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Micro-geographies of clusters of creative industries in Europe

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Abstract. What is special about the geography of creative industries clusters? This paper considers the influence of the symbolic knowledge-base of such clusters, and also the preference for locating in urban spaces. Our study avoids classic research designs based on synthetic knowledge bases, and on regional-based administrative-constrained designs, and uses instead micro-data (550,000 firms belonging to the creative industries) and geo-statistical algorithms. Our results contribute to a better understanding of economic geography by: (i) addressing spatial dimensions within cluster theory; (ii) identifying and mapping Europe's creative industry clusters; and (iii) exploring particular forms of agglomeration and co-location (urban and non-urban) characteristics of creative industry clusters. The results have implications for scholars and policy-makers, especially in so far as they suggest a need to emphasise the importance of strategies that address existing clusters and relations between them, rather than concentrating simply on fostering the generation of new clusters.

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

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1. INTRODUCTION

From out of a real need – the search for new models of development in post-industrial societies – policies of intervention are being designed to promote *creative industries* (CI), backed up by the growth of an expanding theoretical body. This development is not surprising given that recent studies have shown that CIs are the most influential causal factors for explaining differences in wealth between European regions (De Miguel et al. 2012), and that they are highly clustered in space, producing thereby a particular geography (Lazzeretti et al. 2008).

What is different about the geography of CI clusters? In answer to this question, it can be said that so far the literature has not provided a specific theory on CI clusters, but, however, enough is known to indicate that important components of a CI cluster theory will differ from traditional theories of manufacturing clusters, and from more recent ones on high-tech clusters. The bases of the difference are twofold, namely that the knowledge-bases of creative clusters are neither synthetic nor analytic, but symbolic (Asheim et al. 2011); and that creative industries are particularly orientated to urban environments (Cooke and Lazzeretti 2008).

Such observations suggest three important questions need to be answered. Can we address clusters that have symbolic bases - which are mainly located in urban spaces - without allocating a more significant role to urbanization economies? Can CI clusters be framed through the traditional lens of the manufacturing synthetic knowledge-base? How can CI clusters be properly identified and addressed?

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

To date, the empirical evidence on clusters ranges from the territorial micro-scale (e.g. quartiers, or parts of a region) to the macro-scale (e.g. regions, or states). But scale is not neutral when it comes to the question of creative industries clusters. In particular, and in distinction from manufacturing clusters, the relevant factors for explaining the clustering of creative industries (i.e. basically services with a symbolic knowledge base) are not only the benefits of localization (and specialization) economies, but also, in great part, to the effects of old and new types of urbanization economies (Cooke and Lazzeretti 2008; De Propris et al. 2009; Lazzeretti et al. 2012). Urbanization economies produce location patterns of service cluster overlapping and a sharing of the same geographical space, which is not the case for manufacturing clusters with a synthetic knowledge base. Such patterns cannot be observed through a macro-scale perspective and so it is vital that the micro-scale be used in order to capture specific CI cluster subtleties.

In general, there is a need for an improvement of knowledge in the cluster literature, bolstered by new evidence on CI clustering patterns. This will provide an analytical tool to inform policy makers' decisions about CI. Our paper makes an effort to respond to the claims made by Boschma and Klosterman (2005, p.2-3) that there is a need for more empirical work, due to the fact that many of the cluster studies to date "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 CI clusters mainly focuses on isolated cases of study (e.g. Bathelt 2005; De Propris and Hypponen 2008; Krätke 2002), whilst what little general evidence exists only encompasses a few countries (e.g. Lazzeretti et al. 2008; De Propris et al. 2009), or focuses on an excessively aggregated scale such as at the level of the region (e.g. Power and Nielsén 2010).

