
# Micro-geographies of creative industries clusters in Europe: from hot spots to assemblages

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**Abstract**. What is the degree of clustering of CI? Where are located the clusters of CI in Europe? And, what are their basic patterns of clustering and co-clustering? These basic questions have never been answered satisfactorily for a representative number of European countries because of the trade-off between accuracy and coverage that imposed the administrative databases. The purpose of this paper is to produce a detailed map of clusters of creative industries in Europe and to provide the basic stylized facts about their spatial patterns of location and co-location. The research proposes a novel methodology to a detailed spatial delimitation of clusters, based on a geostatistical algorithm and firm-based micro-data that solves the limitations of previous research. The procedure is applied to a continuous space of sixteen European countries and fifteen creative industries in 2009. The investigation yields three main findings: creative firms are highly clustered; clusters of creative industries concentrates more in a creative belt from the south of England to the south-east of Germany, are predominantly metropolitan, heterogeneous and cross-border; and creative clusters are co-located among them. The paper concludes with a discussion about the use of these results in subsequent parts of the research programme and the implications for policy.

**Keywords**: creative industries, clusters, co-clustering, symbolic knowledge, micro-data, geo-localization
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## 1. INTRODUCTION

Creative industries (CI) are a set of knowledge-based activities focused on the generation of meaning, contents and aesthetic attributes by means of creativity, skill and talent, and with the potential to create wealth from trade and intellectual property rights (DCMS 2001; UNCTAD 2010). Although some of these industries date back centuries, the idea of studying them as a set of activities linked by the relevance of creative processes is new. Its emergence as a research program is a reflection of the current socio-economic changes and the evolution of technological paradigms. The British Labour government of Tony Blair popularized the notion in its necessity of finding new bases of growth for the UK's postindustrial economy (DCMS 1998; O'Connor 2007).

Since the DCMS (1998) elaborated *The creative industries mapping document*, Scopus has registered more than 700 articles related to creative industries. The evidence is sufficient to say that, although fragmented, fractured, uncoordinated and scattered, there is a research program around the creative industries. Due to its recent emergence, a multiplicity of disciplines, schools and approaches have converged simultaneously on the programme, using approaches as diverse as neoclassical economics, behavioural economics, critical Marxism, regional economics, cultural geography, evolutionary economic geography, constructivist structuralism, etc. This multiplicity of approaches has fostered a formidable growth of the literature on CI. On the downside, different research interests and different epistemological spaces have generated complexity, confusion, competition, exclusion and risk of dualism between different research groups, thus making it difficult to understand the phenomenon.

One of the most salient features of CI is clustering. This has been highlighted since the first studies of DCMS and subsequent articles and monographs, becoming one of the most referenced topics (see for example, Cooke & Lazzeretti 2008). Borrowing the terminology of Lakatos, we can say that the debate on clusters would be one of the most relevant issues in the protective belt of the research programme (about 15% of the articles). Here, researchers have used different notions of cluster, covered every creative industry, used different methodologies, and focused on different places and scales of analysis, although it has been impossible to reconcile enough precision with enough coverage. We can illustrate this point by dividing the literature according to the precision of the spatial and industrial dimensions, setting four categories[1]:

a) Specific space and specific industry, e.g.: Turok 2003 for the TV and film industry in Scotland; Scott 2002 and De Propris & Hypponen 2008 for the film industry in Hollywood; Bahtelt 2005 for the media industry in Leipzig; Lazzeretti et al. 2011 for the restoration and museum cluster in Florence.

b) General space and specific industry, e.g.: Florida & Mellander 2008 for the music industry in USA regions; Campbell-Kelly et al. 2010 for the software industry in metropolitan areas of the USA.

c) Specific space and general industry, e.g.: Pratt 2011 for CI in London; Capone 2008 for CI in the local labour markets of Italy; De Propris et al. 2009 for CI in the local labour markets of the UK.

[1] The list does not cover all the references of specific cases of study (about 100), only some of the most

d) General space and general industry, e.g.: Lazzeretti et al. 2008 for local labour markets in Italy and Spain; Boix et al. 2012 for local labour markets in Italy, Spain, France and the UK; Power and Nielsén 2010 for the EU regions.

A first conclusion from this distinction is that the literature has been prolific in studies providing insights into cases of specific place-industry, although their results are difficult to generalize in a collection of stylized facts due, on the one hand, to the limits of the cases of study, and on the other hand to those different research interests and epistemological approaches we have remarked. Little general existing research only encompasses a few countries (e.g. Lazzeretti et al. 2008; Boix et al. 2012), or focuses on an excessively aggregated scale such as at the level of the region (e.g. Power and Nielsén 2010). With the available evidence we cannot answer three really basic questions: *What is the degree of clustering of CI? Where are located the clusters of CI? And, what are they basic patterns of clustering and co-clustering?*

To avoid limitations of previous research and solve these questions, we propose a novel methodology based on the use of micro-data at the firm level and a hierarchical nearest neighbour clustering algorithm to identify CI clusters. This procedure has some noteworthy characteristics: data requirement is limited, is independent from the administrative definition of the unit of analysis, allows for multiple scales of clusters from the territorial micro-scale (e.g. quartiers, or parts of a region) to the macro-scale (e.g. regions, or states), provides the spatial boundaries of the cluster, takes into account

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representative.

simultaneously size and concentration, allows the identification of multiple clusters covering the same space, yearly updates, and is applicable to large economic areas such as Europe, the United States or Asia.

We apply this methodology to a continuous space formed by sixteen European countries. The final objective is to obtain a map that allows to answer the research questions and provides an input for subsequent parts of the research programme.

The article is divided into six parts. After the introduction, section 2 proposes an introductory framework for the clustering of CI. Section 3 presents the methodology. Section 4 introduces the elaboration of the database. Section 5 explains the main findings. Section 6 is devoted to the discussion of the results and their implications.

