levels of economic development. Associated with the existence of socialization opportunities such as "third places" (Oldenburg, 1991) like cultural services, pubs, restaurants, etc., tolerant urban climate shapes a *people's climate* that complete the mainstream *business climate* based on firms attraction through low taxes physical assets. Then, high quality *people's climate* is crucial to attract creative people. They will in turn attract or create innovative firms. Creative class approach considers that *jobs follow people* instead of *people follow jobs*. It reverses this last well-known causality link and this approach became a questionable tool of economic development policy (see Peck, 2005 for a complete survey of these different discussions).

2.2 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 in Europe (see Chantelot, 2009 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). They found their relevance through the importance of talent on local economic growth (Lucas, 1988; Simon, 1998; Glaeser and Saiz, 2004). Then, measurement of creative people allows to produce human capital index. It based on occupational approach and differs to mainly used educational approach, *i.e.* diploma level. Moreover, some works tend to show that 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 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 (Lorenzen and Andersen, 2009; Boschma and Fristch, 2009). Location analysis of creative people is seen through several entries. First, it's about the question of creative people mobility: the strong mobility of creative people is a founding assumption of the creative class approach, because they 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 true in Europe. Hansen and Niedomysl (2009) note that Scandinavian creative people are not more mobile than other people. In the ACRE project framework, Martin-Brelot, Eckert and *al.* (2008) and Grossetti (2009) show that mobility of European creative people is not a *panacea*: 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. This project lies on a survey driven in 13 cities of 12 European countries gathering 1700 questionnaires answered by European creative people. These results demonstrate that the importance of soft factors such as tolerance and openness to diversity or third places are overestimated[2] (Scott, 2006). Marlet and Van Woerkens (2005) note that

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[2] 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*".

highest proportions of creative people are located in Dutch cities supplying a huge pool of professional opportunities, low automobile congestion rate and real estate prices instead of *people's climate*. However, it contrasts with « *Technology, Talent, Tolerance in European cities: A comparative analysis* » project's findings: This project examines the co-location of creative people and people's climate, through factors such as tolerance, openness and diversity (measured through proportions of artists or foreign-born people), urban amenities (third places, public sector proportion) and economic opportunities (job density, past economic growth). Results for eight European countries show that cities with higher levels of creative people also are those that offer a high-quality people´s climate. Particularly, location of creative people from technological and economical spheres is strikingly correlated with location of bohemians, i.e. individuals that own a creative occupation in domains such as arts, culture, design, fashion, etc. (Isaksen, 2005; Haisch and Klöpper, 2005; Andersen and Lorenzen, 2006; Fritsch, 2007; Hansen, 2008; Clifton, 2008; Boschma and Fritsch, 2009). The statistical correlation level appears to be very high in all countries studied. However, there is no indication on the causality direction: Lorenzen and Andersen (2009) bring some answer elements by analyzing the relation between urban hierarchy and proportions of creative people in Scandinavian cities. The authors observe a population threshold where these proportions strongly decrease. Several answers are given to this threshold: First, specific and highly-specialized creative occupations are mainly located in large agglomerations as shown by Julien (2002) in France. Next, creative people´s preferences for large urban environments lie on their high consumption propensity of artistic and cultural goods that huge cities can offer. At last, university can represent another bias leading to this threshold by irrigating the local labor market with high skilled human capital. However and even if these results participate to strengthen the analysis of factors that shape the creative people geography, no indication is given about relevance of local development policies founded on creative people attraction (Lang, 2005).

3. Research problem

Although the creative class approach has been largely developed and adapted in Europe, it remains quite unexplored in France if we except Chantelot (2008; 2009; 2010) and the French part of ACRE project (Martin-Brelot, Eckert and *al.,* 2008; Grossetti, 2009). However, it tends to be include in some works (Vivant, 2006; Suire, 2006; Gaschet and Lacour, 2007; Lacour and Puissant, 2008) but without being a first-order question. Therefore, there is some relevance to analyze the creative people location in France: To what extent creative people are geographically concentrated? What can constitute their location patterns? A first discussion on identification of creative occupations appears to be necessary: 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 real creative skills contents. Next, French creative people geography lies on exploratory spatial data analysis (ESDA) tools: On one hand, locational Gini index estimates creative people concentration. On the other hand, spatial autocorrelation calculation identify global location patterns of creative people. 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 map 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 comes from first results of the 2006 French population decennial census from INSEE[3]. These individual data informs about the whole occupations for each 36549 French municipalities. The identification method of creative occupations among French local labor market issued from Chantelot (2010). The composition of the creative class raised a great dilemma: Some authors deal 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 occupational classification (Isaksen, 2005; Andersen and Lorenzen, 2006; Marlet and Van Woerkens, 2008; Hansen, 2008). But Florida´s original composition 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 measure about creative occupational contents. Then selection is mainly made through occupation titles. That's why McGranahan and Wojan (2007) and Chantelot (2010) identify creative occupations lying on occupations themselves – and not on occupational groups – and by using a selection method that includes occupational creativity measure. Chantelot (2010) 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 his identification method. This selection has been used by INSEE in the framework of the preliminary short exam of French creative class (INSEE, 2009). 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 (2010), Table 1 contains descriptive statistics on creative people in France in 2006.

