Papers in Evolutionary Economic Geography

12.09

Micro-geographies of clusters of creative industries in Europe

Rafael Boix, José Luis Hervás-Oliver and Blanca De Miguel-Molina

Utrecht University
Urban & Regional research centre Utrecht

Micro-geographies of clusters of creative industries in Europe

Rafael Boix[a], José Luis Hervás-Oliver[b] and Blanca De Miguel-Molina[b]

Rafael.boix@uv.es

Abstract. What makes special the geography of the clusters of creative industries (CI)? This paper considers the symbolic knowledge-base and the preference for location in urban spaces observed in those clusters. The study avoids classic research designs based on synthetic knowledge bases and regional-based administrative-constrained design, using instead micro-data (550,000 firms in creative industries) and geo-statistical algorithms. Results contribute to the economic geography by: (i) providing a specific observation of the spatial dimension (where) in the cluster theory; (ii) identifying and mapping the clusters of CI in Europe; (iii) exploring particular forms of agglomeration and co-location (urban and non-urban) followed by clusters of CI. Results present implications for scholars and policy-makers suggesting to stress the articulation of within and between-cluster policy strategies for existing clusters rather than fostering the generation of new clusters.

Keywords: creative industries, clusters, symbolic knowledge, micro-data, geo-localization

JEL: R12, C49, Z0

[a] Departament d'Estructura Econòmica, Facultat d'Economia, Universitat de València (SPAIN). E-mail: rafael.boix@uv.es

[b] Departament d'Organització d'Empreses, Universitat Politecnica de València (SPAIN) E-mail: jose.hervas@omp.upv.es; bdemigu@omp.upv.es.

1. INTRODUCTION

On the basis of a real need – new models of development in the post-industrial societies – a policy of intervention based on the idea of *creativity* and *creative industries* (CI) is being articulated, as well as a theoretical body upholding it. This interest is not strange since recent studies have showed that CI are the most influential causal factor in order to explain the differences in wealth between the European regions (De Miguel et al. 2012) and are highly clustered in the space producing a particular geography (Lazzeretti et al. 2008).

What make special the geography of clusters of CI? From the point of view of the cluster theory (considering as such the integration of the different theories of clusters), the research on clusters of CI faces several key shortcomings and tensions. The first is the existence of clusters with different knowledge bases (Asheim et al. 2011) which call into question the traditional cluster theory (Lorenzen and Frederiksen 2008). The literature has not provided a specific theory on the clusters of CI yet. However, there are enough elements as to know that some of their important components will differ from those of the traditional theories of manufacturing clusters or from those more recent on the high-tech clusters, basically because the knowledge-bases of creative clusters are neither synthetic nor analytic, but symbolic (Asheim et al. 2011), and because the CI have an exaggerate preference for urban environments (Cooke and Lazzeretti 2008). In this chain of thought, three important questions remain unanswered. Can we treat clusters of symbolic base - which are mainly placed at urban spaces - without giving a more relevant role to urbanization economies? Can those clusters of CI be framework using the traditional lenses of the manufacturing synthetic knowledge-base? How can clusters of CI be properly identified and tackled?

Facing these questions forces to deal with other three shortcomings of the cluster theory: first, the spatial scale at what clusters operate and the geographical boundaries of clusters (Boschma and Klosterman 2005); second, an operative methodology of identification able to operate with variable scales in all the European territory and to cover the epistemological aspects of, at least, one of the definitions of cluster (Boschma and Klosterman 2005); and third, the existence of clusters sharing the same geographical space (De Propris et al. 2009).

So far, the empirical evidence realm has covered from the territorial micro-scale (e.g. quartiers, parts of a region) to the macro-scale (e.g. regions, states), but the scale is not neutral here. In particular, and distinctively from manufacturing clusters, the relevant factors for the clustering of CI (basically services with a symbolic knowledge base) are not only localization (specialization) economies but, in great part, old and new types of urbanization economies (Cooke and Lazzeretti 2008; De Prorpis et al. 2009; Lazzeretti et al. 2012). The action of urbanization economies produces patterns of location of service clusters overlapped and sharing the same geographical space, and differing from those of manufacturing and synthetic knowledge base. These patterns cannot be observed using macro-scales and make vita the use of micro-scales in order to capture the specific subtleties of those clusters of CI.

All in all, the cluster literature needs to improve knowledge with new evidence on the patterns of clustering of CI, providing an analytical tool to help in those decisions of policy making that focus on CI. Our paper makes an effort to respond to the claims made by Boschma and Klosterman (2005, p.2-3) about more empirical work, due to the fact that many of the cluster studies "have been based on just one or two case studies, providing insights into particular cases, but lacking any general validity … The comparative studies that have been undertaken to identify clusters also suffer from an empirical undetermination". So far, the empirical evidence available on clusters of CI mainly focuses on isolated cases of study (e.g. Bathelt 2005; De Propris and Hypponen 2008; Krätke 2002) whereas the little general evidence only encompass a few countries (e.g. Lazzeretti et al. 2008; De Propris et al. 2009) or focuses on an excessively aggregated scale such as regions (e.g. Power and Nielsén 2010).

These points challenge a turn towards a more spatial dimension in the cluster theory and empirics. Echoing the criticism of Hoover and Giarratani (1971) on the position of geographers resorted to mere description and mapping but lacked of explanations, Maskell and Kebir (2006) argue that in the construction of a more general theory of clusters the relevant questions are *what*, *how*, and *why*. However, Hoover and Giarratani are indeed criticising the tendency of disciplines to lose contact with one another neglecting the mixture of approaches necessary to solve problems, so that, jointly with geographers: "traditional economists ignored the where question altogether, finding plenty of problems to occupy them without giving any spatial dimension to their analysis". The complete question involves "What is where, and why – and so what?" (Hoover and Giarratani 1971, p.3). Despite the criticism of Maskell and Kebir (2006), the spatial dimension (*where*) is still as valid as any other while it contributes to put into question the previous rationale and to provide incremental elements for a new rationale developed into new propositions and testable hypotheses.

Hence, treating properly the clusters of CI requires changes in the theoretical framework as well as improvements in the empirical methods in order to offer a proper research design which facilitates the identification of the clusters of symbolic base within urban spaces. Obviously, this cannot be done using traditional regional-based administrative-constrained databases which do not envisage the specificities of the urban economies. Therefore, it is necessary to use micro-data at the firm level. This paper fills those gaps and offers an improved conceptual framework and a proper methodological design to explore the clusters of CI in Europe. Our research contributes to the economic geography and, in particular, to the theory and empirics of clusters in the following points:

i. Providing an specific observation of the spatial dimension (*where*);
ii. Identifying and mapping the clusters of CI in 16 European countries departing from firm-level micro-data;
iii. Exploring and detailing the particular forms of agglomeration and co-location followed by clusters of CI within urban and non-urban spaces.

The paper is structured in six parts. After the introduction, the second section provides a review of the literature about CI and clusters. The third and fourth sections focus on the method and data. The fifth section focuses on the micro-geography of clusters of CI and its main characteristics. The paper ends with the conclusion and a discussion about the limits of this approach.

2. CREATIVE INDUSTRIES AND CLUSTERS

2.1. Creative industries

The *creative economy* refers to a holistic concept with complex interactions between culture, economics and technology in an economy dominated by intangible contents like symbols, texts, sounds and images (UNCTAD 2010, p.3). The most popular approaches to the creative economy are those of the *creative industries* (DCMS 2001 and 2009) and the *creative class* (Florida 2002). Whereas the creative class takes the point of view of the human capital, the CI can be assimilated to an industry-based approach. The term *creative industry* (DCA 1994) was popularised by the Department of Culture, Media and Sports in United Kingdom (DCMS 2001) during the British Labour government of Tony Blair, looking for new bases of growth for the UK's postindustrial economy. Reviews of the literature on CI can be found in Howkins (2007), O'Connor (2007), Flew and Cunningham (2010) and UNCTAD (2010).

There are dozens of definitions and taxonomies of CI (O'Connor 2007; UNCTAD 2010). The most commonly used come from the DCMS, although the most comprehensive has been proposed by UNCTAD. UNCTAD (2010, p.8) defines CI as "cycles of creation, production and distribution of goods and services that use creativity and intellectual capital as primary inputs; constitute a set of knowledge-based activities, focused on but not limited to arts, potentially generating revenues from trade and intellectual property rights; comprise tangible products and intangible intellectual or artistic services with creative content, economic value and market objectives; are at the cross-road among the artisan, services and industrial sectors; and constitute a new dynamic sector in the world trade". In addition, UNCTAD classification has the advantage of being the less restrictive as encompasses both cultural and technological dimensions of CI, whereas other taxonomies (e.g. DCMS, WIPO or KEA) are biased towards one of the two dimensions. UNCTAD classification includes both manufacturing and service industries, although the majority of the sectors included in CI are services, especially knowledge-intensive services (Table 1).

This definition remark one of the most relevant characteristic of CI regarding the rest of activities: its knowledge base is not *analytical* (derived from the production and use of codified knowledge that originates from science and technology) or *synthetic* (knowledge is created through a more inductive process of testing, experimentation and practical work), but *symbolic*: knowledge is related to the creation of contents, desires and aesthetic attributes of products. CI is thought mainly to have a *symbolic* knowledge base involving the creation of new realities and artistic or cultural expressions in the form of contents, desires and aesthetic attributes Asheim et al. (2011).

