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Clusters of Cultural and Creative Industries: Any Role in Location Decisions of Firms?

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Clusters of Cultural and Creative Industries: Any Role in Location Decisions of Firms?

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Abstract

This paper focuses on the location patterns of Cultural and Creative Industries (CCIs) and the role played by existing clusters of these industries when entering markets. Departing from previous identification of clusters in CCIs, we analyse location determinants patterns and whether entering firms are attracted by these existing clusters. The aim of this paper is to identify if clusterisation of CCIs provides strong locational advantages for entering firms or if, by the contrary, firms also consider not clustered areas. The study uses firms' data from Mercantile Register (SABI).

Keywords: creative industries, clusters, location.
JEL codes: C38, R12, Z10.

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1. Introduction

Cultural and Creative Industries (CCIs) are receiving a growing attention by scholars from different academic disciplines ranging from sociology, geography, economics, urbanism and business. Our interest in them combine focuses of several of these areas as we care about how CCIs firms locate, why CCIs firms choose to be close to other firms and, finally, whether spatial proximity is needed for the interactions that CCIs firms have with each other. As the title of this paper indicates, the main interest of it is location issues, but this is not only about pure geographical issues but, on the contrary, about implications of these location decisions.

In this paper we focus on CCIs for several reasons, the most important one being the fact that these industries are hypothesized to have an important economic role (at least) in more developed countries. Nevertheless, when dealing with CCIs it is not clear at all what do scholars mean when talking about them. In this sense, literature is quite wide and departs from seminal contributions by the Department of Media, Culture and Sport (DCMS, 1998), but has been later followed by a wide literature trying to better define and identify which activities to be included as CCIs, which is still controversial. Nevertheless, there are extensive contributions by public organizations as UNCTAD and OECD that may help, as well as extensive work by authors as Luciana Lazzeretti (see, among others, (Lazzeretti et al., 2008, 2012)).

As we do not aim to carry out a methodological contribution dealing with the identification of the activities to be considered as being part of CCIs, we will use a wide definition of them, trying to have a broad perspective in terms of activities having a cultural and/or creative dimension.[1] Accordingly, we have selected twelve industries to be taken into account by this analysis. Concretely, these are advertising; architecture and engineering; cinema, music, TV and radio; fashion; graphic arts and printing; jewelry, music

[1]Check Appendix 1 for a detailed list of these activities.

instruments and toys; photography; publishing; research and development; software and video-games; writing, performing arts, visual art and craft; activities related to heritage.

This is an empirically driven analysis aiming to identify location patterns of CCIs and the way in which existing clusters of these industries may modulate these decisions. Concretely, we depart from a previous analysis by Maddah et al. (2020) in which CCIs clusters are identified in the Functional Urban Area of Barcelona (FUAB) using data from Mercantile Register corresponding to 2009 and 2017. As this paper clearly identifies the number and extend of clusters for these industries, we use similar data for 2010-2013 about new firms entering the same area, computing their location choices and inferring their locational determinants. Our results provide empirical evidence about persistence of location patterns (i.e., clusters attract firms of the same industries).

The relevance of the study on firms' entries and clusters is observed by its recent centrality in academic and empirical literature, as well as policy discussion. Both theoretically and empirically, in the analysis of modern economic geography, the spatial knowledge spillovers, industrial clusters, firms' entry, entrepreneurship, growth and survival, are all topics getting much attention from the scholars. As for policy debate, the current shift on European political and economic agendas is towards a more regional and local "place-based" policy approach. This is in line with Smart Specialization strategies. As emphasized in the (European Commission, 2013) report on the role of clusters in smart specialization strategies, "Cluster policies can provide a core toolkit to engage with and develop sectors of the economy in which a region has a significant position. They have the ability to guide the concentration and integration of economic policies around specific areas of the economy. And they can help avoid the pitfalls of traditional industrial policies, which often use tools that limit competition and thus ultimately competitiveness" (p.4). More specifically on cultural and creative industries, since 2012, the European Union has been addressing issues related to the contribution of cultural and creative industries/clusters to economic transformation through smart specialization (European Union, 2012). As the aim of this paper is to identify whether clusters of CCIs affect the location decisions for firms in the FUAB, thus it contributes to aligning local public policy agendas to offer tailored support for CCI cluster policies. This in turn reinforces the role of CCIs in local economy and innovation.

We have structured the paper as follows. In the next section, we review the literature on location determinants, with particular focus on specificities of CCIs firms. Then, we present data and the methods used. Next, we discuss the main results. Finally, we summarise our main conclusions and discuss some policy implications.

2. Location determinants: specificities of Cultural and Creative Industries (CCIs)

By and large, place matters. Firms tend to search for *strategic* locations in search for advantages of agglomeration factors, local knowledge spillovers and spatial proximity to urban amenities, similar producers or targeted consumers. Numerous studies in literature emphasize agglomeration economies as a determinant for firm location(Arauzo-Carod et al., 2010; Delgado et al., 2010; Wenting et al., 2011). On location determinants of high-manufacturing activities Arauzo-Carod (2009) found that new manufacturing establishments are positively influenced by firm density and the percentage of high-tech firms. This reflects the importance of industrial concentration and specialization in attracting firms' entries. Distance to main cities and the density of high-tech workforce have a negative influence as shown in the latter study, thus undermining the influence of urbanization aspects and occupational characteristics. Other studies have found diverse impacts on location decisions of firms given the variation in the nature of the industries. For example, Arauzo-Carod & Viladecans-Marsal (2009) for the metropolitan areas in Spain, found that urbanization economies had a positive influence on the location of new firms belonging to the low- and high-technology groups, but there was no effect for intermediate technology firms. Whereas localization economies had a positive significant impact on all the industries analysed. Hence, evidence emphasizes the importance of sectoral specialization at local level in attracting new firms in this sector.