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

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, INSEE, 2006

This last table doesn't deal with creative people evolution since the last 1999 French population decennial census: Indeed, French occupational classification (PROF) used by INSEE in 1999 was elaborated in 1982 and was recast 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

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[3]   Institut National de la Statistique et des Etudes Economiques

were broken up to take into account of emergence of new occupations (mainly among ICT domains).

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

A location quotient (*LQ*) of creative people is produced for each French district. It represents local proportion of creative people among local labor market related to national proportion of creative people regarding national employment. Several LQ also are produced for each subgroup of creative people, creative core, creative professionals and bohemians. Then, LQ >1 indicates an overrepresentation of creative people in the district compared to national mean. Conversely, LQ <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 measure of agglomeration dynamics. Among the panel of measurement choices and according to Guillain and Le Gallo (2008), we are convinced that people agglomeration, just like economic activities, needs on a first hand 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.

Spatial concentration measurement can be done through several global indexes: Hirshman-Herfindhal spatial index, locational Gini coefficient or Ellison-Glaeser concentration index. Following Guillain and Le Gallo (2008), we use locational Gini index. It measures relative structure of a random variable associated to 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:

$$G_c = \frac{\Delta}{4x_c}$$

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

Where *c* is the creative group considered (creative class, creative core, creative professionals, bohemians), *n* is the number of spatial units (French districts); $x_{i,c}$ the creative workforce of the district *i* (resp. *j*), x_c the mean creative workforce by districts. This index values 0 if the workforce of the variable *c* is equally distributed among districts and 0.5 if this workforce is entirely concentrated into one district. Moreover it allows comparisons between index 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 are not neutral in regards to agglomeration measure. These two

aspects are not taken into account in locational Gini index and other indexes quoted upper. It results in 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. Exploratory Spatial Data Analysis (ESDA) is used.

ESDA is a set of techniques that aims at describing and visualizing spatial distributions, at identifying atypical locations 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. Guillain 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 locations, 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 location with those in neighboring locations. 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:

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

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

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

These quadrants represent negative spatial autocorrelation indicating spatial clustering of dissimilar values. Moran scatterplot may thus be used to visualize atypical locations (HL or LH). Moreover, using standardized variables allows Moran scatterplot to be comparable across time. The detection of outliers 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, LISA for each observation gives an indication of significant spatial clustering of similar values around that observation. Second, the sum of 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:

$$L_i = \frac{(x_i - \overline{x})}{m_0} \sum_j w_{i,j}(x_j - \overline{x}) \quad \text{with} \quad m_0 = \sum_i w_{i,j}(x_j - \overline{x})^2 / N$$

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 existence 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 Moran scatterplot and LISA statistics allow obtaining maps of Moran significance. These maps 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 stands 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.

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, INSEE, 2006

Table 2 results obviously show that creative people concentration is more important than for employment and for population. This first result shows that factors shaping location process of creative people lie on particular mechanisms involving 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´s *I*. One of fundamental element of this index is the choice of the weight matrix that constraints 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 location process of creative people lies, determinants of weight matrix can be exogenously fixed. We test several possibilities: Matrix based on queen or rook contiguity4 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

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[4] 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.

values for creative class and its subgroups LQ index according to different weight matrix for 3644 French districts sample in 2006.

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

Groups	Moran statistic	k-nearest neighbors				Rook contiguity	Queen contiguity
		k=5	k=6	k=10	k=15		
Creative Class	Moran's I	**0.6441**	0.6369	0.6181	0.5913	0.6358	0.6360
	p-value	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
Bohemians	Moran's I	**0.3254**	0.3044	0.2896	0.2757	0.3117	0.3119
	p-value	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
Creative core	Moran's I	**0.4775**	0.4711	0.4540	0.4272	0.4641	0.4641
	p-value	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
Creative Professionals	Moran's I	**0.4747**	0.4706	0.4491	0.4303	0.4711	0.4714
	p-value	0.0001	0.0001	0.0001	0.0001	0.0001	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, INSEE, 2006

Results in table 3 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. Conversely, spatial structure of creative class location is characterized by clusters of same LQ index values. Next, in order to catch on the best way spatial interactions between districts, i.e. that maximizes spatial autocorrelation, we choose here the matrix associated with higher Moran *I*'s value. The *k*-nearest neighbors matrix 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´s *I* lead to same conclusions about sign and significance of global spatial autocorrelation. It puts light on robustness of these results whatever spatial weight matrix used. Also, whatever the sample of creative individuals, 5-nearest neighbors is here the best spatial weight matrix in catching global spatial autocorrelation.