[Insert Table 1 near here]

2.2. Theoretical and operative approaches to the notion of "cluster"

There is an intense discussion in the literature about the notion of *cluster* (Gordon and McCann 2000; Martin and Sunley 2003; Vom Hofe and Chen 2006). Gordon and McCann (2000) distinguish three stylized forms of spatial clustering depending on the dominant or characteristic process in the cluster: *pure agglomeration*, based on geographical proximity and agglomeration economies; *industrial complex*, based on input-output linkages and co-location in order to minimize transactions costs; and *social-network*, based on high levels of embeddedness and social integration. Vom Hofe and Chen (2006) propose another classification based on their methodological identification: clusters à la Marshall, clusters based on inter-industry relationships, and Porter's (1998) clusters.

Martin and Sunley (2003 p.19) remark that the vagueness of the concept does not lend to easy or precise delimitation, so that "there is no agreed method for identifying and mapping clusters, either in terms of the key variables that should be measured or the procedures by which the geographical boundaries of clusters should be determined". Among the several problems that usually arise in the empirical delimitation of clusters, there are the identification of the cluster core industries, the lack of inter-industry trade data for sub-national geographical areas, the collection of data on the basis of pre-given administrative and political units, the difficulties to identify the geographical boundaries of the clusters, the selection of data (employment, firms, added value, productivity) and the arbitrariness of the rules to distinguish clusters.

The literature exhibits a wide range of methods to identify industrial clusters depending on the type of cluster and data availability (Bergman and Feser 1999; Vom Hofe and Chen 2006): path dependency, expert opinion (Delphi, MSQA), a critical mass of firms in a region of the same or complementary sectors, concentration indexes (location quotients, Gini indexes, Ellison-Glaeser measures), input-output (triangularization; cluster, factor and principal components analysis), and network analysis. Combinations of several procedures are possible in a multidimensional perspective (Brachert et al. 2011).

Feser and Sweeney (2002) propose to extend the range of methodologies to incorporate spatial statistics, which offers not only a method to complement previous methodologies (Vom Hofe and Chen 2006) but also, when combined with the each time more detailed databases, a new and promising way when the spatial dimension of the cluster is the most relevant. Spatial statistics distinguish between discrete and continuous space, and global versus local indicators derived from first and second order statistics (Feser and Sweeney 2002; Jacquez 2008). Global indicators give information about the general trends of clustering whereas local indicators provide information about where are the clusters and their spatial boundaries.

2.3. A review of earlier research on spatial clustering of creative industries

Most of the studies on clusters of creative studies have focused on cases of study of a creative industry and/or a creative place. They have used different methodologies (description of the case, value chains, social network analysis) and encompassed the three types of clusters described by Gordon and McCann (2000). To give only some examples, the *complex* approach is used for the film industry in Hollywood by Scott (2002) and De Propris and Hypponen (2008), and in Potsdam/Babelsberg by Krätke (2002). The *social network* approach is found in Bahtelt (2005) for the media industry in Leipzig, and Lazzeretti et al. (2011) for the restoration and museum cluster in Florence. The *pure agglomeration* cluster approach is used by Turok (2003) for the TV and film industry in Scotland, DCITA (2002) for a set of creative and digital industries in Australia, and Pratt (2011) for a set of CI in London. In other geographical scales, the general mapping exercises have relied basically on the use of location quotients. For example, Florida and Mellander (2008) research on the clustering of music industry in USA regions, Campbell-Kelly et al. (2010) for the software industry in the metropolitan areas of the USA, Power and Nielsén (2010) for cultural and CI in the European regions, Capone (2008) for the CI in the local labour markets of Italy, Lazzeretti et al. (2008) for the CI in the local labour markets of Spain and Italy, and De Propris et al. (2009) for the CI in the UK local labour markets and Super Output areas.

A different question relies on the reasons for the clustering of CI. O'Sullivan (2007) remarks that the main causes of clustering are related to traditional localization and urbanization economies: sharing of common labour pool, labour matching, knowledge spillovers, pooling of workers, sharing information, intermediate goods and access to the demand. CI are in great part business services, and Keeble and Nachum (2002) remark that the clustering of business services in large cities like London is determined by the access to localized and relatively immobile tacit knowledge and knowledge spillovers, collective learning (networking, collaboration and skilled labour flows), accessibility to global networks, clients and knowledge, and accessibility to the local knowledge base. Malmberg and Maskell (2002) theory of spatial clustering could be also used as a point of departure, although the specificities of the CI knowledge base (symbolic) ask for a more specific approach. Lorenzen and Frederiksen (2008) integrate external agglomeration economies (localization and urbanization) with cultural factors and the creative class, arriving to the conclusion that clustering of cultural industries depends on the coexistence of localization and urbanization economies. The estimates of Lazzeretti et al. (2012) highlight the urbanization economies as the most important factor to explain the patterns of clustering of CI.

2.4. Patterns of location and co-location of clusters of creative industries

One of the most neglected aspects in the literature of clusters has been the spatial patterns of location and co-location of clusters sharing a same geographical space. This is not particularly surprising, as in the Porter's thought the focus of the analysis has been the organization of the value chain whereas the spatial dimension was actually secondary. This is due to the fact that "a cluster is a spatial concept in which a-spatial processes play a prominent role" (Boschma and Klosterman 2005, p.2). Thus, the profusion of cases of study in the cluster literature have not paid, in general, any attention to the existence of other clusters closer or sharing the same geographical space. In addition, general cluster mappings have focused on some particular industry (e.g. automotive, chemicals) or involved methodologies in which the selection of an industry as representative of the place prevented from the study of other locally clustered industries (e.g. the ISTAT procedure for the identification of industrial districts in Becattini et al. 2009). Later on, most of the literature has focused on manufacturing clusters, many times located in small and medium places, small in excess to hold more than one relevant specialization. This give place to spatial formations of clusters in isolation that we name *hot spots*, and sets of clusters with similar or different specializations in close proximity (but not overlapped) forming *bunches* of clusters (figure 1).

The reality of CI is different enough in, at least, three points. First, CI are basically advanced services. Second, advanced services have a preference for location in large places such as big cities and metropolitan areas. Third, this preference cannot be explained by localization economies and, as remarked by Lorenzen and Frederiksen

(2008) and Lazzeretti et al. (2012), urbanization economies are crucial to explain the formation, growth and competitiveness of clusters of CI. The urban space is expensive and density is a consequence of the high land rents, forcing to different types of activities to share the land. Co-location provides cross-fertilization urbanization economies (Jacobs 1969), opportunities for related varieties (Boschma and Frenken 2011), buzz (Storper and Venables 2004), and access to collective learning and shared knowledge resources (Keeble and Nachum 2002). As a result, clusters of different advanced industries, such as the CI, can overlap on the same geographical space. When urbanization economies are particularly focused on a single point of the city, then we found clusters of different activities and with different spatial thresholds organized around this point in the form of a *hub* (Figure 1). This is frequent in medium cities where the size and the urban form have not allowed the expansion of urbanization economies to other less central spaces. In large cities, the dynamic of land rents make impossible to maintain the concentration in a single point, the city becomes multicentric and urbanization economies arise in many points of the city. In this case, clusters of the same activity can be found in different parts of the city, partially overlapping with clusters of different activities and taking the form of a *cloud* of clusters (Figure 1). This shape is propitious for the formation of synergies and complementarities between the multiple clusters that share the urban space. *Hubs* and *clouds* are probably revealing the existence of creative *milieux*.

It is not strange that the literature on CI begins to be aware of co-location, for example in De Propris et al. (2009) and Mommaas (2004). Camors and Soulard (2010) and Freeman (2010) suggest that there are not one but several clusters of the same or different CI in Paris and London. Pratt (2011, p.132) is able to find evidence of a cluster *cloud* in London when he change the scale of the analysis and look for the micro-geographies of micro clusters detailing the analysis industry by industry: "… in London at least, I argued that analytically there are multiple and overlapping media industries clusters. Moreover, and this is important, the nature of overlap, or interaction, produces a second level of interaction that needs to be analysed. In a very simplistic sense this is the 'spillover'. However, the use of this term in normative literature does not touch upon the complexities of social, cultural, political and economic hybridisations that take place and are constitutive (not simply contextual) of the media industries clusters."

[Insert Figure 1 near here]

3. METHODOLOGY

3.1. Methodological approach

The methodology we propose to map clusters of creative industries shows some parallelisms with the stages followed by Crouch and Farrell (2001) for the general identification of clusters and Capone (2008) for the identification of creative local systems: first, an operative notion of cluster is defined. Second, a list of CI is proposed. Third, the basic observation is the firm; firms' data are extracted, treated and geo-codified. Fourth, a geo-statistical algorithm is selected (in this case the spatial nearest neighbour hierarchical clustering or NNHC), and the procedure runs on each creative industry separately.

The first issue is the operationalization of the notion of cluster of CI. Two considerations are made here. First, the ideal models of cluster described by Gordon and McCann (2000) have been used in empirical research on clusters of CI and no one has proved to be superior to the others. With independence of the approach, the only common characteristic of CI clusters has proved to be the spatial agglomeration. In addition, data to measure *pure agglomeration* clusters are less exigent than those to measure *complexes* and *social networks*. For this raison, we propose an incremental work departing here from the more modest approach (agglomeration) and to enhance the research to the other types of clusters in later studies (e.g. using DCMS/Frontier Economic operative chains). Second, we can differentiate between *creative clusters* – defined as a blind aggregation of all the types of CI - and *clusters of creative industries* – where each type of creative industry is considered separately from the rest. One of the conclusions of the previous section is that the patterns of location of CI are not homogeneous or exhibit differentiated geographies so that that the blind aggregation is probably closer to the idea of *creative place* than to that of cluster. As exposed by Pratt (2011) the micro-geographies of the CI and their rich patterns of co-location are only revealed by a differentiated treatment of each creative industry. These arguments suggest to identify the clusters industry by industry. Following Schmitz and Nadvi (1999, p.1503) we define clusters as “sectoral and spatial concentrations of firms”.