## 2. CREATIVE INDUSTRIES AND CLUSTERING

### *2.1. General and specific reasons for clustering of creative industries*

In such research, a particular question of interest has been the reasons for the clustering of CI. *General* reasons for spatial clustering have been explained by the regional and urban economics in terms of transaction costs (e.g. transportation costs), localization economies (specialized labour pool, specialized providers through the different phases of the productive chain, knowledge spillovers, trust, learning), urbanization economies (size of the local market, productive diversity, social diversity, public goods), incubation, and public policies and planning. Being more specific, a great proportion of CI are business services and knowledge-intensive business services (KIBS). Keeble &

Nachum (2002) and Cuadrado-Roura (2013) have noted that the clustering of KIBS, particularly in large cities, is determined by specific factors such as: access to skilled staff; access to localized and relatively immobile tacit knowledge; access to knowledge spillovers; the presence of collective learning (through networking, inter-firm collaboration and movement of skilled labour between enterprises); accessibility to global networks, clients and knowledge; and accessibility to a local knowledge base. Berg & Hassink (2013) have adapted several evolutionary topics as general reasons for clustering that are applicable to CI, such as windows of locational opportunity and path creation, path dependence and lock-in, related variety and branching, and co-evolution.

There are also *specific* reasons affecting the clustering of CI: cultural infrastructure (collective and durable objects, rules, activities or phenomena), soft factors (quality of life, tolerance, diversity and cultural scene, buzz), hard factors (e.g. transport and telecommunication infrastructures), patronage and proximity to the political power, tradition, serendipity and randomness, the location of "star" artists and creative class, identity , and brand and image (Andersson & Andersson 2008; Pareja et al. 2008; Lazzeretti et al. 2012). One of the most important specific reasons for clustering is related to the dominant type of knowledge base in CI. Asheim & Parrilli (2012) differentiate three types of knowledge bases:

a) *analytical,* derived from the production and use of codified knowledge that originates from science and technology (e.g. pharmaceutical industry);

b) *synthetic, where* that is created through a more inductive process of testing, experimentation and practical work (e.g. mechanical engineering),

c) and *symbolic*, in which knowledge that is related to the creation of the contents, desires and aesthetic attributes of products (e.g. creative industries).

The distinction between knowledge bases takes account of the rationale of knowledge creation, development and use and the way the knowledge is transmitted and absorbed. Each base has different spatial implications and, as a consequence, different sensitivity to geographical distance. Analytical knowledge is highly codified and usually non-dependent on the context. Synthetic knowledge is partially codified and embodied in technical solutions, although tacit knowledge is also relevant due to the importance of the experience at the workplace, learning by doing, and using and interacting processes. Symbolic knowledge associated with creative industries - where a crucial share of work is dedicated to the creation of new ideas and images - is related to a deep understanding of the habits and norms of specific social groups so that it is highly embedded, tacit and context-specific. Consequently, whereas analytical and synthetic knowledge is less sensitive to distance-decay, symbolic knowledge tends to be extremely local and in consequence spillovers are also highly local and CI tend to be highly clustered.

Lorenzen & Frederiksen (2008) and Lazzeretti et al. (2012) have performed quantitative analysis integrating some of these factors, such as external agglomeration economies (i.e. localization and urbanization), cultural factors, the presence of a creative class and related variety, to arrive at the conclusion that the high levels of clustering of creative industries depends on the coexistence of agglomeration economies and specific factors, although highlight urbanization economies as the most important factor to explain patterns of CI clustering.

### *2.2. From clustering to co-clustering*

One of the most neglected aspects in the cluster literature has been the issue of spatial patterns of co-location of clusters sharing the same geographical space. This is not particularly surprising, given the influence of Porter's work (e.g. Porter 1998) and the fact that the focus of his analysis has been on the organization of the value chain, such that the spatial dimension has been given only secondary attention. Thus, the profusion of case studies in the cluster literature has not generally paid much attention to the phenomenon of clusters sharing the same geographical space (co-clustering). In addition, cluster mappings have focused on a particular industry (e.g. automotive, or chemicals), or involved methodologies in which an industry has been selected as representative of a place which thereby prevented study of other locally clustered industries (e.g. the ISTAT procedure for the identification of industrial districts in Sforzi 2008).

Authors such as De Propris et al. (2009), Mommaas (2004), Camors & Soulard (2010), Freeman (2010) or Pratt 2011) have found effective evidence of several clusters of CI co-located in the same cities. The co-clustering and their basic patterns can be explained using a simple mechanism of *pull* and *push*. There is a *pull* for CI clusters to develop in the most central spaces of the cities, where the relational density and potential clients are higher as a consequence of urbanization economies. But urban space is expensive with strong density being a consequence of high land rents, forcing (*push*) a range of different types of clusters to share the land and causing co-clustering. Both mechanisms feed back. The patterns of co-clustering will depend then on the number and balance of centres of the city and the intensity of urbanization economies. This is too simple as to be considered a *model* although is enough to provide an operative taxonomy of patterns of co-clustering as in Figure 1:

a) Low urbanization economies and low levels of polycentricity rise to the identification of the spatial formation of clusters in isolation (*isolated hot spots*).

b) Higher levels of polycentricity with low levels of urbanization economies associates with sets of clusters in close proximity forming *bunches* of clusters with similar or different specializations.

c) Low or unbalanced patterns of policentricity and high urbanization economies makes CI clusters focus at a single point in the city, then we find clusters of different activities and with different spatial thresholds organized around this point, similar to a *hub*; this phenomenon should be a frequent occurrence in medium-large cities where the size of the city, and the urban form, have not allowed an expansion of urbanization economies to other less central spaces.

d) In very large cities, the dynamic of land rents make it impossible to maintain a concentration at a single point, and the city becomes multicentric with urbanization economies arising at many points. In such a 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; 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 indicative of the existence of creative *milieux*.

## 3. METHODOLOGY

### *3.1. Methodological approach*

The methodology we propose to map creative industries clusters is a mix of an extended geographical analysis machine (Openshaw et al. 1988; Sforzi 2009) and the logic exposed by Capone (2008) and Lazzeretti et al. (2008) for the identification of creative local systems. First, we define an operative notion of a creative industry cluster. Second, a list of CI is proposed. Third, 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.