Locational Gini index and Moran´s *I* are tools measuring global concentration. If Moran´s *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 district *i* value is significantly influenced by value of neighboring district values as defined in spatial weight matrix. Reciprocity can be also true. Moran scatterplot allows to identify location patterns of creative people among French

districts. All these location patterns are mapped in map 15. It enables to qualify dependence relations between districts regarding creative people. Then, map 2 indicates some significant LISA areas where district LQ value is dependent on surrounding district values. This is particularly obvious with NUTS -2 regions like *Ile-de-France, Rhône-Alpes, Provence-Alpes-Côte d´Azur (PACA), Midi-Pyrénées* and *Languedoc-Roussillon*6. Creative occupational clusters are mapped with HH districts: these districts show high LQ values of creative people and are surrounded by districts with high LQ values of creative people. Moreover HL districts are isolated pole with high LQ values surrounded by low LQ value districts. HH and HL districts are mapped in red and pink on the map 1. Location patterns (HH, HL, LH and LL) of districts in each NUTS-2 region are displayed in table A1 in appendix. As we study creative clusters, LH and LL districts are not detailed here.

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

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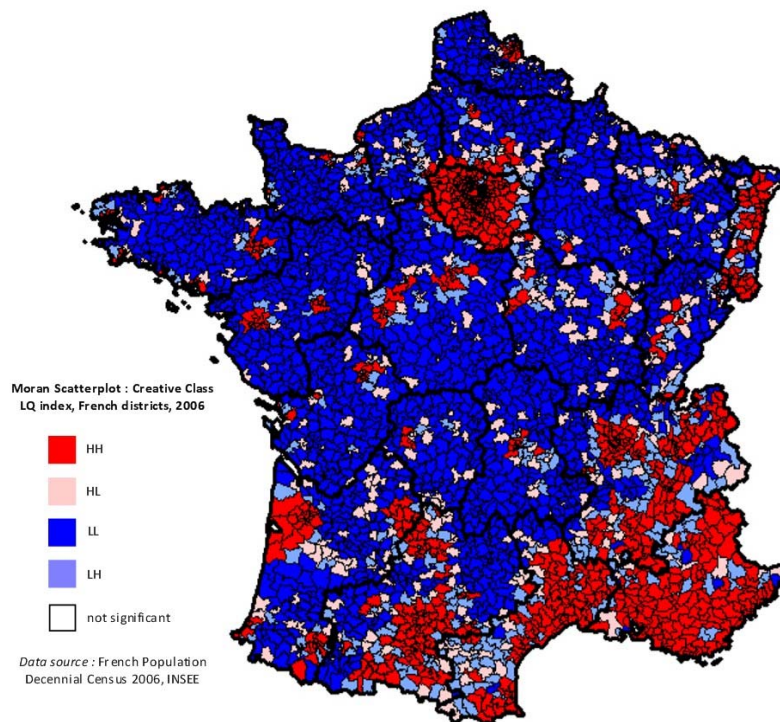
[5] Maps A1, A2, A3, A4, A5 and A6 in appendix map location patterns for Bohemians, Creative core and Creative professionals LQ index among French districts.

[6] Table A1 gives descriptive statistics for each French NUTS-2 region.

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Map 2. LISA, Creative class LQ index, French districts, 2006
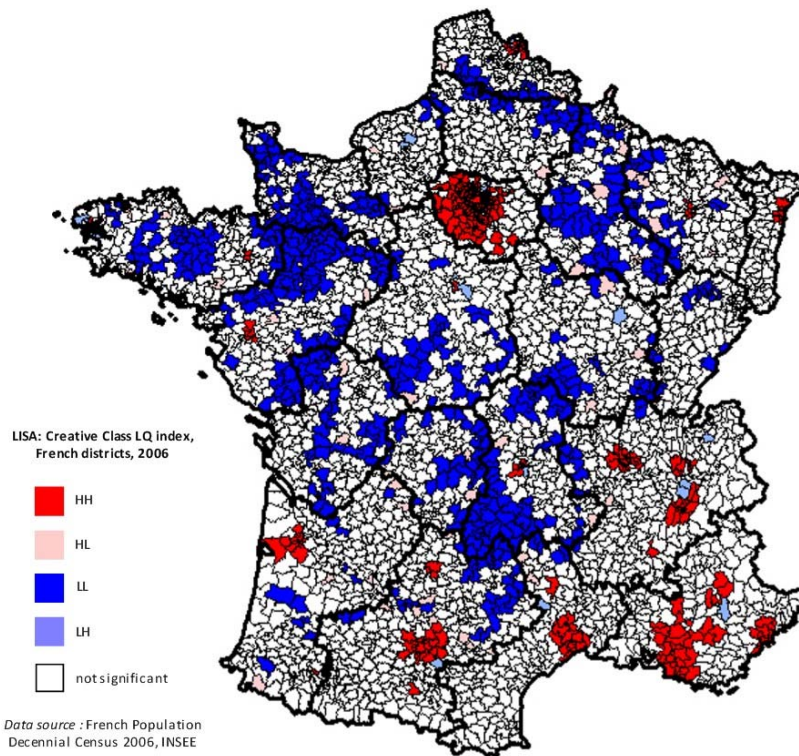
In order to produce a compared analysis of French hotspots of creativity, we detail location patterns at NUTS-2 level. This aggregate level allows to identify creative clusters in function of HH and HL districts' number within each region. In addition to maps 1 and 2, graph 1 shows the number of HH and HL districts in each French NUTS-2.