The second issue is the selection of the list of CI, where not only accuracy but also comparability is necessary. We follow the UNCTAD (2010) definition (Table 1) because is the most comprehensive. Each industry is considered separately as the objective is to distinguish clusters of CI and not creative places[c].

The third issue is the selection of the observations and type of data. Until now, research on clusters of CI in Europe is affected by two constraints. First, regions are too big to provide an appropriate detailed geography of the clusters of CI. The problems come from the average effects of regional units (ecological fallacy), the possibility that several clusters of the same creative industry exists in the same region, the heterogeneity in the definition of NUTS 2 (some are small whereas others are huge) (Hautdidier 2011), and the incapacity to provide the real location and boundaries of the clusters. In addition, it is impossible to detect cross-regional and cross-national clusters (Crawley and Pickernell 2012). An example is Power and Nielsén (2010) where the authors use NUTS 2 and a location quotient, which is the most extended methodology to deal with cluster identification at a regional level. A second constraint has arisen when the strategy has been the collection of data at infra-regional administrative levels (e.g. municipalities and local labour markets). Eurostat does not centralize this information and the only option is to collect it from the national statistical offices, which is difficult, slow and costly. For these reasons, and following previous research on location of the activity (Feser and Sweeney 2002; Combes and Overman 2004; Duranton and Overman 2005) we use micro-geographic data for cluster identification. This type of data permits the use of geo-statistics in continuous space, particularly *hot*

[c] Two of the industries included in UNCTAD (2010) definition are not strictly symbolic: engineering (synthetic base) and R&D (analytical base). Since the methodology treats each cluster individually, we conserved the UNCTAD list separating engineering from architecture. The difference of including or not engineering and R&D is basically a reduction in the number of clusters although the conclusions do not change.

spot techniques, which allow to define concentration (agglomeration) on the basis of the density of firms in the space.

3.2. Spatial nearest neighbour hierarchical clustering (NNHC)

Justification for the selection of the algorithm

There are dozens of hot spots techniques, grouped in six typologies (NIJ 2004): point locations (total number of cases, e.g. fuzzy mode), hierarchical (grouping hierarchically the cases, e.g. nearest neighbour methods), partitioning (partitioning the sample in groups, e.g. spatial k-means), clumping (partitioning techniques with overlapping), density (density of cases, e.g. kernel methods), and risk-based (weighting by a risk variable such as population, e.g. Kulldorff scan).

The different techniques have different uses and solutions. The NNHC was selected due to some properties we found more advantageous than other methods: first, it works well with a very large number of observations in a continuous space. Second, it does not need to reduce the space to grids, such as for example kernel techniques, so that avoids the selection of the size of grids (Sweeney and Feser 2003). Third, it is possible to select a threshold random distance for the firms in the cluster (so that avoids to set it manually) or to provide this distance on the basis of economic or relational criteria. Fourth, it does not need to assume any shape for the search radius such as in the scan methods; it can detect large and small clusters, even inside cities. Fourth, it is possible to obtain the enveloping shape of the cluster. In addition, the NNHC also offers the possibility of taking into account the localization of firms in the rest of industries (non-

CI) if needed, in the way of typical specialization indexes (risk-adjusted NNHC). However, as we are looking for pure agglomeration, it is more consistent to consider only the pure density of firms in the targeted industry as the continuous space is already acting as a corrective base for the index, this is, is a pure spatial concentration index.

The output meets most of the desirable qualities for spatial concentration measurement proposed by Combes and Overman (2004): it is comparable across activities and spatial scales, proves to be reasonably robust to the existence of a deterministic component, the significance of results can be controlled, is not sensitive to changes in the administrative boundaries, is reasonably unbiased respect to changes in the industrial classification (firm level data reports old and new NACE classifications), and can be confronted with theoretical considerations. Some of these aspects also depend on the choices we do during the application of the methodology.

Algorithm

The spatial nearest neighbour hierarchical clustering (NNHC) (NIJ 2004) departs from the matrix of distances d_{AB} between all the pair of points. The second step is the selection of a threshold distance t_{AB} below which a pair of points could be considered as clustered. Those pairs of points where $d_{AB}<t_{AB}$ forms the random distance matrix d'_{AB}. Next, for each point the pairs of distances d'_{AB} are sorted in a descending order. The point with the largest number of threshold distances (most connected point) is selected for the initial seed of the first cluster and those points within the threshold distance of the initial seed are included in the first cluster. We can fix the condition of a minimum number of points in the cluster (size criterion) ranging from 2 to N; in our case we

consider a minimum of 50 firms to consider the cluster as significant[d]. If the cluster satisfies the criterion of size then it is kept and we proceed with the next most connected point don't included in a previous cluster until all the selectable points have been assigned to a cluster or discarded (Figure 2).

At the end of the procedure, a convex hull (an irregular polygon) can be calculated for each cluster as the enveloping line to the points of the cluster, so that we can also know basic features such as the area of the cluster.

[Insert Figure 2 near here]

Selection of the distance

It is possible to manually select the distance threshold, although there is not an agreement about the distance radius in clusters. For example, Fundenburg and Boarnet (2008) found an average of 5-7.5 miles in their study of manufacturing clusters in Southern California, Feser and Sweeney (2002) a distance of 26 kilometres for manufacturing industries in San Francisco Bay area, and May et al. (2001) a range up to fifty miles for the British high-fidelity industry. Rosenthal and Strange (2004) argue that the spatial range of agglomeration economies is small for localization economies in agglomerated industries, falling up to 15 miles, whereas for urbanization economies it could extend hundreds of miles.

[d] This number introduces certain arbitrariness since there is not any rule about what is the minimum number of firms in a cluster. The trials to introduce an automatic criterion based on *knee* techniques suggested a number of firms about 0.025% of the sample. However, the results are not very different from the fixed value and the absolute value makes more homogenous the comparison between industries.

An option to avoid the problem is to select as a threshold the random distance to the nearest neighbours that is based on the probability of selecting any pair of points on the basis of a random distribution. Most of the software packages (e.g. ArcGis, Crimestat) compute the mean random distance to the first neighbour ($0.5\sqrt{A/N}$) because it is easy to relate on a confidence interval defined for a specific one-tailed probability and to compare it with Student *t* tables. However, the hypothesis that firms are related only with the nearest single firm in the cluster is unreal and we should select a number of *n* nearest neighbours with which a firm could be linked.

As the high-order pairs are correlated, it is not possible a priori to fix a level of statistical significance and calculating the radius departing from this level for more than the fourth neighbour (Aplin 1983). Several solutions have been suggested in the literature (see Dixon 2006 for a synthesis), none of them definitive: Kolmogorov-Smirnov type statistics using Monte-Carlo tests, squared distances, graphical methods, and the use of auxiliary functions like Rypley's K.

We propose a two-steps method, based in the previous calculation of the distance to the K-order nearest neighbour (NJI 2004) and then using this distance in the algorithm. As we fixed the minimum number of firms in a cluster in 50, we calculated the mean real distance $d(K_{NN})$ and the mean random distance $d(K_{ran})$ for an order of 50 neighbours ($d(K_{ran}) = (K(2K)!)/((2^k K!)^2 \sqrt{N/A})$) and then calculated the Nearest Neighbour Index as $NNI = d(K_{NN})/d(K_{ran})$. For each point, the NNI compares the average distance from the closest neighbour with a distance that is based on chance. In practice, the NNI index increases fast for the first neighbours (indicating than the interaction decreases at each step) and then becomes more stable (indicating that additional neighbours have a reduced impact). The point of inflexion indicates the possible boundaries of the cluster. An example advanced from the results is in Figure 3.

In previous simulations, we compared the results of the point of inflexion with those for the first and the 50th neighbour. The former produces a large number of extremely small microclusters (in our trials, of a radius of 1 to 2 kilometres) whereas the latter tends to merge medium-sized clusters that are independent to produce macro-clusters. The inflexion point produces the most satisfactory results. This also points out that, in general, there is not a unique solution and the distance for clustering depends on the scope of the research.

This procedure has the advantage that we obtain a distance for each creative industry and that we can examine the spatial patterns in order to detect anomalies. The main disadvantage is that we cannot establish with detail the statistical significance of the probability of clustering. We only know that if the NNI is below 1 then the observed average distance is smaller than the mean random distance and this provide evidence of non-random clustering. The lower is the NNI index, the higher the robustness of clustering patterns.

[Insert Figure 3 near here]

4. DATA

Micro-geographic data used in the research comes from Amadeus database (Bureau van Dijk). Amadeus provides data for all the EU countries, detailed by postal address, and four digits NACE Rev 2. Whereas several years ago the number of registers included in the database was clearly insufficient, at this moment the number of firms and the significance of the sample is good enough to be used in geo-statistical algorithms[e].

The data covers 966,000 firms in the UNCTAD (2010) list of CI (Table 1) in the EU 27 during the period 2001 to 2009. The postal address of the firm was translated to geographic coordinates which are used by the geostatistical algorithms. There was only good cartography available at a postal address for 16 countries, so that the mapping only includes Austria, Belgium, Cyprus, Denmark, Finland, France, Germany, Greece, Italy, Luxembourg, Malta, Netherlands, Portugal, Spain, Sweden and the UK. The initial sample for these countries was 780,000 creative firms. We decided to focus on the more recent year available, so that the data were treated and only 554,603 firms active in the year 2009 were included.