Other studies have focused on the differences between urban and rural areas, rather than industrial differences, in evaluating the impact of agglomeration economies. Artz et al., 2016) found that firms are more likely to locate in markets with an existing cluster of firms in the same industry (with concentrations of suppliers or customers, and college-educated workers) and that firms are less likely to enter markets with no incumbent firms in the sector.

The influence of geographical concentration of firms on location decision, mainly acknowledged by the work of Marshall (1890) has further called an additional strand of literature that focuses on the role of clusters. The general confirmation is that clusters fuel the firms' entries. Frenken *et al*., (2018) show that there is strong evidence that clusters promote entry, but little evidence that clusters enhance firm growth and survival. The authors reveal the need to emphasize sectoral heterogeneity in this line of research.

Belussi (2018) studies MNEs entries in relation to the cluster life-cycle and finds that evolving clusters attract foreign MNEs that are interested in absorbing the newly created pool of local knowledge, which in turn allows the co-development of MNEs and local firms. As well mature clusters encourage the entries of MNEs; this encourages further cooperation with local institutions and research centres. This finding emphasizes the role of clusters as engines not only for firms' entries but also for creating an attractive environment of numerous cluster actors such as the universities and public institutions. Similarly, Delgado *et al*., (2010) address the role of regional clusters in regional entrepreneurship. The authors find that strong clusters are also associated with the formation of new establishments of existing firms, thus influencing the location decision of multi-establishment firms.

2.1. Location of CCIs

Despite the growing importance of cultural and creative industries, studies on location determinants of firms' entries in those industries are still scarce. A general study by Coll-Martinez and Arauzo-Carod (2019) shows that location determinants are quite similar both in creative and non-creative industries and that both industries are positively influenced by the specialization level of creative industries. In a thoroughly focused approach on software and video game firms in Barcelona, Méndez-Ortega and Arauzo-Carod (2019) found that SVE and video game firms follow patterns similar to other service industries by tending to cluster around some central areas of the Metropolitan Area of Barcelona (MAB) as a whole, and Barcelona city center in particular. However, the authors found limited influence of inter-industry localization economies as they emphasized that f the SVE and video game firms differ do not tend to locate close the same type of industries.

On the other hand, Cook and Pandit (2008) found that strong clusters in Film and Television sectors promote entrepreneurship, which in turn promotes cluster strength in a self-reinforcing dynamic and that some firms are better able than others to benefit from cluster location due to superior firm competencies and absorptive capacity. Heebels and Boschma (2011) address the publishing sector in Amsterdam and found that the Amsterdam cluster did not function as an attractor for publishing firms from other regions, but rather acted as an incubator for firms that relocated to other regions. Finally, applying a qualitative case study approach, a study on the leather products cluster in Florence by Randelli (2018) found that among all clusters, only the Florence cluster had an asymmetric path in the period 1995-2011, compare to a general trend of decline in the number of firms. The Florence fashion leather cluster, lead by Gucci, continue to have a positive rate of new firms, even faced with the global crisis. This finding calls attention to the importance of well-established brands in attracting entrepreneurship in same sectors.