**Graph 1. Number and significance of HH and HL districts by French NUTS 2, 2006.**

Data source: French population decennial census, INSEE, 2006
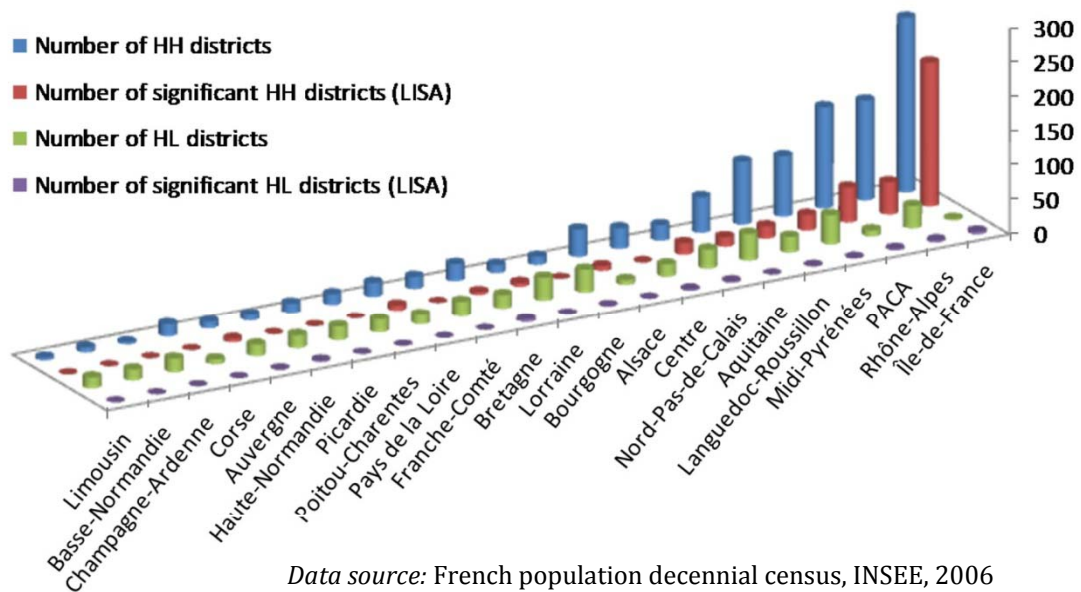
Moreover, this graph contains the number of significant LISA districts. Then we group here French NUTS-2 regions following their spatial structure issued from Moran scatterplot in terms of HH and HL districts' number. We shape 5 groups of regions defined in table 4 and mapped in map 3:

Table 4. Typology of creative French NUTS-2 regions, 2006.

Group	Regions	Main characteristics
Group 1	Ile-de-France	Particular case Capital city-region
Group 2	Rhône-Alpes, PACA, Midi-Pyrénées, Languedoc-Roussillon	Large number of HH and HL districts
Group 3A	Aquitaine, Centre, Alsace, Bretagne, Pays de la Loire	Average number of HH and HL districts Number of HH districts > number of HL districts
Group 3B	Nord-Pas-de-Calais, Bourgogne, Lorraine, Franche-Comté, Poitou-Charentes, Picardie	Average number of HH and HL districts Number of HH districts < number of HL districts
Group 4	Haute-Normandie, Basse-Normandie, Auvergne, Champagne-Ardenne, Limousin	Weak number of HH and HL districts