The NNHC can deal with jobs or establishments, although the latter is more usual in this type of research (Sweeney and Feser 2003). Lazzeretti et al. (2008) and Clifton and Cooke (2009) provide arguments favourable to the use of jobs, whereas De Propris et al. (2009) use the number of establishments. However, the information about the number of employees by firm is poor and irregular in Amadeus and the average firm size in CI

[e] A precedent in the use of Amadeus in studies on the cultural sector in Europe is KEA (2006).

is small (less than 5 workers). For this raison we use the firm as basic observation for the procedure.

Eurostat Structural Business Statistics (SBS) is used as a proxy to provide a basic control on the quality of the sample (Table 2). Amadeus/Eurostat ratio ranges from a minimum of 13.4% in design and photography to a maximum of 130% in broadcasting. The average is 34.7%, which is slightly lower than, for example, Feser and Sweeney (2002) sample. In any case, it is a substantial sample size; the sampling error considering $P(-Z<z<Z)=0.99$ stays below 0.75% for all the industries and is less than 0.2% for the sample as a whole. The controls by country don't give evidence of problems of over or undervaluation, with the exception of Greece and Malta, where the sample is poor.

The database has some other limitations. The coverage of Amadeus for firms behind 20 employees is irregular, which is particularly significant as the average firm size in CI is small. In addition, in CI it is usual to find freelancers, so that there are an undetermined number of freelance workers who do not show up as individual firms in business databases (neither in Amadeus nor in Eurostat SBS). These biases are impossible to control at this moment for the entire sample of countries.

[Insert Table 2 near here]

5. MICRO-GEOGRAPHIES OF CLUSTERS OF CREATIVE INDUSTRIES IN EUROPE

5.1. General patterns of clustering of creative industries

The algorithm generates a map of pure agglomeration clusters for each creative industry, producing a detailed geography of creative clusters in Europe that is independent of geographical boundaries (Figure 4a). The number of neighbours for the calculation of the radius varies from 3 (research and development) to 13 (engineering), and the mean and median is about 7. The mean random distance ranges from 8.4 (advertising) to 34 kilometres (design) and the average is 16.5 kilometres, which is not very different from Fundenburg and Boarnet (2008) or Rosenthal and Strange (2004).

CI are highly clustered in Europe. We identified 1,784 clusters across 15 CI. About 61% of the firms of the sample were located in these clusters (Table 3 and Figure 4a). The average number of clusters by industry is 119, ranging from 10 (heritage) to 358 (engineering) (Table 3).

Patterns of clustering are not homogeneous among CI. The most clustered industries are film, video and music; software, cultural trade, engineering, videogames, design, and architecture, in which more than 60% of the firms are in clusters (Table 3). Only in Photography, R&D and Heritage more than 50% of the firms are not in clusters.

The localization of clusters is also different among industries. For example, whereas fashion clusters tend to be concentrated in Mediterranean countries, software clusters are more dispersed and particularly important in the south of England, north of France, west part of Germany and the Benelux (Figure 5a).

[Insert Table 3 near here]

[Insert Figure 4 near here]

[Insert Figure 5 near here]

5.2. Geographies and scales

Even if creative clusters are distributed across all the European territory, there are great concentrations covering large areas such as the *South of England* (e.g. New Hampshire host 44 clusters, Inner London 24, Kent 21, Outer London 19, North and North East Somerset/South Gloucestershire 19, Essex 18), the Benelux (e.g. Brussels host 22 clusters, Groot Amsterdam 19, Groot-Rijnmond 18), and Île de France (Paris host 14 clusters) (Figure 4a). Other regions, most of them containing medium and large cities, host more than 14 clusters (Bouches-du-Rhône, Madrid, Greater Manchester South, Milano, Utrecht, Köln, Kreisfreie Stadt, Nord, Zuid-Limburg, Berlin, Grande Porto, Hertfordshire, Rhône, Barcelona, Birmingham, Calderdale, Kirklees and Wakefield, and Glasgow City).

Clusters are not limited by administrative borders. Cross-country clusters are detected across France and Belgium, France and Germany, Belgium and Nederland, Germany and Nederland, Germany and Belgium, Germany and Luxembourg, and Sweden and Denmark, as well as dozens of cross-regional clusters and more than one hundred of clusters shared between metropolitan areas (Figure 4a).

Clusters are predominantly metropolitan. About 77% are located in metropolitan areas (here represented by Eurostat's Large Urban Zones) (Figure 4a and Table 3). The largest clusters are located in the central part of the largest European cities. If we consider for simplicity those clusters of more than 1,000 firms in the sample, Paris and London host 11 large clusters each one; Madrid and Stockholm host 5 large clusters; Berlin, Brussels, Lisbon and Munich host 3 large clusters; Barcelona, Helsinki, Milan and Roma host two large clusters; and Copenhagen and Goteborg host 1 large cluster each one. The only large cluster none located in a LUZ is the fashion cluster of Guimaraes in the north of Portugal.

The patterns of distribution industry-city are varied. To give only two examples, in Paris, clusters of research and development, radio and TV, and videogames are located only in the central city whereas in London they are also distributed in other places of the metropolitan area. Fashion shows a central location in Paris and London whereas in Barcelona is also located in those subcentres that were textile centres in the XIXth century.

5.3. Co-location and articulation versus isolation

CI clusters, particularly the largest ones, tend to share the space with other clusters of the same or different CI (Figures 6 and 7). Thus, creative cities are made of a great number of creative clusters overlapped, which, according to the Figures 3 and 6, nourish with a complex range of localization economies and related variety externalities internal to the place, as well as other external economies arising from synergic and complementary networks between neighbour clusters.

We found evidence of the four types of patterns described in the section 2. *Hot spots* and *bunches* are usual in non-metropolitan areas, *hubs* are found in medium-large metropolitan areas, and *clouds* are basically observed in the largest metropolitan areas. The figure 7 provides an example: in London and Paris the clusters are distributed in the central city and in the subcentres forming a dense *cloud*. In Barcelona, most of the clusters are concentrated in the central city forming a hub whereas in the Emilia-Romagna we can observe a hub focused on Bologna and a bunch of small clusters.

We detected 34 complex groupings of clusters forming *clouds*, 145 *hubs* encompassing between two and ten clusters and 22 *bunches*. These three categories encompass 93% of the clusters, and only 7% of the clusters were isolated forming *hot spots* (130 clusters). However, the application of these ideal categories has been difficult in some cases where clouds, hubs and hot spots combined or overlapped forming more complex structures, for example in the Netherland or in the London area.

[Insert Figure 6 near here]

[Insert Figure 7 near here]

5.4. A comparison between NNHC-microdata and LQ-region methodologies

We compared the results of the NNHC algorithm with those obtained using a traditional methodology based on regions (NUTS 2) and location quotients[f].

The map using microdata and NNHC (Figure 4a) shows a precise and detailed geography of CI in Europe: the clusters are located with precision (exact boundaries of the cluster versus the centroid of the region's polygon), and the reality is not reduced to a point by region and industry. The map using NUTS 2 and LQ (Figure 4b) is subject to several problems related to the modifiable areal unit problem (MAUF): it is unable to found more than a point by industry and region, it cannot indicate in what part of the region is really located each cluster, it emphasizes the relevance of countries with smaller regions, and cannot found some clusters if the share of the industry in the region is not large enough to be remarked by the location quotient. As a consequence, the number of clusters identified by the NNHC algorithm (1,784) is 2.3 times larger than by the LQ methodology (774), even if the share of CI firms in clusters is quite similar in both cases (61% in the NNHC and 63% in the LQ methodology). In addition, we can observe than the spatial patterns revealing groups of clusters differ in both figures.

[f] The location quotient is defined as LQ = /Lij/Li)/(Lj/L) where Lij is the number of jobs or firms in the industry i in a region j, Li is the total number of jobs or firms in the industry i in the EU regions, Lj is the number of jobs or firms in a region j, and L is the total number jobs or firms in EU regions. If the LQ is more than 1 the region is more specialized in an industry than the European average so that we conclude that the industry is clustered. This indicator is also used by Lazzeretti et al. (2008) and De Propris et al. (2009) although in this case the territorial unit is the local labour market.

The differences are even more evident industry by industry. The figure 5 provides the detail for fashion and software industries. The LQ methodology with regional data identifies the importance of fashion in Italy and the north of Portugal but produces imprecise information about the spatial patterns as only finds 18 clusters. The NNHC algorithm with microdata identifies 102 clusters, their position, size and distribution, and succeeds in identifying important clusters in the east coast of Spain, the north of Italy and Paris, as well as other clusters non detected by the other methodology. For the software industry, the LQ methodology identifies 102 clusters but only highlights important patterns of clustering in Germany, the Benelux and the south of England. The NNHC algorithm identifies 313 clusters, revealing also important groups of clusters in many other countries.

6. CONCLUSIONS

When we have looked at the existing research on the location of clusters of CI in Europe we have found large voids. These gaps encompass complex open questions which challenge whether clusters of CI constitute an object of analysis different from the traditional manufacturing clusters, whether clusters of CI can be tackled without stressing the role of old and new kinds of urbanization economies, and how can clusters of CI be identified in order to answer other basic but relevant questions such as how many clusters of CI are in Europe and where they are really located. Consequently, this study has addressed clusters of CI as symbolic knowledge-based, overcoming traditional methodological approaches of manufacturing clusters - in which the importance of the spatial dimension (*where*) and urbanization economies in the construction of a more general theory of clusters has been usually constrained -, and proposing a method for a fine-grained identification of clusters of CI in vast territorial areas.