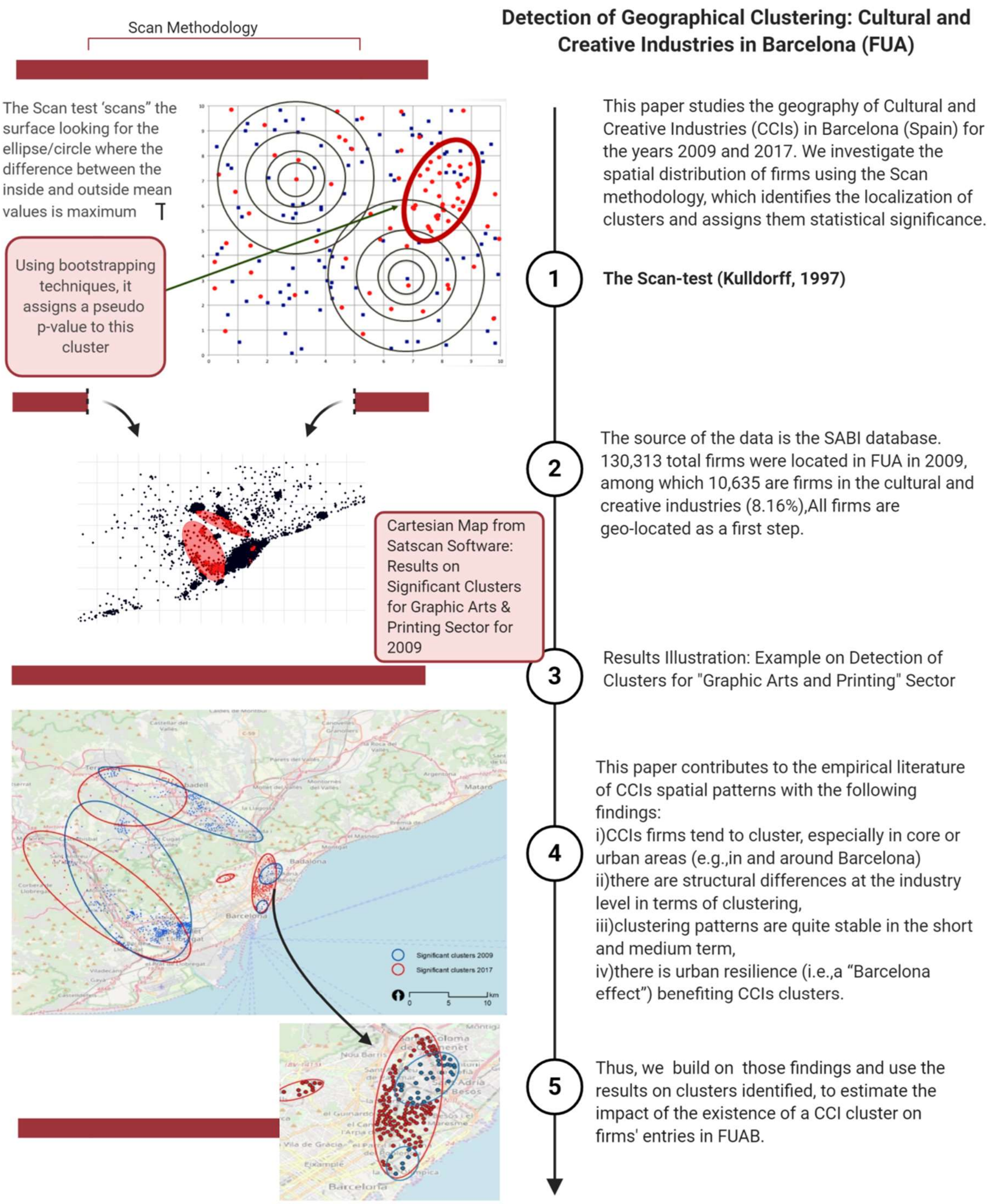
Location of creative firms is very much associated with a direct access to urban amenities, consumer market (tourists for example), lifestyle, places that act as platforms/catalysts for individual expression and inspiration, social networks and other socio-psychological dimensions. A strand of literature that complements the discussion on firms' entries and location decision is one that focused on artistic/cultural entrepreneurship (Heebels and Van aalst, 2010; Rius, 2012; Cunningham and Tolonen, 2019 and Murzyn-Kupisz and Dzialek, 2019). The majority of those studies used a qualitative methodology. Scott (2005) emphasized the importance of spatial agglomeration for creative firms' entries to the Hollywood film cluster, arguing that firms benefit from informal networking, knowledge spillover and creativity stimulation, more available and efficient local services, specialized organizations and cultural facilities. Similarly, Heebels and Van aalst (2010) advocated the importance of spatial concentration for creative firms' entries, yet reflected on the individual characteristics by differentiating between location decisions of "experimental" and "established" creative entrepreneurs. Other researchers as well highlighted the importance of both social and spatial context ((Cunningham and Tolonen, 2019). Murzyn-Kupisz and Działek (2019) linked the artistic and cultural firms' physical location decision to four dimensions (1) specific quarter type (2) potential economic and spatial advantages (3) desired visibility in urban space and (4) targeted customer types. The authors found differences among respondents, as for example some favor locating their firms in inner city areas (historic quarters) to benefit from social contacts, large flows of customers (mainly tourists) and prestigious image of the city and cultural heritages, while others prefer less prestigious periphery parts of the city, targeting local clients and benefiting from other advantages.

2.2. Clustering of CCIs

Mainly studied in the field of economic geography, Lorenzen and Frederiksen (2008) described clusters as "geographical agglomerations of firms that enjoy economies (positive externalities) from being located the same place" (p. 2).Clustering of cultural and creative industries has been a focus of numerous studies in the last decade (Maddah et al., 2020; Coll-Martínez et al., 2019; and Boix et al., 2015, among others). Theoretically, Lorenzen and Frederiksen (2008) explained cultural and creative clusters in terms of urbanization and localization economies. Localization economies are those positive externalities firms may enjoy from co-location, in effect of industrial specialization. Whereas urbanization economies are allocated to positive externalities related to urban location. Examples of urban clusters of CCIs as identified in preceding literature are software and videogames (Maddah et al., 2020 for Barcelona; Méndez-Ortega and Arauzo-Carod, 2020 for Barcelona, Lyon and Hamburg), ICT and biotech (Lorenzen and Frederiksen, 2008), advertising, cinema, music, TV and radio, graphic arts and printing, photograph, publishing, writing, performing arts, and crafts (Maddah et al., 2020). Such urban clusters benefit from urban amenities, universities, as well as research and public institutions and investment. However, mature industries such as furniture (Lorenzen and Frederiksen, 2008) and fashion manufacturing (Maddah et al., 2020) cluster in nonurban areas because they rely on product flexibility, variety, and incremental innovation, and benefit hugely from localization economies.

Inner cities are commonly a preference for CCIs clustering (Landry, 2012). In Europe, the largest clusters of CCIs are located in the inner parts of the largest cities (Boix et al., 2015). Agglomeration benefits, knowledge spillovers, social networking, historical quarters and rich cultural districts are, among others, benefits that CCIs exploit in such places. As we focus on Barcelona city in this paper, we build on a detailed study on clustering of CCIs, at sub sectoral level, in the FUAB provided by Maddah *et al.* (2020). Thus, we present in Figure1 a brief description on the approach of Maddah et al. (2020) and in Figure 2 their detailed findings on clusters in the FUAB between 2009 and 2017, using the SaTScan Methodology, which will be the departing point of this paper and the source of the main measure of firms' agglomeration, our variable of interest (existence of a cluster) in the estimation of firms' entries.