*Stage 1: Operative approaches to the cluster*

The first stage is to operationalize the notion of CI cluster. There is an intense discussion in the literature about the notion of *cluster* (see for example the connections between the core literatures on clustering in Feser & Sweeney (2002) and the taxonomical discussions in Gordon & McCann (2000) and Vom Hofe & Chen (2006)). Gordon & McCann (2000) distinguish three stylized forms of spatial clustering, depending on the dominant or characteristic process occurring 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. This multiperspectival approach results in an eclectic and polycentric notion of clusters, with the consequence that there is not a unique method for identifying and mapping clusters (Benneworth et al. 2003). Significant examples of how the different logics translate to different procedures are Openshaw et al. (1988) Geographical Analysis Machine (representative of pure agglomeration clusters), Porter (1998) industrial linkages (representative of industrial complexes) and Sforzi (2009) industrial districts (representative of social networks).

Among the several problems that usually arise in the empirical delineation of clusters, can be mentioned: the identification of the cluster's core industries; the lack of inter-industry trade data for sub-national geographical areas; the problems of collecting data on the basis of pre-given administrative and political units; the difficulties of identifying a cluster's geographical boundaries; the issue of which data to select (such as relating to employment, firms, added value, or productivity); and the arbitrariness of the rules for distinguishing clusters.

The literature includes a wide range of methods for identifying industrial clusters depending on the type of cluster and data availability (Bergman & Feser 1999; Vom Hofe & Chen 2006). Methods include: path dependency; expert opinion (e.g. Delphi, MSQA); the identification of a critical mass of firms in a region in the same or complementary sectors; the use of concentration indexes (such as location quotients, Gini indexes, or Ellison-Glaeser measures); the employment of input-output methods (such as triangularization, and cluster, factor and principal components analysis); and use of network analysis. Combinations of various approaches are possible (Titze et al. 2011).

Feser & Sweeney (2002) propose an extension of the range of methodologies to include the incorporation of spatial statistics. Spatial statistics are able to distinguish between discrete and continuous space, and between global and local indicators derived from first and second order statistics (Feser & Sweeney 2002; Jacquez 2008). Global indicators provide information about general clustering trends, whereas local indicators provide information about clusters' locations and their spatial boundaries.

For this, experience so far is of limited value. Hitherto, ideal models for clusters described by Gordon & McCann (2000) have been used for guiding empirical research on CI clusters but none of them have stood out as particularly more effective than the others. Moreover, the only characteristic of CI clusters that so far has been identified has proved to be spatial agglomeration. Given the limited knowledge, we propose to undertake an incremental work, starting with a modest approach (focussing on agglomeration clusters), with the aim of enhancing the research later by extending our interest to the other types of clusters (industrial complex and social network clusters).

Furthermore, we will differentiate between *creative places* – defined as an aggregation of all the types of CI - and *clusters of creative industries* – where each type of creative industry is considered separately from others. The patterns of CI location are expected to be not homogenous but to exhibit differentiated geographies. Pratt (2011) argues that the micro-geographies of CI and their rich patterns of co-location are only revealed by a differentiated treatment for each creative industry. These arguments imply a need to identify clusters industry by industry. We define clusters as sectoral and spatial concentrations of firms, represented by a high density of firms of the same industry in the same space.

*Stage 2: A list of creative industries*

At a second stage it is necessary to select a list of CI. For this we utilise the UNCTAD (2010) definition (Table 1) because it is the most comprehensive and was designed for cross-country comparison. UNCTAD's classification has the advantage of being less restrictive because it encompasses both cultural and technological dimensions of CI, whereas other taxonomies (e.g. DCMS, WIPO or KEA) are biased towards one or the other of the two dimensions. UNCTAD's classification includes both manufacturing and service industries, although the majority of the sectors it includes in CI are services, especially knowledge-intensive services (Table 1). Each industry is considered separately as our objective is to distinguish clusters of CI and not creative places and there is no evidence of integration of the different industries in a true creative chain [2].

[Insert Table 1 near here]

*Stages 3 and 4: Data and algorithm*

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

The third and fourth stages involve the selection of observations and appropriate data, and the selection of an algorithm. Until now, research on CI clusters in Europe has been affected by two constraints. First, the level of the region is too big to provide an appropriate detailed geography of the CI clusters (e.g. Power & Nielsén 2010), because of a number of effects. These include: the average effects of regional units (i.e. the ecological fallacy); the possibility that several clusters of the same creative industry exist in the same region; the heterogeneity in the size definition of NUTS 2 (Hautdidier 2011); and an incapacity to identify actual locations and boundaries of clusters. In addition, it is impossible to detect cross-regional and cross-national clusters (Crawley & Pickernell 2012).

A second constraint has arisen when a strategy has involved the collection of data at infra-regional administrative levels such as municipalities and local labour markets (e.g. Boix et al. 2012). Eurostat does not centralize this information and the only option is to collect it from national statistical offices, which is difficult, slow and costly.

For the above reasons, and following recent studies on patterns of industrial location (Feser & Sweeney 2002; Combes et al. 2004; Duranton & Overman 2005), we use micro-geographic data for cluster identification. This type of data permits the use of geostatistics in continuous space, which in turn permits the definition of concentration (agglomeration) on the basis of the locational density of firms in space.

### *3.2. Spatial nearest neighbour hierarchical clustering (NNHC)*

#### *Selection of the algorithm*

There are many hot spot techniques, including 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 NNHC approach was selected by us because of the occurrence of some advantageous properties. First, it works well with a very large number of observations in a continuous space. Second, it does not require a reduction of the space to grids, such as for example is required using kernel techniques, which means we can avoid having to select the size of grids (Sweeney & Feser 2003). Third, it is possible to select a threshold random distance for the firms in the cluster, or to provide this distance on the basis of economic or relational criteria. Fourth, it is not necessary to assume any shape for the search radius, such as happens in scan methods. The NNHC approach can detect large and small clusters, even inside cities. Fifth, it is possible to see the enveloping shape of the cluster. In addition, the NNHC approach also offers the possibility, if necessary, of taking into account the localization of firms belonging to other (non-CI) industries (through a method similar to that used typically by specialisation indexes). However, as we are looking for evidence of pure agglomeration, it would be more consistent to consider only the pure density of firms in the targeted industry since the continuous space is already acting as a corrective base for the index.