It is found that the symbolic nature of knowledge in CI makes the clustering process highly sensitive to the geographical distance, intensive in the use of old and new urbanization economies and presumes different placements and boundaries for clusters. Under these conditions, the conclusions based on one or two cases of studies (e.g. Bathelt 2005; De Propris and Hypponen 2008; Krätke 2002) can lack general validity and have problems to deal with co-location, whereas those based on large administrative units (e.g. Power and Nielsén 2010) sacrifice precision and suffer from aggregation bias and the modifiable areal unit problem. The paper has challenged how to conciliate the necessity of working with the precision of micro-scales and the coverage of macro-scales without imposing restrictions to the scale at what clusters operate, as well as with the necessity of dealing with flexible and differentiated patterns of co-location. The turn towards a more spatial dimension has made necessary a theoretical reflection about the interrelation between clusters agglomerated in proximity and the introduction of categories for the analysis of co-location.

Synthesizing the findings in an aggregate fashion, we found that there were a large number of clusters of CI in Europe (1,784 clusters across 16 countries and 15 CI), concentrating 61% of the creative firms, having an exaggerated preference for metropolitan areas and co-locating with other clusters of similar and different CI. The findings about the relative concentration of firms and the preference of clusters of CI for metropolitan areas, and in particular for the central part of the largest cities, are indeed in line with other studies (Lazzeretti et al. 2008; Power and Nielsén 2010; Pratt 2011).

The number of clusters identified is 2.3 times larger than using traditional methods and units, such as location quotients and regions. However, the most relevant finding relies on the patterns of co-location: most of the clusters (93%) are not isolated but co-located with other clusters of CI, which can be attributed to the relevance of urbanization economies and the requirements of density of urban spaces. Most of the studies on clusters of CI have not succeeded into observe this fact, being a rare exception Pratt (2011). *Hot spots* and *bunches* have been found to be more frequent in non-metropolitan areas, *hubs* in medium and large cities, and *clouds* in the largest cities. This finding refines the underlying theory introducing as a factor of birth and success of clusters, and of creation/location of firms in CI, the existence of other clusters in similar or related CI.

The design and findings of the study have implications for scholars. First, clusters of creative industries (symbolic base) are different from manufacturing clusters and other services clusters (synthetic and analytical bases) which suggest that at least incremental changes are necessary into the cluster theory. Second, we claim for a refinement in the empirics of clusters towards more scale-flexible and precise procedures of identification in wide-coverage studies, moving towards the micro-perspective to avoid the constraints of administrative and region-based units.

The differentiated nature of clusters of CI means that probably a customized approach will be necessary in the design of policy strategies. First, it is difficult to imagine how many policy strategies are based on vague definitions of clusters at a macro-scale whereas, on the other hand, many other agents are not aware of the existence of these clusters in their space. At a European scale, it seems difficult to elaborate efficient policy strategies without a detailed and comprehensive identification of these clusters and the linkages between them. Understanding how many possible clusters exist, where they are located, and their characteristics, is an effective way to target policies towards specific objectives. Second, one of the most criticised aspects in the implementation of the cluster policy is a sort of generalized obsession for the, usually unsuccessful, creation of new clusters. On the contrary, our findings show that, regarding CI, in most of the places the priority wouldn't be the generation of clusters of CI but the articulation of policy strategies encompassing those clusters that already exist. Third, if clusters of CI are not isolated, collocation should be taken as a relevant dimension in research and in policy-making. The distribution of clusters, their diversity (hot spots, bunches, hubs and clouds) and the differences between CI, suggest to advance towards strategies to support not only the clusters but also the linkages between clusters. The objective is not only to take advantage from specialization but also from the cross-linkages between clusters and the related varieties when the clusters share the same geographical and relational space. The existence of neighbour or close clusters suggests opening and developing strategies based on networks of synergy and complementarity between clusters.

The study has some important limitations. The most evident is the use of horizontal chains as a simplifier option. This limitation can be relaxed as it is possible to incorporate vertical chains from other studies or from European input-output tables. A second limitation is the use of a sample of firms more than the entire population due to the coverage of the database. A latter limitation is that the procedure is time-static, although the availability of more years in the sample makes possible to incorporate short-medium time dynamics into the procedure. As a counterpart, the simplicity of the procedure (even after improvements) makes possible the replication to other economic areas such as the United States, Asia-Pacific or Latin America.

The results open possibilities for comparative research, new insights into the cluster theory, and further detailed research on the factors of location of CI in clusters and the factors that determine the apparition and evolution of clusters of symbolic base in the space. In addition, the results can be completed with a geography of clusters in non-creative industries and the subsequent comparison between the patterns of clustering of both kind of industries as well as complementarities or crowding-out effects in the patterns of co-location between creative and non-creative industries.

FUNDING

This work was supported by the Spanish Ministry of Science and [ECO2010-17318 MICINN Project].

REFERENCES

Aplin, G. (1983) *Order-neighbour analysis*. Catmog 36. Norwich: Geo Books

Asheim, B.T., Boschma, R., Cooke P. (2011) Constructing regional advantage: Platform policies based on related variety and differentiated knowledge bases, *Regional Studies*, 45 (7): 893-904

Bahtelt, H. (2005) Cluster Relations in the Media Industry: Exploring the 'Distanced Neighbour' Paradox in Leipzig, *Regional Studies* 39(1): 105-127

Becattini, G., Bellandi, M., De Propris, L. (2009) *A handbook of industrial districts*. Cheltelham: Edward Elgar

Bergman, E., Feser, E. (1999) *Industrial and Regional Clusters: Concepts and Comparative Applications*. West Virginia University

Brachert, M., Titzel, M., Kubis, A. (2011) Identifying industrial clusters from a multidimensional perspective: Methodical aspects with an application to Germany, *Papers in Regional Science*, doi:10.1111/j.1435-5957.2011.00356.x

Boschma, R.A., Klosterman, R.C. (2005) Clustering, learning and regional development, in Boschma, R.A., Klosterman, R.C. (Ed) *Learning from Clusters A Critical Assessment from an Economic-Geographical Perspective*, p.1-15. Dordrecht: Springer.

Boschma, R.A., Frenken, K. (2011) The emerging empirics of evolutionary economic geography, *Journal of Economic Geography* 11(2): 295–307

Camors, C., Soulard, O. (2010) *Les industries créatives en Île-de-France*. Paris: IAU

Campbell-Kelly, M., Danilevsky, M., Garcia-Swartz, D.D., Pederson, S. (2010) Clustering in the Creative Industries: Insights from the Origins of Computer Software, *Industry & Innovation* 17(3): 309-329

Capone, F. (2008) Mapping and analysing creative systems in Italy, in Cooke, P., Lazzeretti, L. (Eds.) *Creative Cities, Cultural Clusters and Local Economic Development*, p. 237-257. Cheltenham: Edward Elgar.

Clifton, N., Cooke, P. (2009) Creative knowledge workers and location in Europe and North America: a comparative review, *Creative Industries Journal* 2(1): 73–89

Combes, P.P., Overman, H. (2004) The Spatial Distribution of Economic Activities in the European Union in Henderson, V., Thisse, J.F. (Ed) *Handbook or Regional and Urban Economics* vol. 4, p. 2846- 2909. North Holland: Elsevier

Cooke, P., Lazzeretti, L. (2008) *Creative cities, cultural clusters and local economic development*. Cheltenham: Edward Elgar

Crouch, C., Farrell, H. (2001) Great Britain: Falling through the holes in the network concept, in Crouch, C., Le Galles, P., Trigilia, C., Voelzcow, H. *Local productions systems in Europe: Rise or demise?*, p.154-211. New York: Oxford University Press

Crawley, A., Pickernell, D. (2012) An appraisal of the European Cluster Observatory, *European Urban and Regional Studies*, 19(2): 207-211

DCITA (2002) *Creative industries cluster study: Stage one report*. Canberra: National Office for the Information Economy

DCMS (2001) *Creative Industries Mapping Document 2001*. London: DCMS

DCMS (2009) *Creative industries economic estimates. Statistical Bulletin*. London: DCMS

De Miguel, B., Hervás, J.L., Boix, R., De Miguel, M. (2012): The importance of creative industry agglomerations in explaining the wealth of the European regions, *European Planning Studies*, 20(8)

De Propris, L., Hypponen, L. (2008) Creative industries and governance: the dominance of the Hollywood film cluster, in Cooke, P., Lazzeretti, L. (Ed.) *Creative cities, cultural clusters and local economic development*, p. 258-286. Cheltenham: Edward Elgar

De Propris, L., Chapain, C., Cooke, P., MacNeill, S., Mateos-Garcia, J. (2009) *The geography of creativity*. London: NESTA

Dixon, P.M. (2006) Nearest Neighbor Methods, *Encyclopedia of Environmetrics*, DOI: 10.1002/9780470057339.van007

Duranton, G., Overman, H. (2005) Testing for localization using micro-geographic data, *Review of Economic Studies*, 72: 1077-1106

Feser, S., Sweeney, H.S. (2002) Theory, methods and a cross-metropolitan comparison of business clustering, in McCann, P. *Industrial Location Economics*, p.229-259. Cheltenham: Edward Elgar

Florida, R. (2002) *The rise of the creative class.* New York: Basic Books.