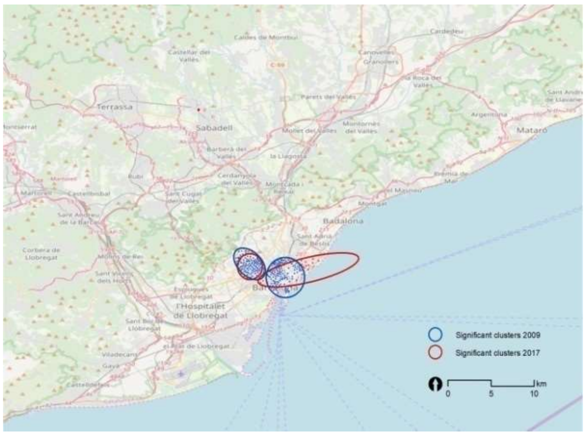
Figure 1 A SaTScan Approach to Identifying Clusters: Summary of Maddah *et al.* (2020)



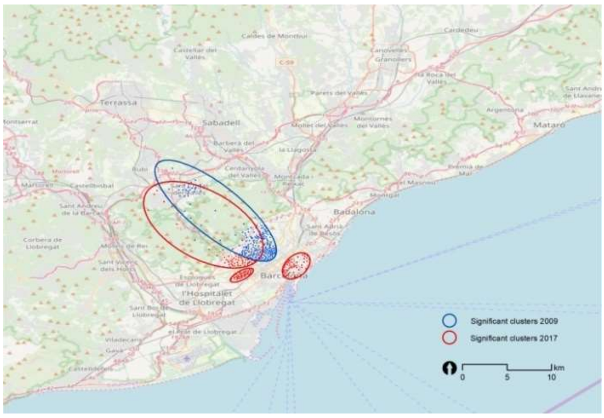
Source: Authors' Own Elaboration

Figure 2 Significant Clusters of Cultural and Creative Industries in FUAB

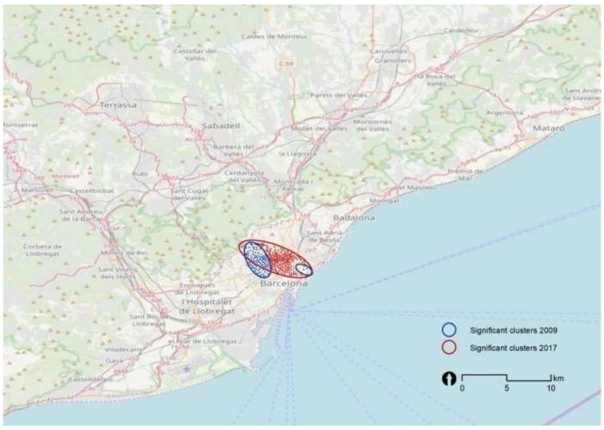
Advertising



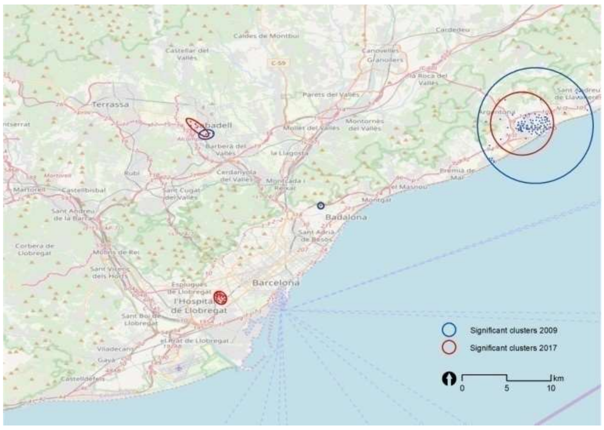
Architecture



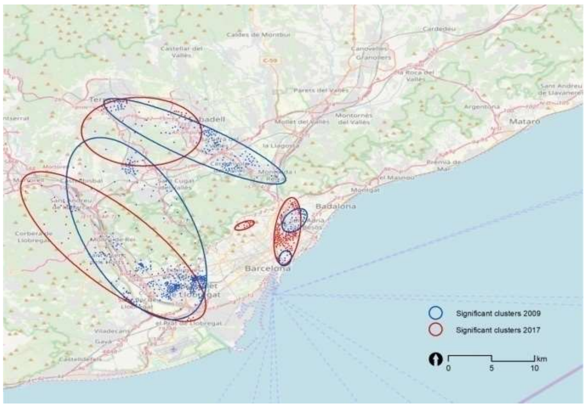
Cinema



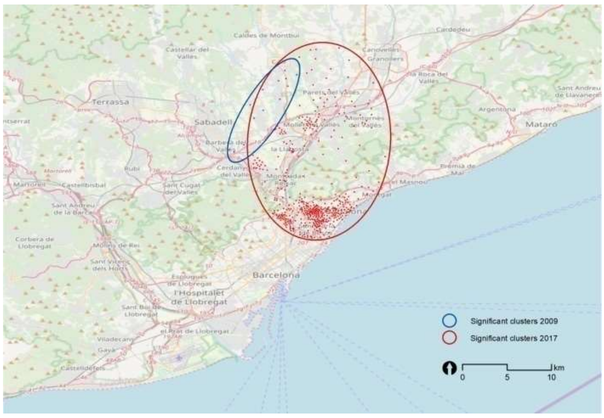
Fashion



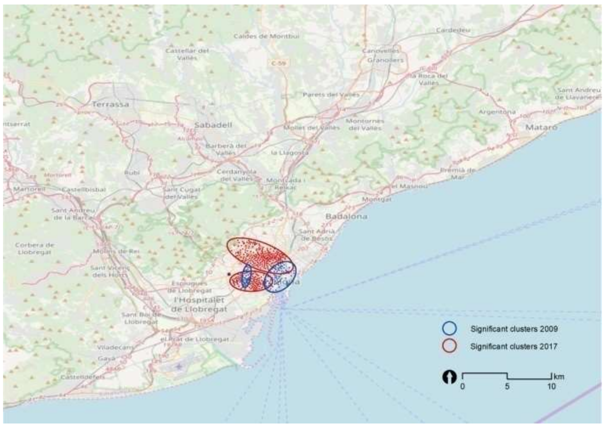
Graphics



Jewellry

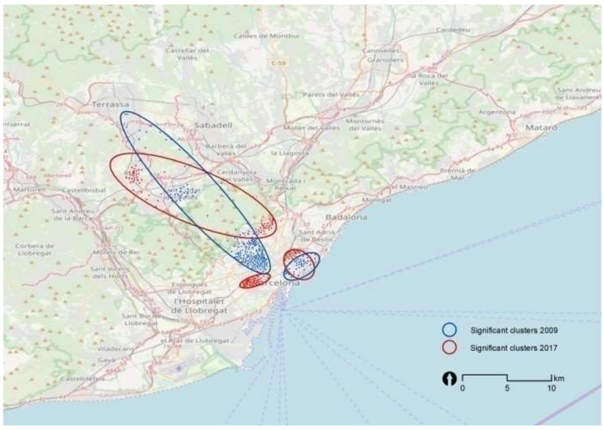


Publishing



Writing

Software



Source: Maddah *et al.* (2020)