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Map 3. Typology of creative French NUTS-2 regions, 2006
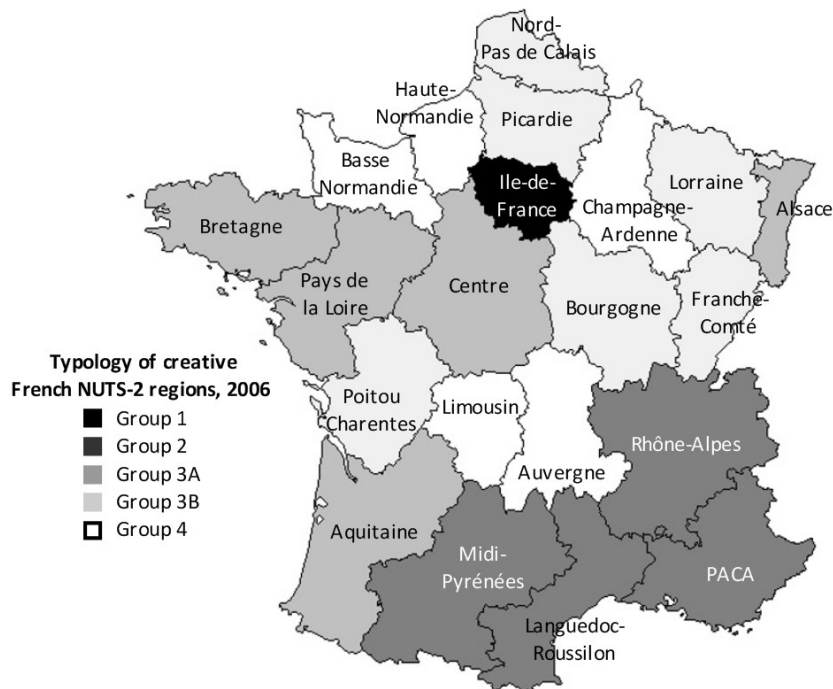
Group 1 only includes *Ile-de-France* NUTS-2 region. France is a centralized country and its capital city, *Paris*, is the biggest city in Europe with *London*. *Ile-de-France* concentrates 19% of French population and 22% of national employment. French political and economical affairs are mainly located 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 statistically significants when looking at LISA statistics values (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 districts´ 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, *PACA* is the second region in terms of HH districts´ number (148) after *Ile-de-France*. 81% of *PACA* districts owns high LQ value of creative people. Most of them are significantly spatially autocorrelated 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 HH districts´ number, this region differs from previous regions because of its monocentric spatial structure. *Toulouse* is the only metropolitan area of

the region. *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 5th position in terms of creative districts´ number (HH and HL), it ranks 4th in terms of HH districts´ number in France. This region counts one major city (*Montpellier*) and 2 secondary cities (*Nîmes* and *Perpignan*). 68% of the total number of districts can be considered as creative but only surrounding districts of *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. These two first groups account for 56% of total French creative districts. Except *Montpellier* (15th urban area in terms of population), we notice that this ranking follows French urban hierarchy.

Group 3 is shaped with 11 NUTS-2 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 NUTS-2 regions with a HH districts´ number > HL districts´ number, i.e. with more creative clustering effect than isolated pole of creative people. Subgroup 3B owns an inverse structure, with 6 NUTS-2 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 districts, *Alsace* is the third French NUTS-2 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 regions 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 urban structure (*Tours* and *Orleans*). *Bretagne* counts 25 HH and 20 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, *Bretagne* gathers a large amount of LL districts. Conversely, *Pays de la Loire* NUTS-2 region 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 4th weaker.

NUTS-2 regions belonging to subgroup 3B share a common spatial structure where HL districts´ number > HH districts´ number. They are mainly shaped with isolated creative districts. *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 regions exactly share the same spatial configuration shaped with one third of HH districts and two third of HL districts.

Above all, these regions gather a large number of significant LL districts. *Dijon* in *Bourgogne* and *Nancy* in *Lorraine* constitute largest regional creative clusters. 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, this quite small NUTS-2 region doesn't show 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 accumulation dynamic of creative people. Same conclusion can be drawn about *Poitou-Charentes* NUTS-2 region, while the great proximity of *Picardie* NUTS-2 region with *Paris* doesn't allow the region to concentrate major creative activities. Globally, creative clustering development in 3B subgroup NUTS-2 regions can be seen as relatively weak.

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

6. Conclusion

The aim of this paper was to specify French creative people geography. First, it wonders about creative people concentration among French districts using locational Gini index. Creative people appear to be very concentrated, particularly within and around *Paris*. For instance, they are more concentrated than total employment and population in France. Among different groups of creative people, *bohemians* are particularly concentrated. Second, Moran´s *I* statistic allows to put forward spatial dependence between French districts in regards to creative people LQ values. Then creative occupational clusters gathering several contiguous districts have been identified. Each French NUTS-2 regions has been characterized following districts´ number that own high LQ value of creative people. The geographic creative people hot spots distribution takes the shape of an anchor including *Paris*, *east/south-east* regions and *middle south-east* regions. This distribution follows French metropolitan regions hierarchy following a major trend in Europe (Lorenzen and Andersen, 2009). It confirms that creative people location essentially occurs in urban environment. Moreover, tests of LISA significance show that larger French cities affect creative occupational clustering. This clustering results from the spreading of these cities. It leads to the evidence of an uneven geographic distribution of creative people and drives the conclusion that some regions are leaders in creative people accumulation while others really loose the race to creativity.