These points challenge researchers to turn more towards the inclusion of a greater spatial dimension in cluster theory and empirical work. Echoing the criticism of Hoover and Giarratani (1971) that geographers resort to mere description and mapping without explanation, Maskell and Kebir (2006) argue that for the construction of a more general theory of clusters the relevant questions are *what?*, *how?*, and *why?*. Moreover, Hoover and Giarratani are also critical of the tendency for disciplines to lose contact with one another, neglecting the need for a mixture of approaches to solve problems. Thus, they say that, along with geographers, "traditional economists (have) ignored the *where* question altogether, finding plenty of problems to occupy them without giving any spatial dimension to their analysis”.

In our view, the complete question should be: “What, 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, since answering it puts into question existing theories and also contributes to new theoretical development, with new propositions and testable hypotheses.

Hence, a proper treatment of CI clusters requires changes in theoretical frameworks, as well as improvements in empirical methods, in order to offer a proper research design that can aid the identification of clusters with symbolic bases and located within urban spaces. Clearly, this cannot be accomplished using traditional regional-based administrative-constrained databases which do not allow for the specificities of 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 for exploring CI clusters in Europe. Our research contributes to economic geography knowledge, and, in particular, to the theory and empirical study of clusters, through the following actions:

i. Providing specific observations on the spatial dimension (*where*);

ii. Identifying and mapping the CI clusters in 16 European countries, based on firm-level micro-data;

iii. Exploring and detailing the particular forms of agglomeration and co-location presented by CI clusters in both 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 methodology and data. The fifth section focuses on the micro-geography of CI clusters and its main characteristics. The paper ends with a conclusion and a discussion about the limits of this approach.

2. CREATIVE INDUSTRIES AND CLUSTERS

2.1. Creative industries

The *creative economy* is a holistic concept that encompasses complex interactions between culture, economics and technology, in an economy dominated by intangible phenomena such as symbols, texts, sounds and images (UNCTAD 2010, p.3). The most popular approaches to the idea of the creative economy are those included within the *creative industries* literature (DCMS 2001 and 2009), and the *creative class* tradition (Florida 2002). Whereas the "creative class" tradition comes from a point of view focussing on human capital, that of "creative industries" is essentially an industry-based approach. The term *creative industry* (DCA 1994) was popularised by the Department of Culture, Media and Sports in the United Kingdom (DCMS 2001) during the British government of Tony Blair, in the context of a search for new bases of growth for the UK's post-industrial economy. Reviews of the literature on creative industries can be found in Howkins (2007), O'Connor (2007), Flew and Cunningham (2010) and UNCTAD (2010).

There are many definitions of, and taxonomies for, CI (O'Connor 2007; UNCTAD 2010). The most commonly used are based on the ideas of DCMS, although the most comprehensive have 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 world trade". 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).

UNCTAD's definition highlights one of the most significant characteristics of CI compared to other activities. That is to say, their knowledge base is not *analytical* (derived from the production and use of codified knowledge that originates from science and technology), nor *synthetic* (knowledge that is created through a more inductive process of testing, experimentation and practical work), but, rather, *symbolic*: knowledge that is related to the creation of the contents, desires and aesthetic attributes of products (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 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. Vom Hofe and Chen (2006) propose another classification: 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 delineation, with the consequence 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 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 and Feser 1999; Vom Hofe and 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 (Brachert et al. 2011).

Feser and Sweeney (2002) propose an extension of the range of methodologies to include the incorporation of spatial statistics (Vom Hofe and Chen 2006). 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 and Sweeney 2002; Jacquez 2008). Global indicators provide information about general clustering trends, whereas local indicators provide information about clusters' locations and their spatial boundaries.