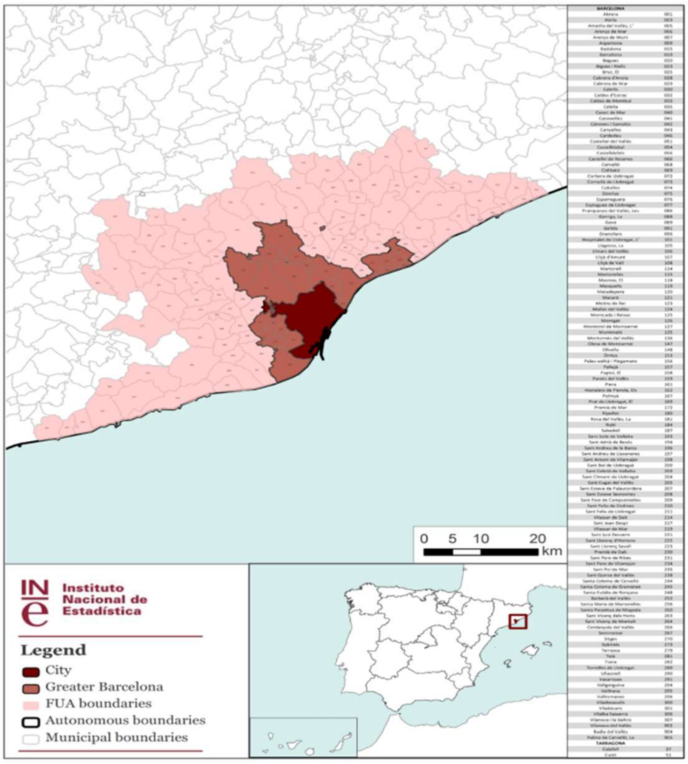
Markusen (2014) argues that city leaders help improve their cities by targeting resources when they know where this capacity is located and how organizations choose sites: “*In fashioning good policy and making funding and planning decisions, what do city leaders and advocates need to know about the location preferences of artists, arts organizations and arts participants?”* (p.581).Through this study, we aim to fill existing gap in this area. In particular, our contribution is that we directly study the firm location choice with respect to the existence of an industry-related cluster, suggesting higher agglomeration benefits attract new firms. Qualitative analysis and case studies still dominate this field of inquiry on the relationship between creative clusters and firms' entries (Markusen, 2014). To the best of our knowledge, our paper is the first empirical study that examines the role of geographically identified significant CCI cluster in encouraging new firm entry. This approach provides a bridge between the empirical new economic geography literature on urban city and clusters and the empirical literature on the firm location.

3. Data and Methodology

3.1. Sample and Data

Our main data source is the SABI database (*Sistema de Análisis de Balances Ibéricos*), from INFORMA D&B. Specifically, SABI collects data from the Spanish Mercantile Registry, where mercantile firms are obliged to deposit their balance sheets on an annual basis. SABI provides information on a large number of variables regarding these firms, including birth date, balance sheets, income, expense accounts, number of employees, industry at 4 digits level, sales and assets, and the geo-referenced location (X and Y coordinates). Although SABI is the most usual source for studies of the location of economic activity in Spain, this database is about firms, not establishments, being that in case of multi-plant firms, data refers to firms, not to their establishments, so in those cases SABI will provide the information in an aggregated way for the firm as a whole, using the location of the headquarter. Obviously, having disaggregated information for all the establishments would allow a much more precise analysis, especially as regards the spatial distribution of economic activity. However, this bias is not presumed to be relevant given that, according to data from 2006, multi-plant firms in Spain are estimated at just over 1% of the total (Jofre-Monseny et al., 2018).

Figure 3. Functional Urban Area of Barcelona



Source: INE

This paper analyses location determinants at the Functional Urban Area of Barcelona (FUAB) (Spain). The FUAB comprises the city of Barcelona and 137 surrounding municipalities (see Figure 3). According to Spanish Statistical Institute (INE), a Functional Urban Area consists of a group of municipalities and their commuting zones. Overall FUA’s are areas where there is an integrated and easily identifiable labor market inside its geographical boundaries. Concretely, FUAs rely on commuting criteria (i.e., areas where 15% or more of the employed population commutes to the city center) and spatial contiguity criteria. In terms of size, the FUAB has a resident population of almost 5 million people (1,5 of them correspond to the city of Barcelona). There are around 2.5 million jobs in Barcelona province (13.6% of jobs in Spain) among which 1.1 million jobs are in Barcelona (5.9% of employed population in Spain and 35.5% of Catalonia). 54.1% of the jobs in Barcelona are knowledge-intensive. The core of the FUAB is thus the city of Barcelona, a global city with plenty of cultural infrastructures where most of Catalan CCIs activities agglomerate, ranked by the Cultural and Creative Cities Monitor (European

Commission, 2017) as the ninth large city in terms of vitality and creativity (Barcelona Data Sheet, 2018).This data on Barcelona city justifies the need to break-down the city to smaller geographical areas to accommodate for the disparities among Barcelona city and remaining FUAB municipalities. Therefore, the spatial units of the analysis include 147 spatial units: i) the core of the FUAB (i.e., 10 districts inside the city of Barcelona) and ii) the periphery of the FUAB (i.e., 137 surrounding municipalities) (see Figure 4 in Section 3 for details).