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

*Algorithm*

The spatial nearest neighbour hierarchical clustering approach (NNHC) (NIJ 2004) starts 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 $d_{AB}<t_{AB}$, form 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 is necessary for the cluster to be counted as significant[3]. If the cluster satisfies the criterion of size, then it is retained and we proceed

[3] This number introduces a certain arbitrariness since there is no 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 a comparison between industries.

with the next most connected point not 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, which allows us to identify 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 yet general agreement about what constitutes an appropriate distance radius for clusters. For example, Funderburg & Boarnet (2008) found an average of 5-7.5 miles in their study of manufacturing clusters in Southern California; Feser & Sweeney (2002) described a distance of 26 kilometres for manufacturing industries in the San Francisco Bay area; and May et al. (2001) indicated a range of up to fifty miles for the British high-fidelity industry. Rosenthal & Strange (2004) argue that the spatial range of agglomeration economies is short for localization economies in agglomerated industries, falling to as little as 15 miles, whereas for urbanization economies it could extend to hundreds of miles.

One way of avoiding the problem is by selecting as a threshold a random distance to the nearest neighbours based on the probability of selecting any pair of points on the basis of a random distribution. Most 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 to 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 to calculate 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 such as Rypley's K.

We propose a two-step method, based on the previous calculation of the distance to the K-order nearest neighbour and then using this distance in the algorithm. As we fixed the minimum number of firms in a cluster at 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 (NNI) 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 quickly for the first neighbours (indicating that 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 taken from the results is set out in Figure 3.

In trials, 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 micro-clusters (in our trials, with a radius between 1 and 2 kilometres), whereas the latter tends to merge independent medium-sized clusters to produce macro-clusters. The inflexion point produces the most satisfactory results. It is clear that, in general, there is no unique solution and that the definitive distance for clustering depends on the scope of the research.

This procedure has the advantage that we can 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 the Amadeus database (Bureau van Dijk). Amadeus provides data for all the EU countries, detailed by firms' postal addresses, and at the four digits NACE Rev 2 level.

The data covers 966,000 firms belonging to the UNCTAD (2010) list of CI (Table 1) in the EU 27 during the period 2001 to 2009. The postal addresses of the firms were translated to geographic coordinates which are used by the geostatistical algorithms. There was only good cartography available for postal addresses for 16 countries, and so 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 most recent year available, and so data was treated for only 554,603 firms active in the year 2009.

The NNHC can deal with jobs or establishments, although the latter is more usual in geostatistics (Sweeney & Feser 2003). Lazzeretti et al. (2008) and Clifton & Cooke (2009) provide arguments favourable to the use of jobs, whereas De Propris et al. (2009) use the number of establishments. However, information about the number of employees by firm is poor and irregular in Amadeus, and the average firm size in CI is small (less than 5 workers). For this reason we use the firm as the 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). The Amadeus to SBS 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 & Sweeney's (2002) sample. In any case, it is a substantial sample size, and 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 do not provide evidence of problems of over or under-valuation, with the exception of Greece and Malta, where the sample is poor.

Although of the coverage of the current sample assures good results, the database has some other limitations. The coverage of Amadeus for firms below 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, and 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).

[Insert Table 2 near here]

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

### *5.1. High levels of creative clustering*

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 political boundaries (Figure 4). 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 kilometres (advertising) to 34 kilometres (design), and the average is 16.5 kilometres, which is not very different from Funderburg & Boarnet (2008) or Rosenthal & Strange (2004).

CI are highly clustered. We identified 1,784 clusters across 15 CI. About 61% of the firms in the sample were located in these clusters (Table 3 and Figure 4). 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 the CI. The most clustered industries are film, video and music, software, cultural trade, engineering, videogames, design, and architecture, for each industry of which more than 60% of the firms are located in clusters (Table 3). Only in photography, R&D and heritage is it the case that more than 50% of the firms in each industry are not located in clusters.

*5.2. The location of creative industries clusters in Europe: uneven distribution, cross-bordering, high metropolitanization and differences among industries*

The answer to the second question of the article (*where CI clusters are located?*) can be summarized as follows:

a) *CI clusters are distributed across the whole of the European territory, although the distribution is uneven*. There are great concentrations covering large areas such as is the case in the South of England (e.g. Hampshire hosts 44 clusters, Inner London 24, Kent 21, Outer London 19, North and North East Somerset/South Gloucestershire 19, and Essex 18), the Benelux countries (e.g. Brussels host 22 clusters, Groot Amsterdam 19, and Groot-Rijnmond 18), and Île de France (Paris hosts 14 clusters) (Figure 4). Other regions, most of them containing medium and large cities, host more than 14 clusters (such as 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).

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

c) *Clusters are predominantly metropolitan*. About 77% are located in metropolitan areas (here represented by Eurostat's Large Urban Zones (LUZ)) (Figure 4 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; Madrid and Stockholm each host 5 large clusters; Berlin, Brussels, Lisbon and Munich are all host to 3 large clusters; Barcelona, Helsinki, Milan and Roma each host two large clusters; and Copenhagen and Goteborg have 1 large cluster each. The only large cluster not located in a LUZ is the fashion cluster of Guimaraes in the north of Portugal. The patterns of how industries are distributed in cities vary. For example, in Paris, clusters of research and development, radio and TV, and videogames are located only in the central city area, whereas in London they are also distributed in other parts of the broader metropolitan area. Also, fashion occupies a central location in Paris and London, whereas in Barcelona it is also located in sub-centres that were industrial centres in the XIXth century. The reasons for clustering of CI introduced in the theoretical framework explain these differences.

d) *The places where clusters locate are also different for different industries.* To give only an example: whereas fashion clusters tend to be concentrated in Mediterranean countries, software clusters are more dispersed and are particularly prevalent in the south of England, the north of France, the west part of Germany and in the Benelux countries[4].