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

Most studies on creative industries clusters have focused on case studies of a creative industry and/or a creative place. They have used different methodologies (such as description of the case, or analysis through a value chain perspective, or social network analysis) and have encompassed the three types of clusters described by Gordon and McCann (2000), as referred to earlier. For example, the *industrial 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 creative and digital industries in Australia, and Pratt (2011) for creative industries in London. At other geographical scales, general mapping exercises have relied basically on the use of location quotients. For example, Florida and Mellander (2008) have researched the clustering of the music industry in USA regions; Campbell-Kelly et al. (2010) have studied the software industry in metropolitan areas of the USA; Power and Nielsén (2010) have looked at cultural and CI in European regions; Capone (2008) has studied CI in local labour markets in Italy; Lazzeretti et al. (2008) researched CI in local labour markets in Spain and Italy; and De Propris et al. (2009) have looked at CI in UK local labour markets and Super Output areas.

In such research, a particular question of interest has been the reasons for the clustering of CI. O'Sullivan (2007) indicated that the main reasons for clustering are related to traditional localization and urbanization economies: such as the sharing of common labour pools, knowledge spillovers, the sharing of information, the availability of intermediate goods, and easy access to sources of demand. A great proportion of CI are business services, and Keeble and Nachum (2002) have noted that the clustering of business services in large cities such as London is determined by: 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. Malmberg and Maskell's (2002) theory of spatial clustering could also be used as a point of reference, although the specificities of the CI knowledge base (symbolic) demand a more specific approach. Lorenzen and Frederiksen (2008) integrate external agglomeration economies (i.e. localization and urbanization) with cultural factors and the presence of a creative class, to arrive at the conclusion that the clustering of cultural industries depends on the coexistence of both localization and urbanization economies. The estimates of Lazzeretti et al. (2012) highlight urbanization economies as the most important factor to explain patterns of CI clustering.

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

One of the most neglected aspects in the cluster literature has been the issue of spatial patterns of location and co-location of clusters sharing the same geographical space. This is not particularly surprising, given the influence of Porter's work 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. 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 case studies in the cluster literature has not generally paid much attention to the phenomenon of clusters sharing the same geographical space. 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 Becattini et al. 2009). More recently, the majority of the literature has focused on manufacturing clusters, which are often located in geographical areas too small to allow for more than one specialization. This has given rise to the identification of the spatial formation of clusters in isolation, that we name *hot spots*, and also to sets of clusters (with similar or different specializations) in close proximity (but not overlapping) forming *bunches* of clusters (figure 1).

The reality of CI demand different approaches for at least 3 reasons: First, CI are basically advanced services, rather than manufacturing activities (which have been the focus of most studies so far). Second, advanced services have a preference for locating in large places, such as big cities and metropolitan areas. Third, this preference cannot be explained by localization economies; as remarked by Lorenzen and Frederiksen (2008) and Lazzeretti et al. (2012), urbanization economies are crucial for explaining the formation, growth and competitiveness of CI clusters. Urban space is expensive with strong density being a consequence of high land rents, forcing a range of different types of activities to share the land. Co-location provides cross-fertilization urbanization economies (Jacobs 1969), opportunities for the co-presence of related variety (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, including CI, can overlap in the same geographical space.

When urbanization economies are particularly focused at a single point in the city, then we find clusters of different activities and with different spatial thresholds organized around this point, around a *hub* (Figure 1). This phenomenon is 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. 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 (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 indicative of the existence of creative *milieux*.

It is not strange that the literature on CI has become aware of co-location, for example in De Propris et al. (2009) and Mommaas (2004). Camors and Soulard (2010) and Freeman

(2010) suggest that in Paris and London there is not one but several clusters of the same or different creative industries. Pratt (2011, p.132) found evidence of a cluster *cloud* in London when he changed his scale of analysis and looked for micro-geographies of micro clusters, and detailed his 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 creative industries clusters shows some similarities with the stages followed by Crouch and Farrell (2001) for their general identification of clusters, and Capone (2008) for his 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.

The first stage is to operationalize the notion of CI cluster. For this, experience so far is of limited value. Hitherto, ideal models for clusters described by Gordon and 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 not homogenous and exhibit differentiated geographies, and, as explained by Pratt (2011), 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. Following Schmitz and Nadvi (1999, p.1503) we define clusters as "sectoral and spatial concentrations of firms".