Several core/periphery structure emerge here: A global one, where *Paris* highly concentrates a major part of creative people in France. It implies a strong shadow effect around *Paris* city-region due to its magnet effect where creative people appear underrepresented. Furthermore, local core/periphery structures emerge around French larger cities spreading in their hinterland, as within Lyon, Marseille, Toulouse and Montpellier metropolitan areas. 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 French territorial specificities: Indeed *Paris* represents one of the European largest cities and may bias ESDA results lying on mean deviation calculation. Then we face here a dilemma: making 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 NUTS-2 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 metropolitan region. It could allow detecting at micro level what drives the core city of French economy regarding creativity. This exam could be the subject of further research. Additionally, a further extension of this analysis could be creative clusters´ dynamics in France since 1982. Actually, spatial occupational data issued from 1982, 1990 and 1999 French decennial population censuses are available. However, as mentioned upper, comparison between 1999 and 2006 data is made impossible because of survey field changes and occupational standard classification changes.

In spite of their oldness, investigating these data could bring some relevant information about creative clusters´ dynamics. It would be interesting to consider the extent to which creative clusters arisen over the last 25 years.

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Appendix

Table A1. Descriptive statistics, French NUTS-2 regions, 2006.

| Pop Rank	NUTS-2 Region	Demography		Creative people demography			
		Population	Workforce	Creative Class	Bohemians	Creative Core	Creative Pro.
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%
	TOTAL	58,260,063	22,715,061	16.2%	1.4%	7.1%	7.7%

Data source : French population decennial census, INSEE, 2006

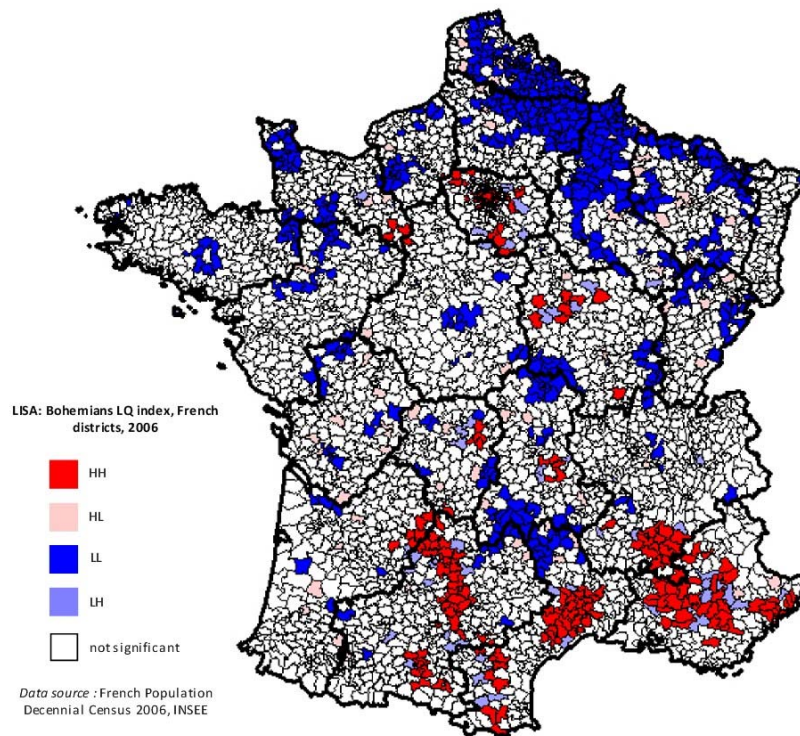**Table A2. Moran scatterplot and LISA, creative class LQ index, French NUTS-2 regions, 2006.**

	Descriptive statistics French NUTS-2 regions			Moran scatterplot Creative class LQ index, 2006 (number of districts)				Significant LISA statistics Creative class LQ index, 2006 (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
	TOTAL	3,687	1,503	1,043	460	400	1,784	411	65	23	554	2,634

Data source : French population decennial census, INSEE, 2006

**Map A1. Moran scatterplot, Bohemians LQ index, French districts, 2006**

Moran Scatterplot : Bohemians LQ
index, French districts, 2006

HH

HL

LL

LH

*Data source : French Population
Decennial Census 2006, INSEE*

Map A2. LISA, Bohemians LQ index, French districts, 2006.