*5.3. Patterns of spatial organization between CI clusters: co-location dominates isolation*

The third question we face is: w*hat patterns of spatial organization are observed between clusters of CI?* We find evidence that CI clusters, particularly the largest ones, tend to share space with other clusters of the same or different CI (Figure 6). Thus, creative cities are made of a great number of overlapping creative clusters, which, according to Figures 3 and 6, are nourished by a complex range of localization and urbanization economies, variety externalities internal to the place, as well as by other external economies arising from synergic and complementary networks between neighbouring clusters.

We found evidence of the four types of patterns described earlier in Section 2. *Hot spots* and *bunches* are usual in non-metropolitan areas; *hubs* are found in medium-large metropolitan areas; and *clouds* are generally observed in the largest cities and metropolitan areas. Figure 6 provides an example: in London and Paris the clusters are distributed in both the central parts of the cities and also in the sub-centres, forming dense *clouds*. In Barcelona, most of the clusters are concentrated in the central city forming a *hub*, whereas in the Emilia-Romagna region of Italy we can observe a *hub* focused on Bologna and also 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 all the clusters. Only 7% of the clusters were isolated *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 to form more complex structures due to the complexity of the urban structure, for example in the Netherlands or in the London area.

### *5.3. A comparison between NNHC-micro-data and LQ-region methodologies*

We compared the results of the NNHC algorithm with those obtained using a traditional methodology based on regions (NUTS 2, data comes from Eurostat SBS) and location quotients[5].

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[4] Due to the limitations of space we don't include the maps detailed by industry. These results are available under request to the authors.

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

A map using micro-data and NNHC (Figure 4) shows a precise and detailed geography of CI clusters in Europe: the clusters are located with precision, and the reality is not reduced to a point by region and industry. A map using NUTS 2 and LQ (Figure 5) is subject to several problems related to the modifiable areal unit problem (MAUF): it is unable to reveal more than a point by industry and region; it cannot show where in the region is actually located each cluster; it exaggerates the relevance of countries with smaller regions; and it cannot identify some clusters if the share of the industry in the region is not large enough to be noted 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), albeit that 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 of groups of clusters differ for the two figures.

The differences are even more evident when comparisons are made industry by industry. For example, the LQ methodology using regional data identifies the importance of fashion in Italy and in the north of Portugal, but it produces imprecise information about spatial patterns, only finding 18 clusters. The NNHC algorithm using micro-data identifies 102 clusters, as well as their positions, sizes and distribution, and succeeds in identifying important clusters on the east coast of Spain, in the north of Italy and in Paris, as well as other clusters not detected by the other methodology. For the software industry, the LQ methodology identifies 102 clusters, but it only highlights important patterns of clustering in Germany, the Benelux countries and the south of England. In contrast, the NNHC algorithm identifies 313 clusters, revealing also important groups of clusters in many other countries.

[Insert Table 3 near here]

[Insert Figure 4 near here]

[Insert Figure 5 near here]

[Insert Figure 6 near here]

## 6. CONCLUSIONS

Existing studies have provided limited evidence and partial detail about the degree of clustering of creative industries, where CI clusters are located in Europe and what are the patterns of spatial articulation between CI clusters (co-clustering). The main limitation to answer these questions was the use of methodologies based on data from administrative sources, either because they imposed a too aggregated scale study or insufficient coverage due to difficulty of obtaining homogeneous data for a sufficient number of countries. We have avoided these limitations by using geo-referenced micro-data and a nearest neighbour hierarchical clustering algorithm. The methodology has been applied to sixteen European countries in 2009. The performance of the methodology has been excellent and has provided a formidable detail in the results. Regarding the research questions, the main conclusions are:

1. Creative firms are highly clustered: 61% of CI firms are in the 1,784 identified clusters.

2. CI clusters can be observed in most of the European territory. It is the first time we can observe detailed results for a large number of European countries. The patterns of location of CI clusters are characterized by:

> 2.1. *Uneveness* of the spatial distribution: there is a huge agglomeration in a *creative belt* from the south of England to the south-west of Germany, including Paris and the Benelux;
>
> 2.2. *Metropolitanization*: 77% of the clusters are located in metropolitan areas;
>
> 2.3. *Heterogeneity:* patterns across industries differ;
>
> 2.4. *Cross-bordering*: clusters are not limited by political borders, which is evidenced by the existence of hundreds of clusters shared between different countries, regions and metropolitan areas

3. CI clusters are predominantly co-located with other CI clusters: most of them are integrated into *hubs* and *clouds* and only 7% are isolated. The *push* and *pull* mechanism foreseen this result in a situation of high preference for metropolitan location of CI clusters, due to the balances between urbanization economies and land price mechanism mediated by the number of urban sub-centres. Even more surprising has been the high complexity of some *clouds* like London or west-central Netherlands, possibly indicative not only of intense urbanization economies, but also of between-cities network economies.

The results of the mapping can be used as an input to reinforce other parts of the research with higher precession and coverage, for example, the reasons of clustering of CI (Lorenzen & Frederiksen 2008; Lazzeretti et al. 2012), why do CI exists in certain locations while in others do not, or the effects of clusters on growth (see for example De Miguel et al. 2012). The results of co-clustering open a complementary line in the research programme. Deluze & Guattari (1984, 1987) introduced the notion of "assemblage" as arrangements endowed with the capacity of acting in different ways depending on their configuration. From this point of view, assemblages shape creative production and each is unique, which determines the uniqueness of the created product. According to this idea, the complexity of social systems in response to stimuli and replication would be difficult, being however prone to the generation of non-deterministic trajectories of change. By contrast, as a consequence of the high number of detected CI clusters and the intensity of co-clustering, the study of the relationships between the clusters as assemblages proposes new solutions from existing elements and recombination of relations between clusters.