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. Each industry is considered separately as our objective is to distinguish clusters of CI and not creative places[1].

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, 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 and Pickernell 2012). An example of research at the level of the region which was influenced by the above effects was that of Power and Nielsén (2010), where the authors used NUTS 2 and a location quotient - the most widely used methodology to deal with cluster identification at the regional level.

A second constraint has arisen when a strategy has involved the collection of data at infra-regional administrative levels (e.g. municipalities and local labour markets). Eurostat does

[1] 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.

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 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, which in turn permits the definition of concentration (agglomeration) on the basis of the locational density of firms in space.

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3.2. Spatial nearest neighbour hierarchical clustering (NNHC)

Justification for the 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 different techniques have different uses. 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 and 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 and Overman (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[2]. If the cluster satisfies the criterion of size, then it is retained and we proceed 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

[2] 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.

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, 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) 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 and 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 (NJI 2004) 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. Whereas several years ago the quantity of firms included in the database was clearly insufficient, now the number, and the significance of the sample, is good enough to be used in geo-statistical algorithms[3].

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

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

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 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, 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 and 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.

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). 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 political 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 kilometres (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 in 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 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.

The places where clusters locate are also different for different industries. For 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 (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 the whole of the European territory, 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 4a). 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).

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 4a).

Clusters are predominantly metropolitan. About 77% are located in metropolitan areas (here represented by Eurostat's Large Urban Zones (LUZ)) (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; 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.

5.3. Co-location and articulation versus isolation

CI clusters, particularly the largest ones, tend to share space with other clusters of the same or different CI (Figures 6 and 7). 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 economies and related 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 metropolitan areas.

Figure 7 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, for example in the Netherlands or in the London area.

[Insert Figure 6 near here]

[Insert Figure 7 near here]

5.4. 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[4].

[4] 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

A map using micro-data and NNHC (Figure 4a) 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 4b) 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. Figure 5 shows details for the fashion and software industries. 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.

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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.

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.

6. CONCLUSIONS

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

It has been found that the symbolic nature of knowledge in CI makes the clustering process highly sensitive to geographical distance, and intensive in the use of old and new urbanization economies, with implications for locations and cluster boundaries. Under these conditions, research based on just one or two case studies (e.g. Bathelt 2005; De Propris and Hypponen 2008; Krätke 2002) can have problems dealing with the phenomenon of co-location, and also can come to conclusions that lack general validity. On the other hand, research projects utilising large administrative units (e.g. Power and Nielsén 2010) sacrifice precision and suffer from aggregation bias, and the modifiable areal unit problem. This paper has sought to reconcile the necessity of obtaining micro level precision, with the desire to obtain macro level coverage, without restricting the scale at which clusters operate, and while addressing the reality of 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 and categories for the analysis of co-location.

Synthesizing the findings in an aggregate fashion, we found that there were a large number of CI clusters in Europe (1,784 clusters across 16 countries and 15 CI), concentrating 61% of the creative firms, showing an exaggerated preference for metropolitan areas and for 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 relates to 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 in observing this fact, a rare exception being 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 serves to refine the theory that a factor explaining the birth and success of clusters, and of the creation and location of firms in CI, is the existence of other clusters of similar or related CI.

The design and findings of our study have implications for scholars. First, clusters of creative industries (with symbolic bases) are different from manufacturing clusters and other services clusters (with synthetic and analytical bases), which suggests that there is at least a need for incremental changes to cluster theory. Second, we suggest empirical research on clusters should become more scale-flexible, with precise procedures for identification in wide-coverage studies, while moving towards the micro-perspective in order to avoid the constraints of relying on administrative and region-based units.