Florida, R., Mellander, C. (2008*) Music Clusters: A Preliminary Analysis*. Toronto: The Martin Prosperity Institute

Freeman, A. (2010) London's creative workforce: 2009 update. GLA Working Paper 40

Fundenburg, R.G., Boarnet, M.G. (2008) Agglomeration Potential: The Spatial Scale of Industry Linkages in the Southern California Economy, *Growth and Change* 39(1): 24–57

Gordon, I.R., McCann, P. (2000) Industrial Clusters: Complexes, Agglomeration and/or Social Networks?, *Urban Studies* 37(3): 513-532

Hautdidier, B. (2011) Featured graphic: What's in a NUTS? Visualizing hierarchies of Europe's administrative/statistical regions, *Environment and Planning A*, 43: 1754-1755

Howkins, J. (2007) *The Creative Economy: How People Make Money From Ideas*. London: The Penguin Press (2nd edition)

Hoover, E.M., Giarratani, F. (1971) *An Introduction to Regional Economics*. New York: McGraw-Hill

Jacobs, J. (1969) *The economy of cities*. New York: Vintage Books

Jacquez, G.M. (2008) Spatial Cluster Analysis, in Fotheringham, S., Wilson, J. (Eds) *The Handbook of Geographic Information Science*, p.395-416. New York: Blackwell Publishing,

KEA (2006) *The economy of culture in Europe*. Brussels: European Commission Directorate-General for Education and Culture

Keeble, D., Nachum, L. (2002) Why do business service firms cluster? Small consultancies, clustering and decentralization in London and southern England, *Transactions of the Institute of British Geographers* 27(1): 67–90

Krätke, S. (2002) Network Analysis of Production Clusters: The Postdam/Babelsberg Industry as an Example, *European Planning Studies*, 10(11): 27-54

Lazzeretti, L., Capone, F., Cinti, T. (2011) Open innovation in city of art: The case of laser technologies for conservation in Florence, *City, culture and society*, 2: 159-168

Lazzeretti, L., Boix, R., Capone, F. (2008) Do creative industries cluster? Mapping creative local production systems in Italy and Spain, *Industry and Innovation*, 15(5): 549-567

Lazzeretti L., Capone F.; Boix R. (2012) Reasons for clustering of creative industries in Italy and Spain, *European Planning Studies*, 20(8). DOI: 10.1080/09654313.2012.680585.

LEG Eurostat (2000) Cultural statistics in the EU, Eurostat Working Paper, Population and Social Conditions Series, 3/2000/E/No1. Final report of the LEG. Luxembourg: Eurostat

Lorenzen, M., Frederiksen, L. (2008) Why do cultural industries cluster? Localization, urbanization, products and projects, in Cooke, P., Lazzeretti, L. (Ed) *Creative cities, cultural clusters and local economic development*, p. 155-179. Cheltenham: Edward Elgar

Malmberg, A., Maskell, P. (2002) The elusive concept of localization economies: towards a knowledge-based theory of spatial clustering, *Environment and Planning A* 34: 429-449

Martin, R., Sunley, P. (2003) "Deconstructing clusters: chaotic concept or policy panacea?", *Journal of Economic Geography,* 3(1), 5-35

Maskell, P., Kebir, L. (2006) What qualifies as a cluster theory?, in Asheim, B.T., Cooke, P., Martin, R.L. (Eds) *Cluster and Regional Development: Critical reflections and explorations,* p. 30-49. London: Routledge

May, W., Mason, C., Pinch, S. (2001) Explaining industrial agglomeration: The case of the British high-fidelity industry, *Geoforum* 32(3): 363-376

Mommaas, H. (2004) "Cultural clusters and the post-industrial city: Towards the remapping of urban cultural policy", *Urban Studies* 41(3): 507–532

NIJ (2004) *Crimestat III: A spatial statistics program for the analysis of crime incident locations*. Washington: The National Institute of Justice

O'Sullivan, A. (2007) Urban economics. Singapore: McGraw-Hill

Porter, M.J. (1998) Clusters and the new economics of competition, *Harvard Business Review*, November-December: 78-90

Power, D., Nielsén, T. (2010) *Priority Sector Report: Creative and Cultural Industries*. Stockholm: European Cluster Observatory

Pratt, A.C. (2011) Microclustering of the media industries in London, in Karlsson, C., Picard, R.G. (Ed) *Media Clusters: Spatial Agglomeration and Content Capabilities*, p.120-135 Cheltenham: Edward Elgar

Rosenthal, S., Strange, W. (2004) Evidence on the nature and sources of agglomeration economies, in Henderson, J.V., Thisse, J.F. (Eds) *Handbook of Regional and Urban Economics*, vol. 4, p.2119-2171. North Holland: Elsevier

Schmitz, H., Nadvi, K. (1999) Clustering and industrialization: Introduction, *World Development*, 27(9): 1503-1514

Scott, A.J. (2002) A Map of Hollywood: The Production and Distribution of American Motion Pictures, *Regional Studies*, 36(9): 957-975

Storper, M., Venables, A.J. (2004) "Buzz: face to face contacts and the urban economy", *Journal of Economic Geography,* 4 (4): 351-370

Sweeney, S., Feser, E. (2003) Business location and spatial externalities: Tying concepts to measures, in Goodchild, M., Janelle, D. (Eds.) *Spatially integrated social science: examples in best practice,* p. 239-262. Oxford: Oxford University Press

Turok, I. (2003) Cities, Clusters and Creative Industries: the Case of Film and Television in Scotland, *European Planning Studies*, 11(5): 549-565

UNCTAD (2010) *Creative economy*. Report 2010. Geneve-New York: UNDP, UNCTAD

Vom Hofe, R., Chen, K. (2006) Whither or not industrial cluster: Conclusions or confusions?, *The Industrial Geographer*, 4(1): 2-28

WIPO (2003) *Guide on surveying the economic contribution of the copyright industries*. Geneva: WIPO

Table 1. Classifications of creative industries

CREATIVE INDUSTRIES	DCMS 2009 (UK)	WIPO copyright industries (2003)	Eurostat LEG (2000)	KEA European Affairs (2006)	UNCTAD (2010)
Printing		X			X*
Publishing	X	X	X	X	X
Advertising & related services	X	X	X	X	X
Architecture and engineering	X	X	X	X	X
Arts and antique markets/trade	X	X			X
Crafts	X	X	X	X	X
Design / Specialized design services	X	X	X	X	X
Designer fashion	X	X			X
Film / Motion picture & video industries	X	X	X	X	X
Music / Sound recording industries	X	X	X	X	X
Performing arts (theatre, dance, opera, circus, festivals, live entertainment) / Independent artists, writers, & performers	X	X	X	X	X
Photography	X	X	X	X	X
Radio and television (Broadcasting)	X	X	X	X	X
Software, computer games and electronic publishing	X	X	X	X	X
Heritage / Cultural sites (Libraries and archives, museums, historic and heritage sites, other heritage institutions)			X	X	X
Interactive media			X	X	
Other visual arts (painting, sculpture)			X		X
Copyright collecting societies				X	
Cultural tourism / recreational services				X	X
Creative R&D					X

* Only used for statistical reasons in comparisons.

Table 2. Comparison of Amadeus with Eurostat SBS. Year 2009[1]

	Amadeus	Eurostat	Amadeus/Eurostat
Fashion	35,136	115,822	30.3
Publishing	35,421	48,656	72.8
Film, video and music	44,137	79,649	55.4
Broadcasting (radio and TV)	9,547	7,345	130.0
Software and videogames [1]	113,319	290,839	39.0
Cultural commerce[2]	47,916	38,081	125.8
Architecture and engineering	163,368	684,453	23.9
Research and development	17,852	33,175	53.8
Advertising	65,424	132,330	49.4
Design and Photography	22,483	167,339	13.4
Total comparable	554,603	1,597,689	34.7
Other creative industries			
Heritage	4,526	-	-
Performing arts	34,804	-	-

[1] Greece and Malta are not included in the comparison due to problems of data in Eurostat.
Source: Amadeus and Eurostat SBS.

Table 3. Main results

	NNHC							LQ	
	k-order	Random distance in metres	Clusters	% Clusters in LUZ	Firms in clusters	Total firms sample	% of firms in clusters	Clusters	% of firms in clusters
Film, video and music	5	10,283	90	93.3	30,021	44,290	67.8	52	68.9
Software	10	10,084	313	75.7	63,849	94,433	67.6	102	68.9
Cultural trade	11	14,825	82	89.0	31,421	48,174	65.2	94	68.2
Architecture*	8	10,691	241	71.8	40,211	66,794	60.2	78	54.0
Engineering*	13	11,385	358	68.2	62,593	96,876	64.6		
Videogames	6	17,087	78	79.5	12,451	19,410	64.1	-	-
Design*	10	34,011	26	96.2	5,118	8,302	61.6	96	70.8
Photography*	10	24,633	45	91.1	7,018	14,204	49.4		
Performing arts	6	12,760	87	87.4	20,317	34,804	58.4	-	-
Advertising	5	8,439	178	79.8	37,596	65,765	57.2	82	60.2
Publishing	7	13,635	92	84.8	20,431	35,775	57.1	97	66.0
Fashion	4	10,193	102	64.7	19,781	35,615	55.5	18	69.8
Broadcasting	7	26,238	23	95.7	5,220	9,661	54.0	70	68.2
R&D	3	12,336	59	69.5	7,573	17,864	42.4	85	63.9
Heritage	5	32,168	10	100.0	1,089	4,526	24.1	-	-
TOTAL	-	-	1,784	77.0	364,689	596,493	61.1	774	63.2
AVERAGE	7	16,585	119	77.0	24,313	39,766	56.6		

* These sectors are grouped in the same code in Eurostat SBS.