3.2.CCIs considered

As we want to analyse effects of CCIs clusters in the FUAB identified in Maddah et al. (2020), in this paper we just consider the 11 CCIs used there. Namely, Advertising; Architecture and engineering; Cinema, Music, TV and radio; Fashion; Graphic arts and printing; Jewellery, Music instruments and toys; Photography; Publishing; Research and development; Software and video-games; Writing, Performing arts, Visual art and craft (see Appendix 1 for details). In any case, that selection fits with previous approaches in terms of CCIs identification, such as those of Lazzeretti et al. (2008), Lazzeretti (2013) and Bakhshi et al. (2013).

3.3.Empirical strategy

We estimate the number of firms locating in the FUAB (i.e., our dependent variable) as a function of a vector of local characteristics of the 147 spatial units considered. Specifically, we will estimate location determinants for the 11 CCIs subsectors considered in this paper, as well as for all CCIs together and, in order to control for CCIs specificities, all firms and all non CCIs firms.

Dependent Variable

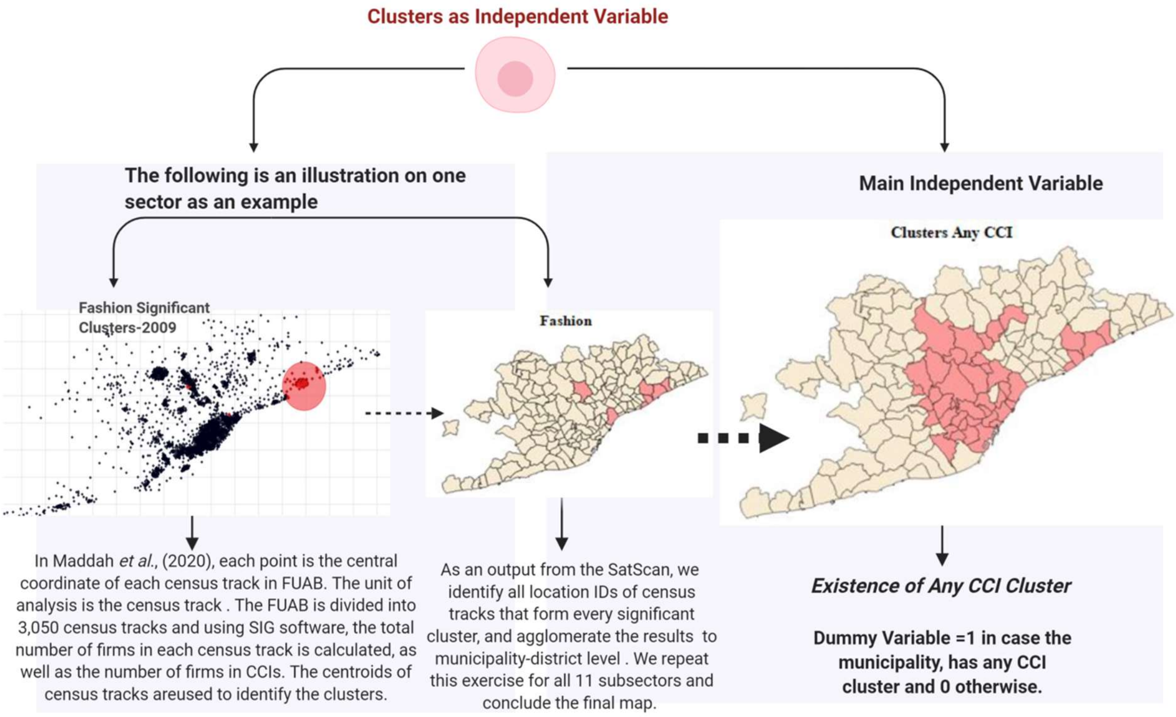
As mentioned previously, the identification of the geographical unit is a first step. For the purpose of this study, we have selected the municipalities of FUA, and disaggregated Barcelona city to ten districts. To construct the dependent variables (1) all firms' entries (2) CCIs entries (3) Non-CCIs entries (4) industry-specific entries, we use firm registration records from SABI to build measures for firms' entries for each year between 2010 and

2013. We identify industrial sector, in which firms operate, at 4-digit level of European Standard NACE-2009 Industry Classification (Appendix 1), and then geo-locate all firms, using QGIS, to assign its relevant location (municipality/district) which is our geographical unit. Our dependent variable is thus the number of firms entering a spatial unit (municipality/district).

Independent Variables

To estimate the location decisions of firms in FUAB, we use preceding theories and empirical methods used to categorize and select variables at local level. We assume that agglomeration economies are of key importance when choosing a new venue. Our main variable of interest refers to the existence of a cluster of CCIs altogether, any CCI, and the specific CCI industry in the same municipality / district (the variable is adapted from Maddah et al., 2020). In Maddah et al. (2020), clusters of firms are identified at census track-level. For the purpose of this paper, the findings are aggregated to municipality and district level using basic estimations on SatScan and QGIS. We identify all location IDs of census tracks for every significant cluster to spot the municipality/district. For example, if a cluster has location IDs census-tracks 801901002, 801901004 and 800610005, then the cluster is aggregated in municipalities 8019 and 8006 (see Figure 4). The focus on local spatial units for creative industries is being emphasized more than ever. Markusen (2014) reflects that city mayors, urban scholars, real estate interests, arts community members, and policymakers have engaged in vital debates about whether to designate cultural districts, what kinds of resources should be devoted to them, and what kinds of success to anticipate if created.