LISA: Bohemians LQ index, French
districts, 2006

HH

HL

LL

LH

not significant

*Data source : French Population
Decennial Census 2006, INSEE*
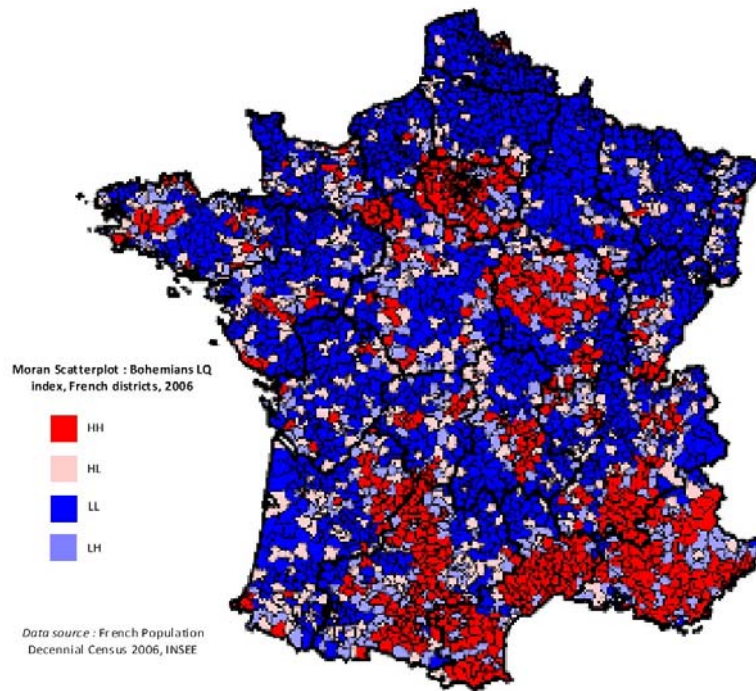
Map A3. Moran scatterplot, Creative core LQ index, French districts, 2006.
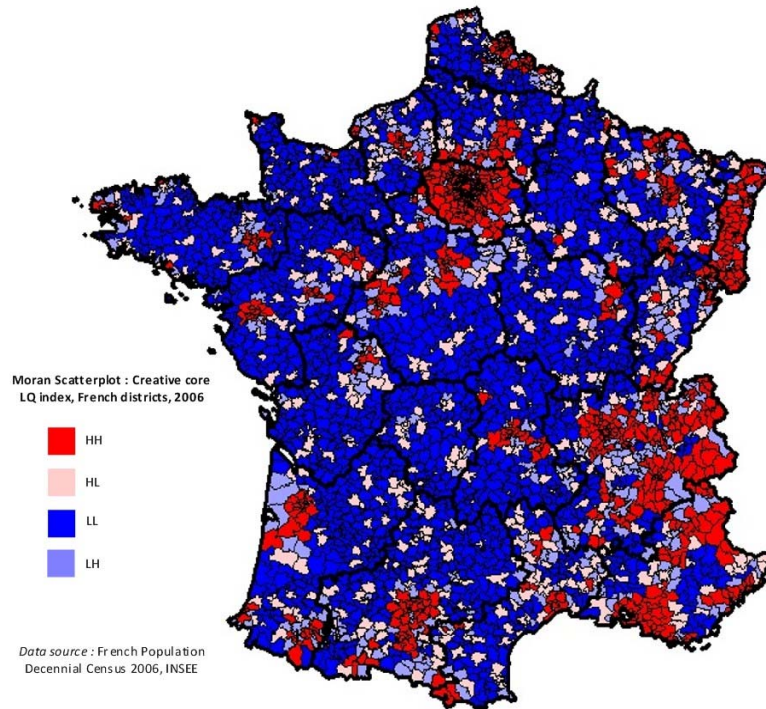
Map A4. LISA, Creative core LQ index, French districts, 2006.
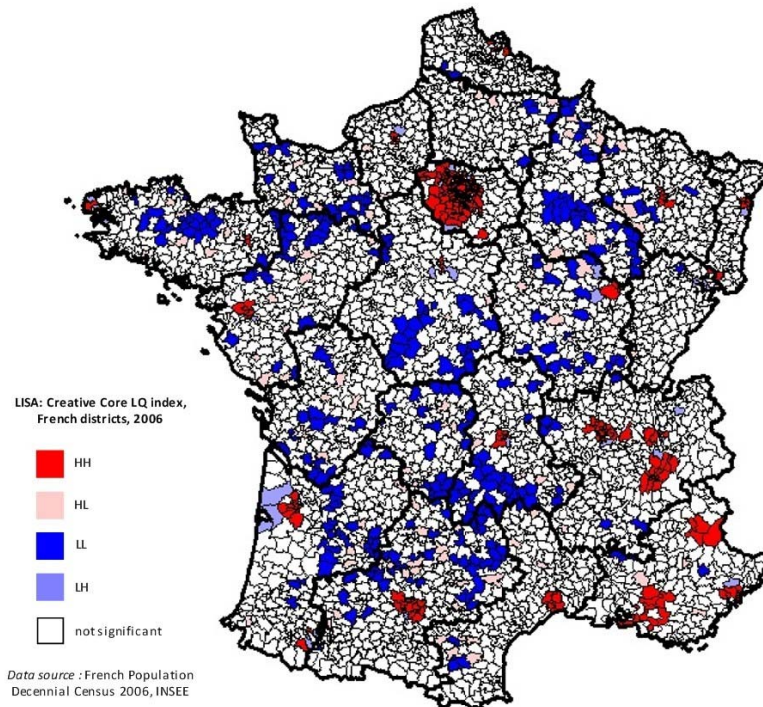
Map A5. Moran scatterplot, Creative professionals LQ index, French districts, 2006