The differentiated nature of CI clusters means that probably a customized approach will be necessary in the design of policy strategies. 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. Also, one of the most criticised aspects in the implementation of cluster policy has been an 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 should not be the generation of new CI clusters but, rather, the articulation of policy strategies encompassing those clusters that already exist. A third point is that if CI clusters are not isolated, then co-location should be taken as a significant dimension for research and 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 related 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.

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, rather than the entire population, due to the coverage of the database. A third limitation is that the procedure is time-static, although the availability of more years in the sample would make it 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 up possibilities for comparative research, new insights into cluster theory, and further detailed research on the factors influencing CI location in clusters, and the factors that determine the appearance and evolution of clusters of symbolic base. In addition, the results can be augmented with a geography of clusters in non-creative industries and a comparison made between the patterns of clustering of both kind of industries, as well as a consideration given to the complementarities, or crowding-out effects, of patterns of co-location of creative and non-creative industries.

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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

Formatted: French (France)

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.

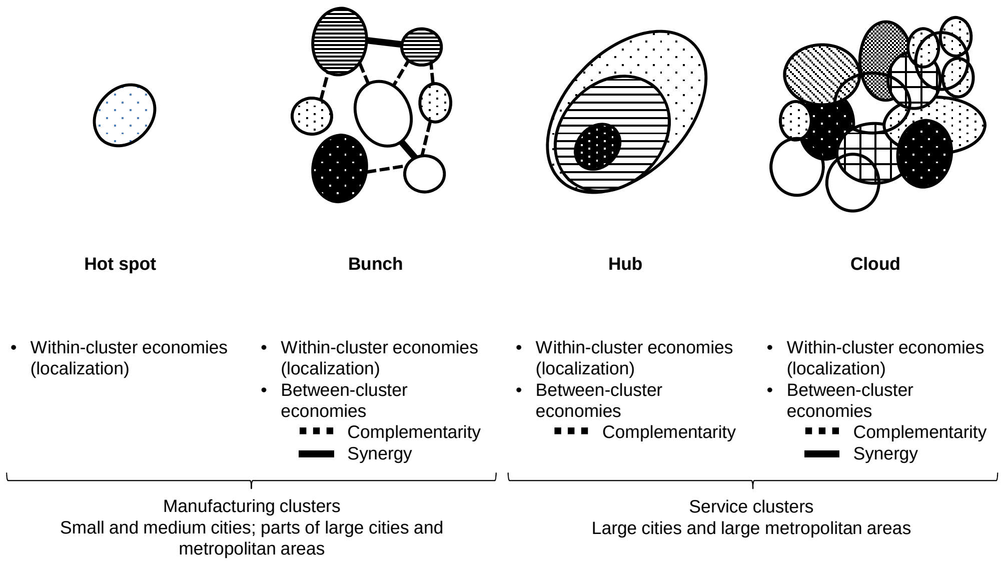


Figure 2. Spatial nearest neighbour hierarchical clustering algorithm

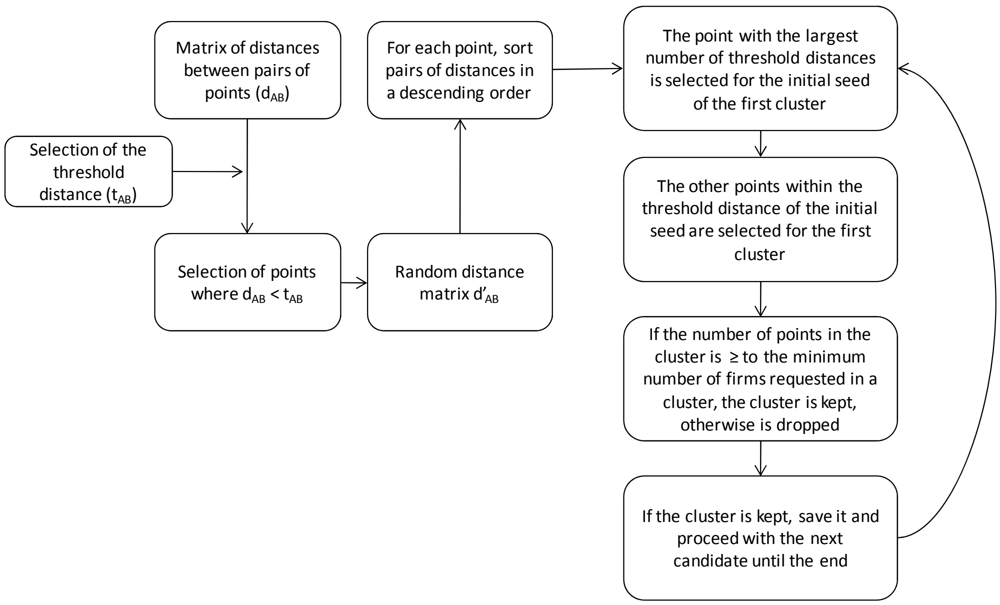


Figure 3. Nearest Neighbour Index for fashion and advertising

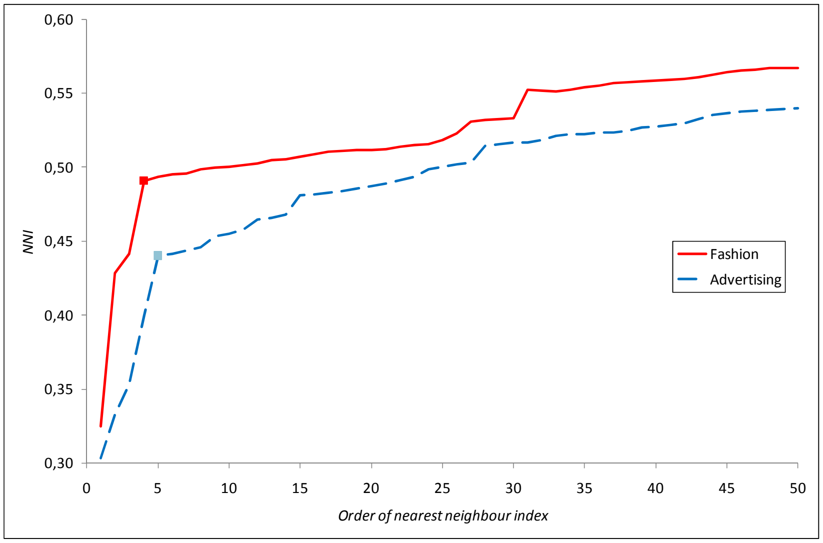
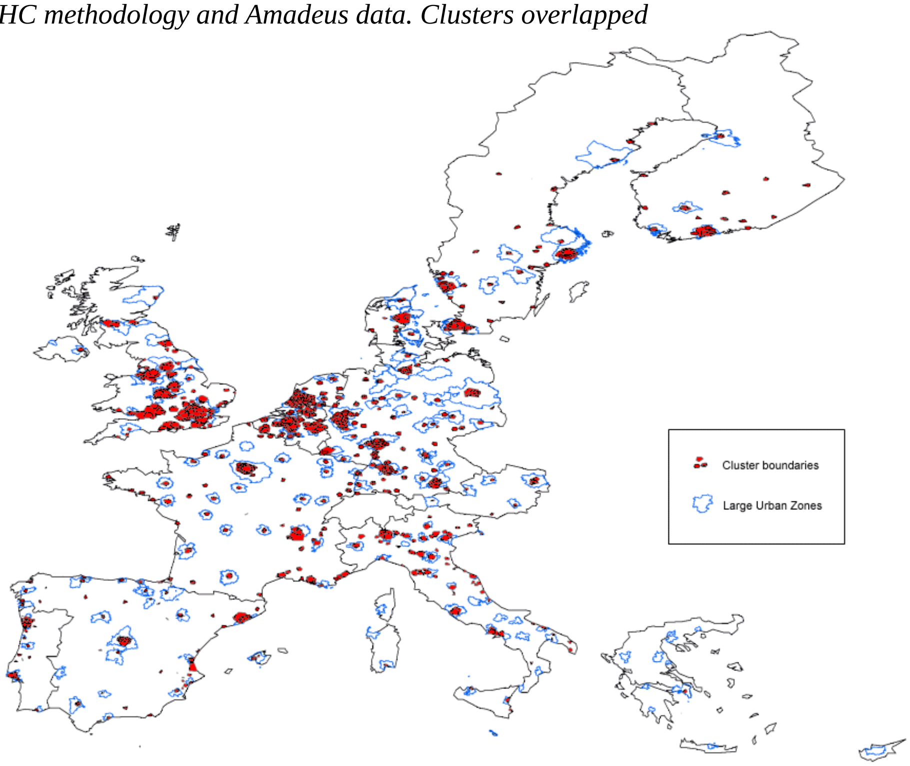
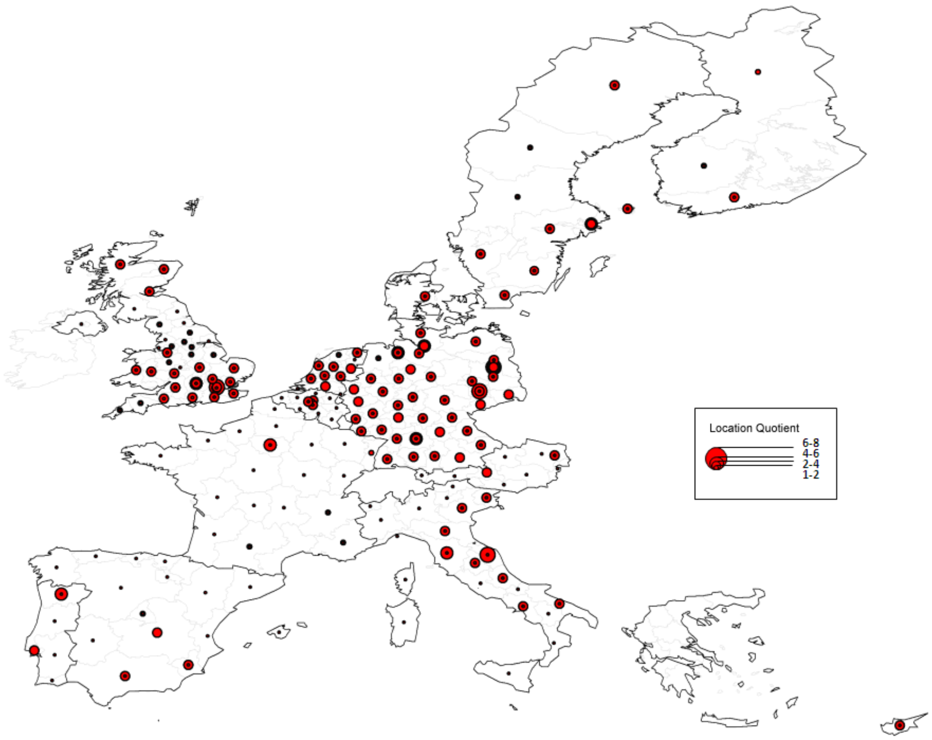


Figure 4. Clusters or creative industries in Europe.

A) NNHC methodology and Amadeus data. Clusters overlapped



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



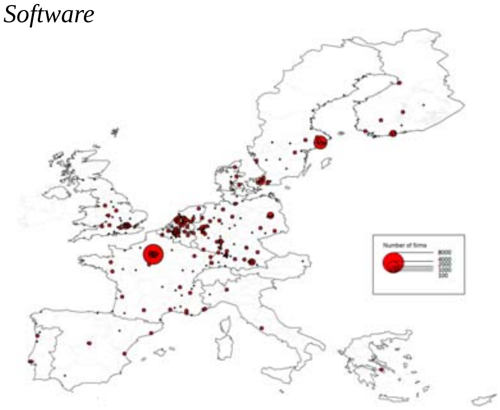
Source: Elaborated from Amadeus, Eurostat SBS and Urban Audit.