Figure 4 Geographical Units Transformation: Clusters in Spatial Units



Source: Authors' Own Elaboration

After testing a set of variables, five additional variables were chosen for empirical estimations of the model. We use the Variance Inflation Factor (VIF) for the selection among variable. For example, variables *Land Price of New Construction* and the *Number of workers affiliated to the General Social Security*, were excluded. Also, our choice of variables depends on the availability of all variables needed at municipality and district level. Table 1 highlights the descriptive statistics of the selected explanatory variables and their definitions. Table 2 shows the correlation matrix of key variables which shows that we do not have a problem of multicollinearity.

Those variables are *pop_09*, the population of municipality/district for base year 2009. This variable is a fundamental demographic variable that measures agglomeration economies. The *stock_09*, the initial total number of firms in municipality/district for

2009, measures the density of incumbent firms. To control for market conditions and business climate we include variable *migr-09,* the total migratory balance of firms. Generally, in theoretical models of entrepreneurship, tax changes influence the creation of new enterprises, which is why we include the variable *irpf_09* that is the general tax base per taxpayer for 2009. Finally, two geographic dummy variables are included (1) *Seaside* and (2) *CBD* (Central Barcelona District). If the municipality is on the seashore, the variable *Seaside* takes the value of 1. As for the CBD, it is "*Eixample*" district. This district is known as the hub of creativity in Barcelona. Referring to Rius (2012) the center of Eixample has witnessed the location of some thirty art galleries since the twentieth century, and ever since has become the place of modern art (as compared to the Gothic Quarter where the traditional art was concentrated). By 2012, Eixample has had the lion's share of medium-importance galleries (56%) as compared to the other 9 districts of Barcelona, and 72% of the high importance galleries (Rius, 2012). Considering the "creative" aspect of the industries in this study, and the argument in preceding literature that artistic entrepreneurs consider the "look and feel of the place" to locate their firms (Heebels and Vaanalst, 2010), this variable is found relevant.

[INSERT TABLE1 HERE]
[INSERT TABLE2 HERE]

3.4. Econometric methodology

Our dependent variable is the number of firms entering a spatial unit (municipality/district), which is a discrete non-negative integer. As we are trying to estimate a possible relationship between clusters' existence and firms' entries at local level, and given the nature of the dependent variable, we follow the preceding research on location of firms (Arauzo-Carod, 2010). For modeling the discrete outcome, we employ count-data models as our methodological approach in conducting this empirical analysis.

The descriptive statistics of the dependent variables show signs of overdispersion and zero inflation. As a matter of example, zeroes scored an average of 50% for entries at sectoral level and more than 25% for CCI firms' entries. But this wasn't the case for total firm's entries and non-creative firms. Referring to Cameron & Trivedi (1998) count-data models have the capacity to deal with the "zero problem". This problem is very common in studies on firms' entries, mainly those which estimate entries in a highly disaggregated spatial unit (Arauzo Carod, 2008). Still, considering municipalities/districts which are not receiving any entry is essential as this provides relevant information because the characteristic of these units (mainly the existence of a CCI cluster/or not) can help to explain why they have not been chosen by any firm to locate (spatial units where y=0). Otherwise, the results will be biased. The structure of the count-data models allows the handling of both positive and zero entries given that both types of dependent variables contribute to the estimation (Cameron & Trivedi, 1998).Another main methodological concern when using a CDM to analyze location patterns is to follow one of the two potential schemes (Arauzo Carod, 2008; Guimaraes et al., 2003): i) to consider that location decisions are taken according to a vector of variables shared by all entrants (zij= zi), and ii) to consider that location decisions are taken according to a vector of variables shared by groups of entrants (zij= zig for g = 1, 2,…, G, where G is the number of groups). In this paper grouping of entrants is done using the specific CCI to which each firm belongs to, although CCIs are also considered altogether, as well as non-CCIs as all firms.

In the selection among count data models, the departure point is the Poisson Model (PM). This model has an advantage in dealing with the excess zeroes problem, however, has limited capabilities in dealing with "overdispersion" (the variance > the mean). The descriptive statistics in this paper specify that there is an overdispersion problem. These results lead to two suggestions: 1) apply the Negative Binomial model (NBREG) or 2) maintain the conditional mean assumption E(ylx) = exp(x'β), and in this case one can proceed to use the Poisson maximum likelihood estimator (MLE), which retains its consistency, but relax the equivariance assumption to obtain a robust estimate of the variance covariance matrix of the estimator (VCE) (Cameron & Trivedi, 1998), p.556). The second approach is chosen for the dependent variable *All Firms entries*. For CCIs entries, and sub-sectoral entries, the Zero-Inflated Negative Binomial model (ZIPM) is used. For the Non-CCIs entries the Negative Binomial Regression model (NBREG) is used. The results of models are quite similar; however, based on the Akaike information criterion, the favored model for entries is selected. On a final note, similarly to Paper [1] in order to control for the spatial dependence, the spatial lagged variable of the existence of CCI cluster, and then for the existence of subsectoral clusters is incorporated in the model.

Table 3 show descriptive statistics of the dependent variables, which show signs of overdispersion and zero inflation. As a matter of example, zeroes scored an average of 50% for entries at sectoral level and more than 25% for creative entries. But this wasn't the case for total firm's entries and non-creative firms (See Table 4).

[INSERT TABLE3 HERE]
[INSERT TABLE4 HERE]

Focusing on the location phenomenon may generate a bias if not considering municipalities / neighbourhoods not chosen by any firm. Concretely, data of CCIs entering firms between 2010 and 2013 shows that municipalities / neighbourhoods out of where effectively chosen by, at least, one firm, whilst zero entries did occur at some of them. Any potential bias disappears when using a CDM as these models show how many times each area is chosen by a firm, being that those where y = 0 (i.e., not chosen by any firm) are also relevant because values of independent variables there explain why they have not been chosen.