Figure 1. Four patterns of location and co-location of clusters: hot spot, bunch, hub and cloud.

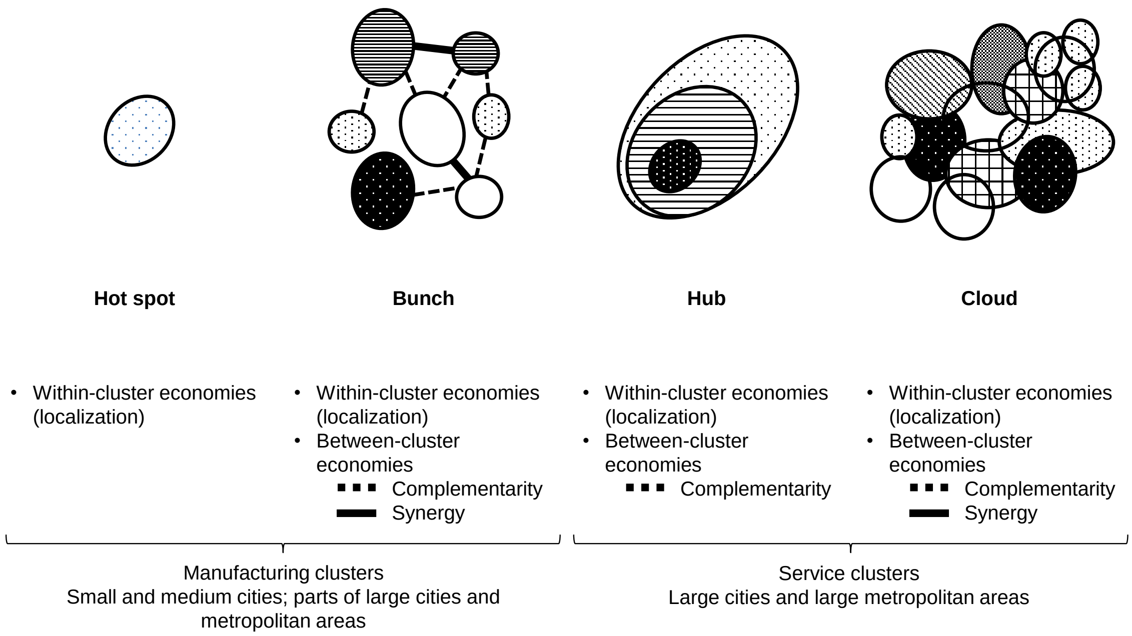


Figure 2. Spatial nearest neighbour hierarchical clustering algorithm

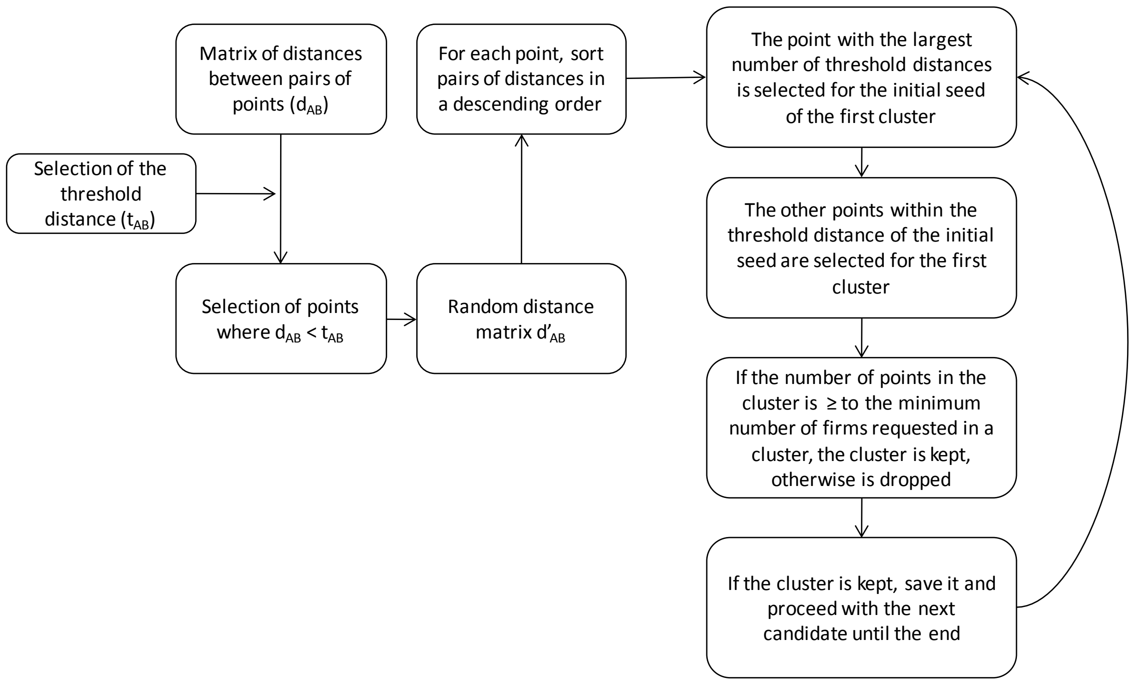


Figure 3. Nearest Neighbour Index for fashion and advertising

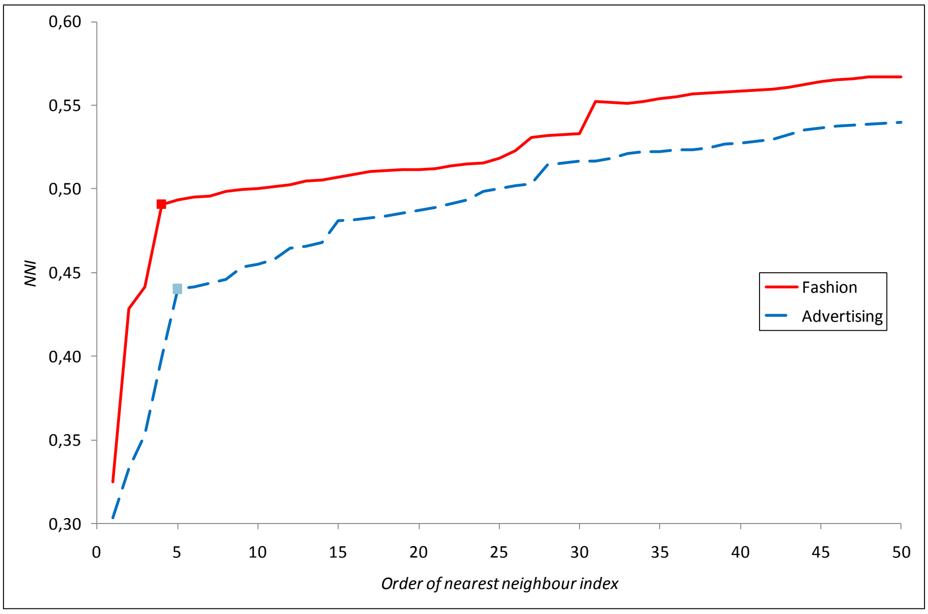
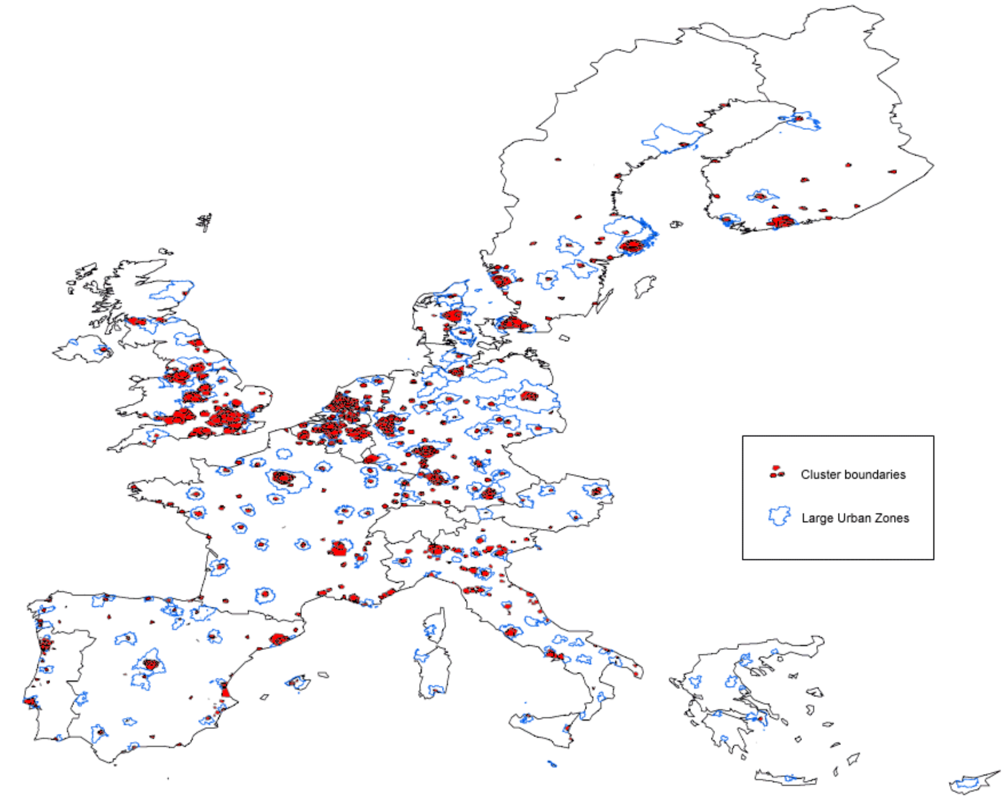
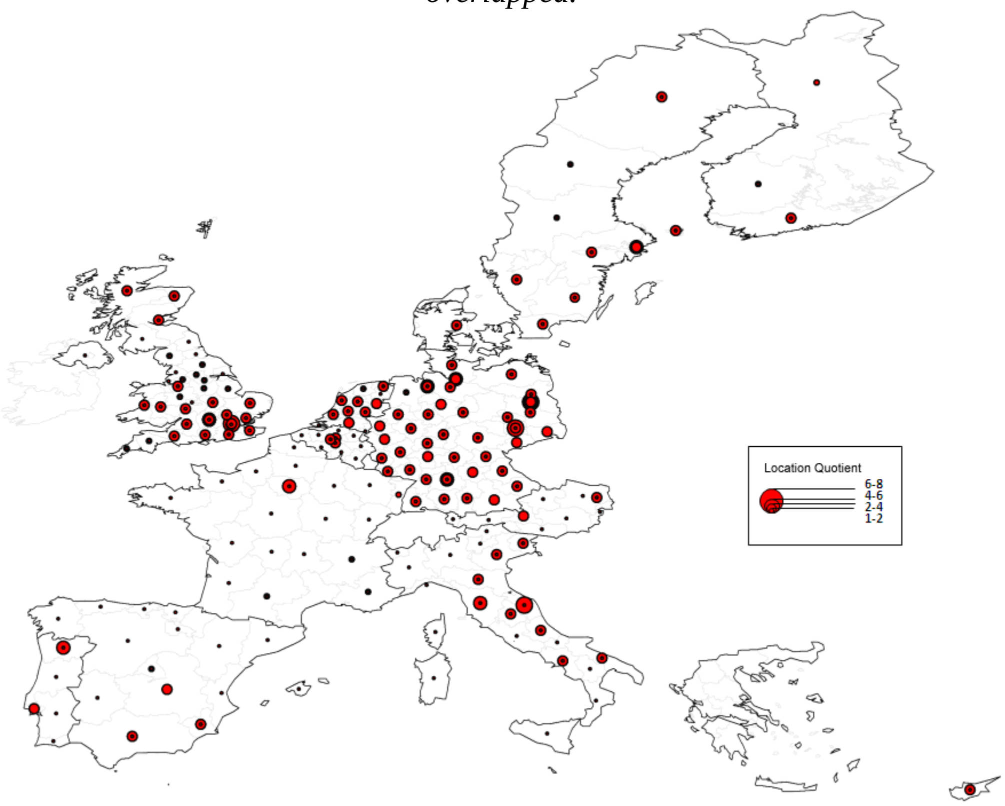