Moran Scatterplot : Creative Professionals LQ index, French districts, 2006

- HH
- HL
- LL
- LH

Data source : French Population Decennial Census 2006, INSEE

Map A6. LISA, Creative professionals LQ index, French districts, 2006

LISA: Creative professionals LQ index, French districts, 2006

- HH
- HL
- LL
- LH
- not significant

Data source : French Population Decennial Census 2006, INSEE
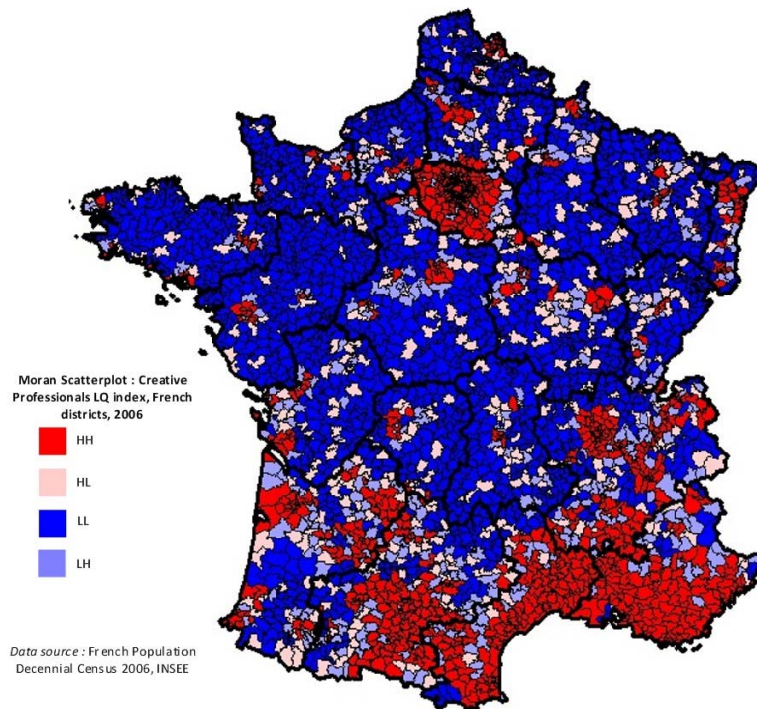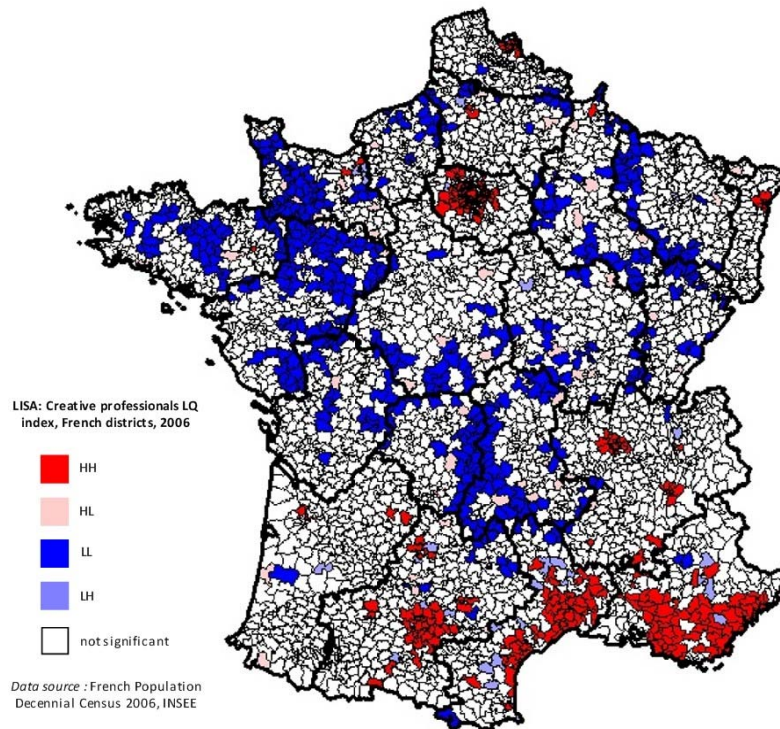
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