The findings also raise some thoughts about policy. One clear is that many policy strategies are weakened by being based on vague macro-scale definitions, while in other cases policymakers are not even aware of the existence of clusters in their space. At the 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 of targeting policies towards specific objectives. Other point is that if CI clusters are not isolated, then co-location should be taken as a significant dimension for policy-making. The distribution of clusters, their diversity (whether they be in hot spots, bunches, hubs or clouds), and the differences between CI, suggest a need to advance towards strategies that support not only the clusters but also the linkages between clusters. The objective would be not only to take advantage of specialization but also of the cross-linkages between clusters, and the varieties of clusters, when they share the same geographical and relational space. The existence of neighbouring clusters suggests opening up and developing strategies based on networks of synergy and complementarity between clusters. From here, any suggestion more explicit enters a slippery slope and requires specific development in further articles.

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*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. Patterns of co-clustering of CI clusters*

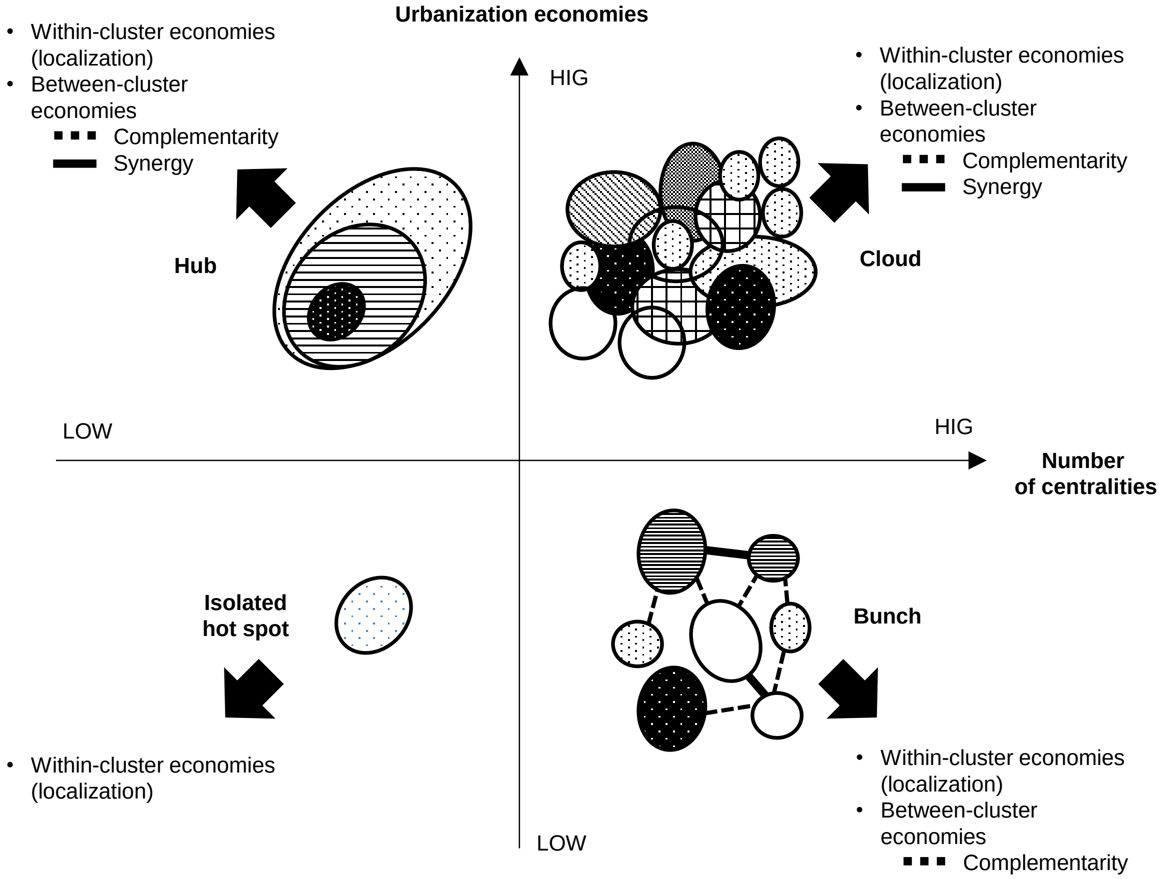


*Figure 2. Spatial nearest neighbour hierarchical clustering algorithm*

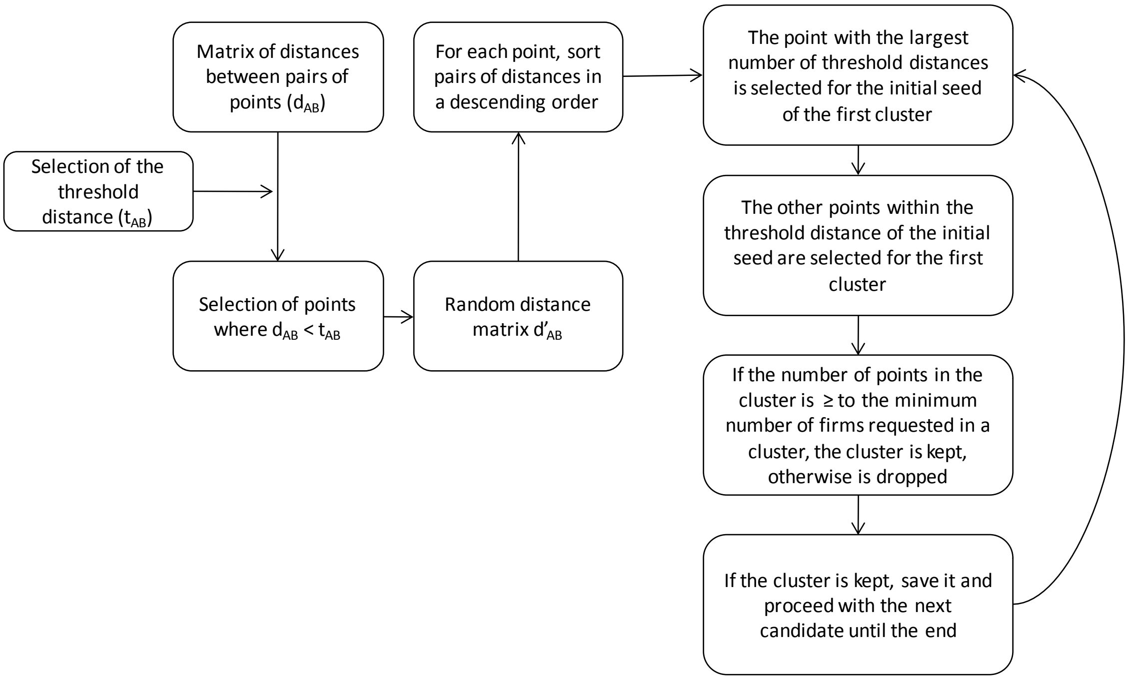


*Figure 3. Nearest Neighbour Index for fashion and advertising*

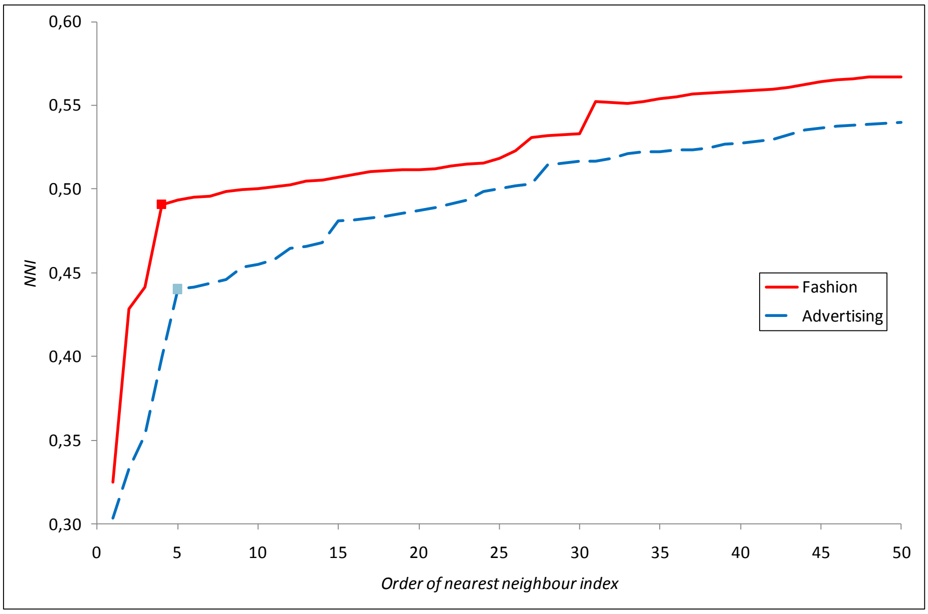
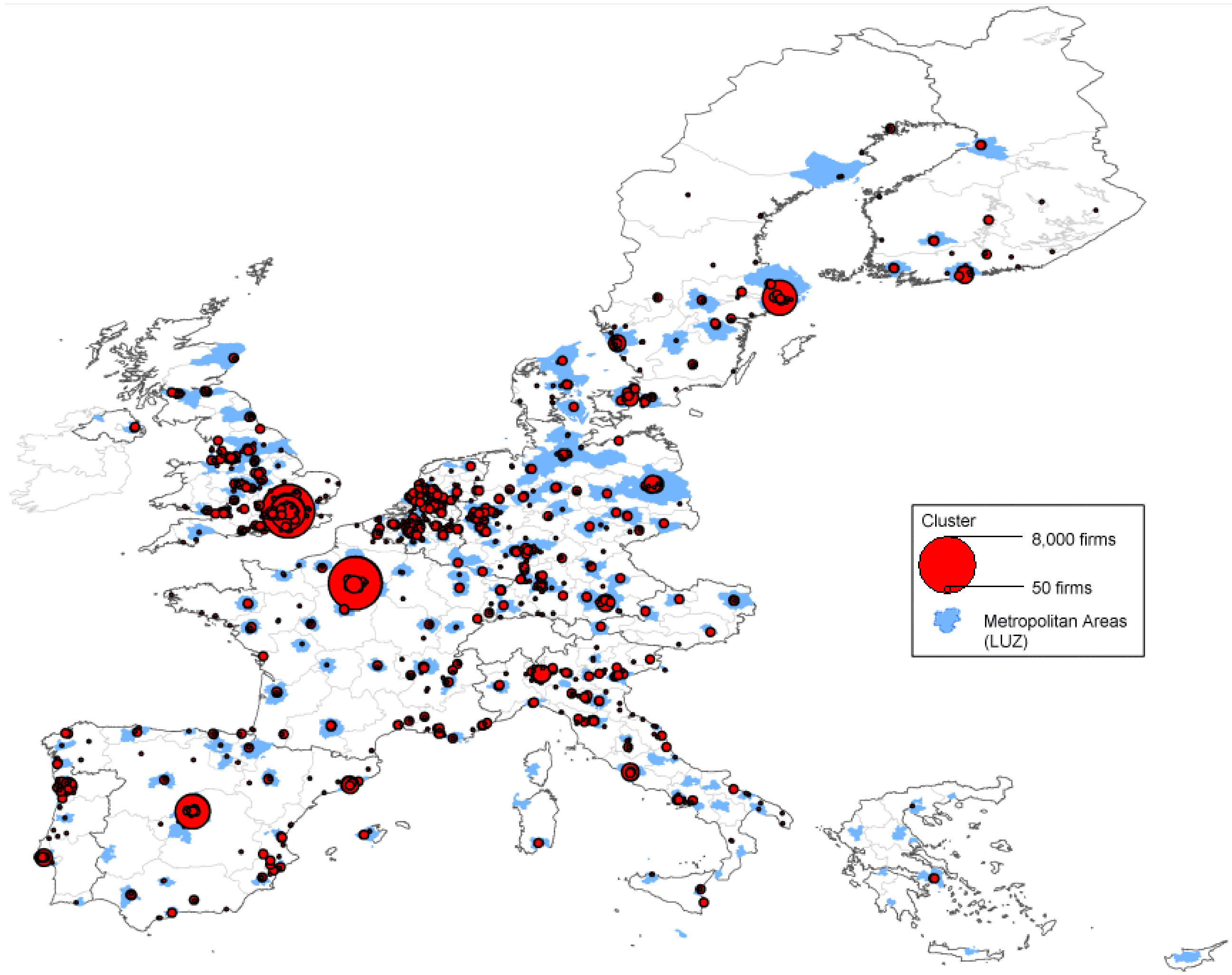
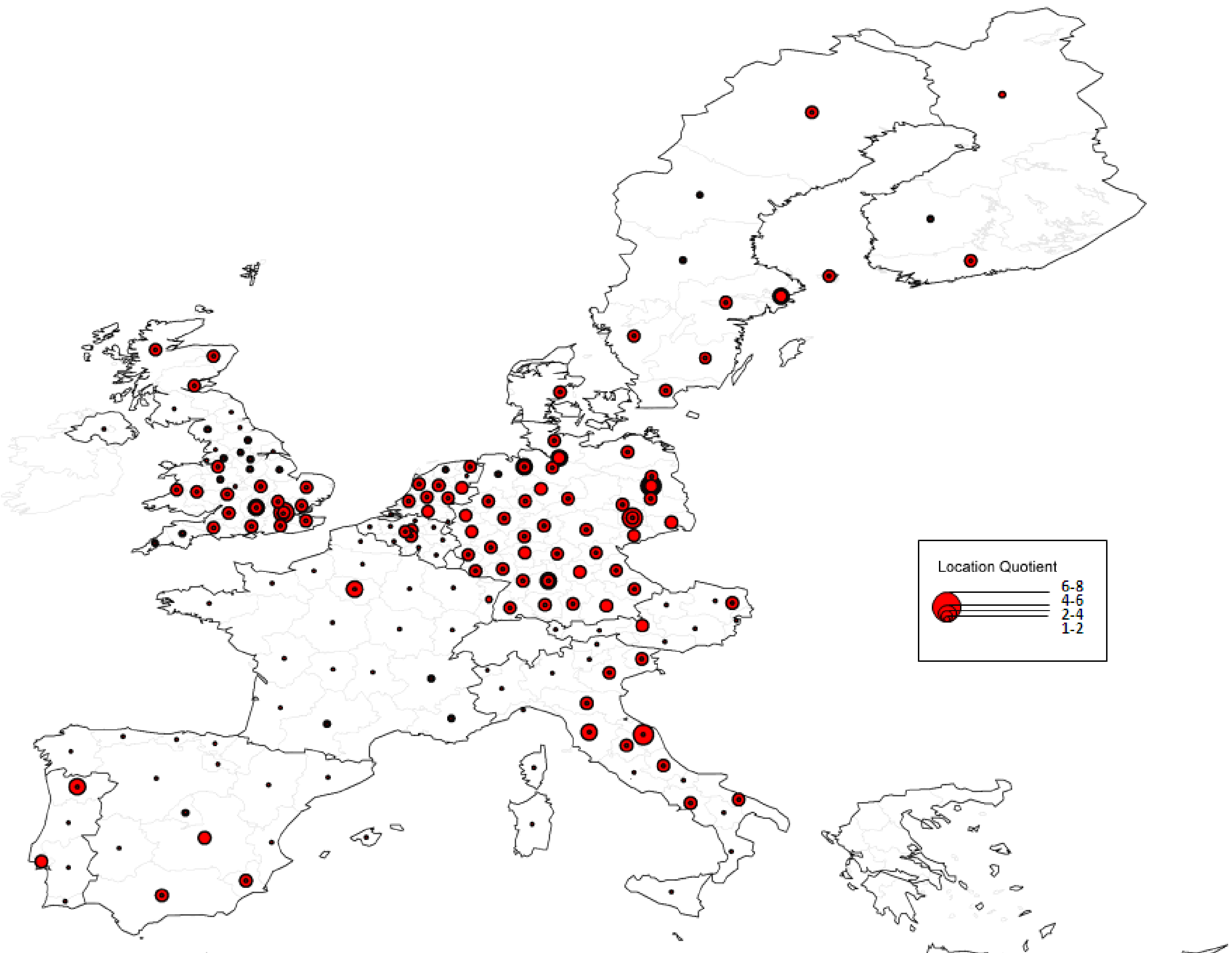