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

Fashion

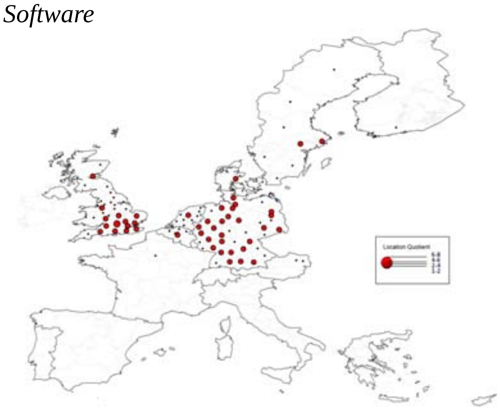
Software



B) LQ by region

Fashion

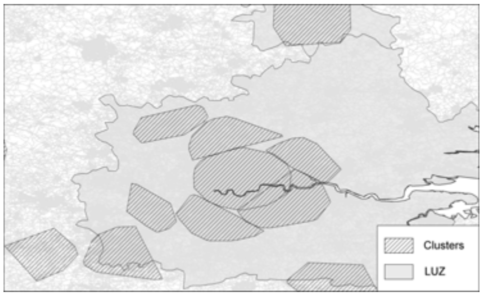
Software



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

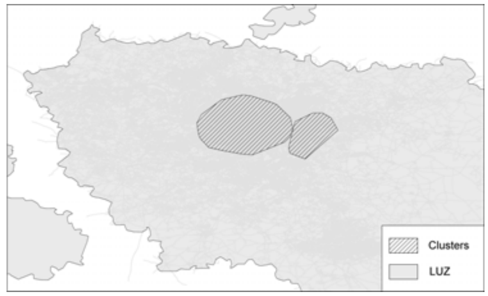
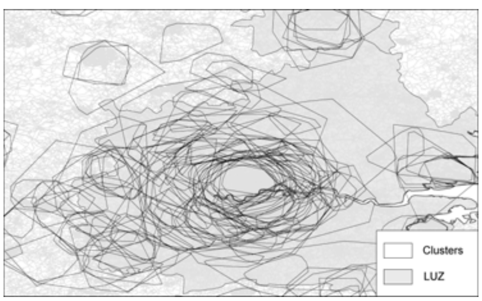
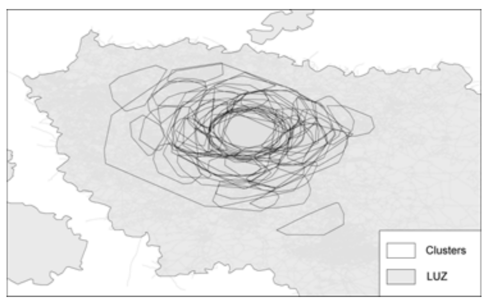


Figure 7. Clusters of creative industries overlapped. Detail for the Large Urban Zones of London, Paris, Barcelona and Rome, in a radius of 20 Km from the centre of the city. Scale 1:750000

a) London: cluster cloud

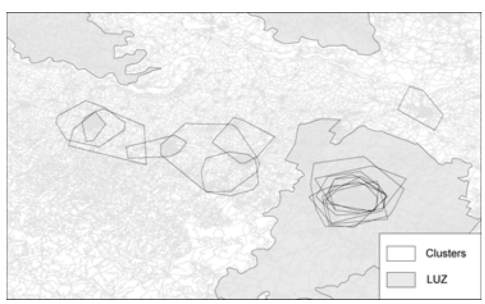


b) Paris: cluster cloud



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).