Figure 4. Clusters or creative industries in Europe.

A) NNHC methodology and Amadeus data. Clusters overlapped



B) Location quotients by industry and region above 1, and Eurostat data. Clusters overlapped.

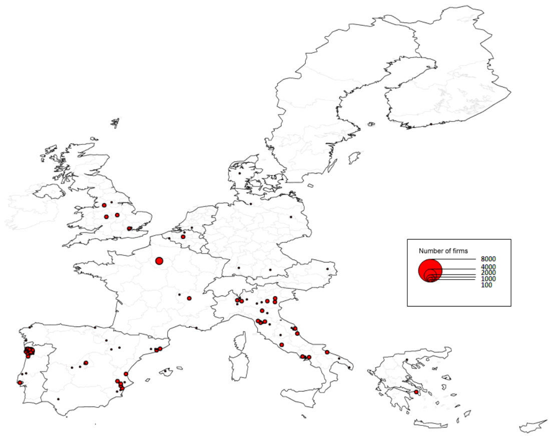


Source: Elaborated from Amadeus, Eurostat SBS and Urban Audit.

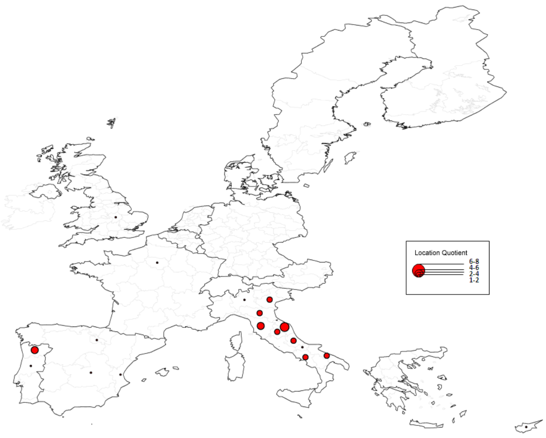
Figure 5. A comparison between the NNHC with geo-referenced microdata and the LQ using Eurostat regional data for two industries

A) NNHC with microdata *B) LQ by region*

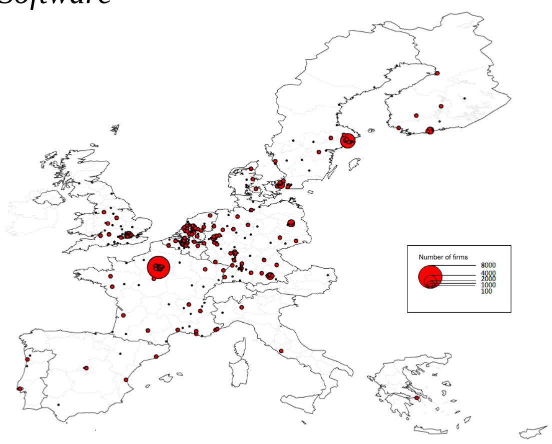
Fashion



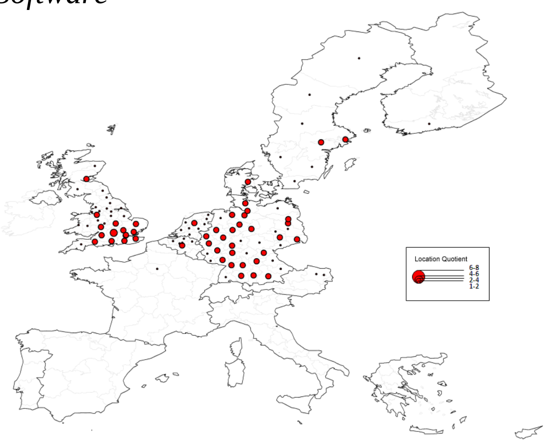
Fashion



Software



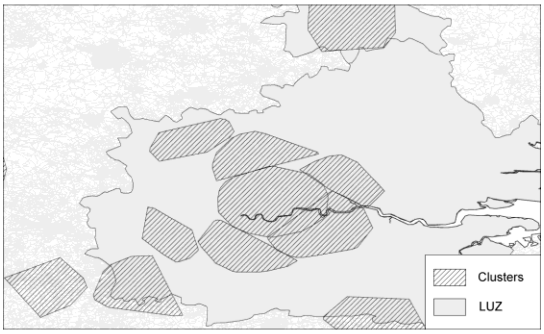
Software



Source: Elaborated from Amadeus and Eurostat SBS

Figure 6. Clusters of creative industries. Large Urban Zones of London and Paris. Detail for the publishing industry. Scale 1:750000

a) London



b) Paris

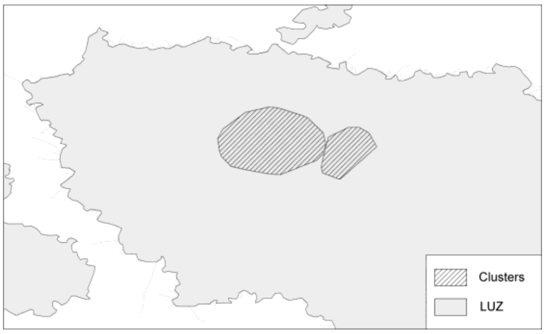
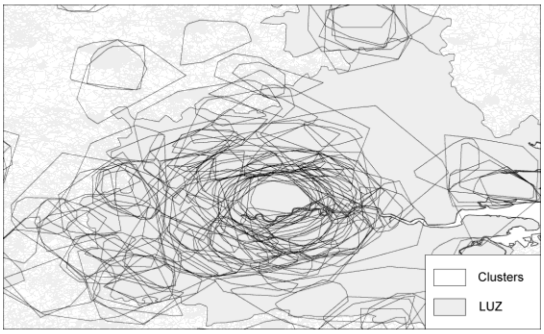
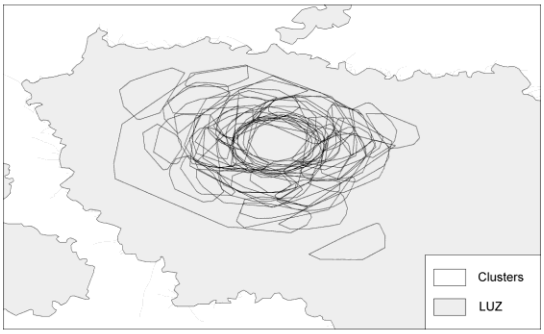


Figure 7. Clusters of creative industries overlapped. Detail for the Large Urban Zones of London, Paris, Barcelona and Rome, in a radius of 20 Km from the centre of the city. Scale 1:750000

a) London: cluster cloud



b) Paris: cluster cloud



c) Barcelona: hub in the centre and bunches in the subcentres

d) Emilia-Romagna: hub in Bologna and bunches in other cities

Source: Elaborated from Amadeus (Bureau van Dijk).