*Figure 4. CI clusters in Europe. NNHC methodology and Amadeus data. Clusters overlapped (each dot is a cluster by CI industry)*




Source: Elaborated from Amadeus and Urban Audit.

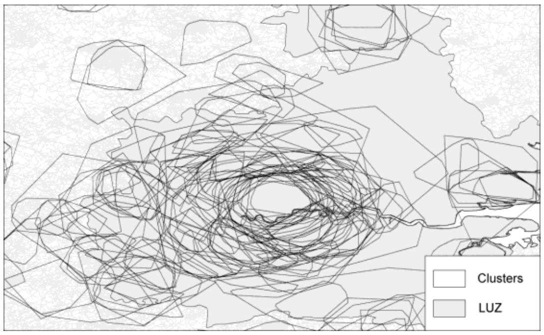
*Figure 5. CI clusters in Europe. Location quotients by industry and region above 1, and Eurostat data. Clusters overlapped.*



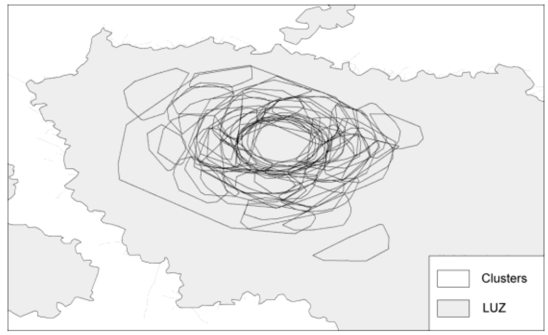

Source: Elaborated from Eurostat SBS.

*Figure 6. 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 and Urban Audit.