When using a CDM to analyse location patterns there are two potential schemes (Arauzo-Carod, 2005; Guimarães*et al.*, 2003): *i)* to consider that location decisions are taken according to a vector of variables shared by all entrants (z_{ij}= z_i), and *ii)* to consider that location decisions are taken according to a vector of variables shared by groups of entrants (z_{ij}= z_{ig} for g = *1*, *2*,…, *G*, where *G* is the number of groups). In this paper grouping of entrants is done using the specific CCI to which each firm belongs to, although CCIs are also considered altogether, as well as non-CCIs as all firms.

Concretely, we model location decisions at neighbourhood level with an exponential conditional mean function (Cameron and Trivedi, 1998):

$$E[Y|X] = \mu = e^{W-X\beta}$$

where the dependent variable Y is a vector that contains the number of new firms located during a time period in one of the municipalities / neighbourhoods. Most of recent contributions that analyse firms' location determinants focusing on the characteristics of sites potentially selected by new firms rely on Count Data Models (CDM) (see Arauzo-Carod *et al*., 2010, for an extensive review of the empirical literature). As the CDM family is quite large[2], in order to discriminate among alternative CDM, we follow Cameron and Trivedi (1998).

Concretely, the number of new firms (i.e., belonging to a CCI or non-CCI industry) in a municipality / neighbourhood is a function of the local specific characteristics previously described:

$$Y_{ij} = \beta X_j + \beta W X_j + \varepsilon_{ij}$$

where Y_{ij} is the number of new firms belonging to industry *i* located in a municipality / neighbourhood j, $X_j$include the previously explained set of covariates, WX_j include the spatially weighted average of neighbouring areas of most of previous covariates (where *W* is a symmetric row-standardised matrix with elements taking values 1/0 depending on whether two areas are considered as neighbours –i.e., if they share a common border-, and X_j includes covariates with spatial variation), and ε_{ij} is an error term.

4. Results

4.1 Exploratory analysis: Descriptive Statistics and Maps

[2] Among the main CDM we may include the Poisson model (PM), the negative binomial model (NBM), the zero-inflated Poisson model (ZIPM) and the zero-inflated negative binomial model (ZINBM). Typically, PM is the starting point for these analyses, although it is not able to deal with the two main problems of data about entries in location analysis: 'overdispersion' and 'excess of zeroes'. That limitation can be easily solved by using NBM, ZIPM and ZINBM.

Figure 4 shows the spatial distribution of total entries (cumulative from 2010 until 2013) to FUAB, CCIs' entries and Non CCIs entries, respectively. The spatial distribution of firms shows a common trend among firms to locate on the urban part of the FUAB, with the periphery part generally having zero entries. The concentration becomes higher in the heart of Barcelona city, with variations within its ten districts.

4.2. Econometrics

The study uses firms' data from Mercantile Register (SABI), and exploits count data models in the analysis, as elaborated in previous sections. The exploratory analysis reveals spatial distribution of firms shows a common trend among firms to locate on the urban part of the FUAB, with the periphery part generally having zero entries. The concentration becomes higher in the heart of Barcelona city, with variations within its ten districts.

To start with, Table 5 shows the location determinants of firms' entries in FUAB. This is the baseline specification in which no spatial effects are included. Our variable of interest, i.e., the existence of a cluster of any CCI *(Cluanycci)* has a significant and positive effect on the entries of all firms, CCIs and Non CCIs. The population and income levels are significant for all entries, whilst the CBD and stock-09 are only significant for all firms specification. Seaside appears to influence CCIs and Non CCIs as well, but not all firms.

[INSERT TABLE5 HERE]

The results from the first step of the empirical analysis show that the existence of any CCI cluster has a positive and significant effect on the entries of all firms in FUAB. This finding emphasizes the argument on CCIs' ability to foster other economic activities, and not only CCIs. Furthermore, this effect remains positive and significant when regressing all CCIs and Non-CCIs separately. The population and income levels are significant for all entries, whilst the CBD and stock-09 are only significant for all firms specification. Seaside appears to influence CCIs and Non CCIs as well, but not all firms.

When incorporating the spatial variable WCluanycci to the model (see Table 6), the results reveal slight changes. Whilst both the cluster and its spatial lag remain significant for all firm entries, being in a cluster of any CCI becomes insignificant for both CCIs and Non CCIs, although the spatial lag is significant and positive for both types of firms' entries.

[INSERT TABLE6 HERE]

This is a surprising finding revealing a spatial spillover effect of clustering that can be interpreted according to the evolution of clusters. Concretely, in this paper data about clusters comes from Maddah et al. (2020) that identified them using Scan-test method (Kulldurff, 1997) in FUA for 2009 and 2017. As for the econometric estimations data about clusters corresponds to 2009, but Maddah et al. (2020) show that there were important changes in the spatial scope of these clusters between 2009 and 2017. In this sense, none of the ones identified in 2009 disappeared, but they changed considerably in their elliptic shape and size by incorporating surrounding districts and municipalities, which is quite consistent with existing theories about clusters life-cycle (Andersson et al., 2014). In this sense, our results show that although for CCIs entries the existence of a cluster is not significantly influencing that location decision, the existence of close clusters matters.

[INSERT TABLE7 HERE]
[INSERT TABLE8 HERE]

Finally, the results on sub-sectors emphasize again the heterogeneity among them. While the existence of a cluster in advertising encourages advertising firms to locate in the relevant municipality/area, publishing firms location decisions are not influenced by the existence of a publishing cluster, in line with the findings of (Heebels and Boschma, 2011) who reveal that the Amsterdam cluster did not function as an attractor for publishing firms. This heterogeneity in the ability of CCIs agglomeration to attract CCIs is emphasized, and reveals that even if the cluster is in the center of Barcelona, it might not have the potential to attract similar firms. This is why designing cluster-oriented policy is essential to compliment policies of urban cities. The findings for the clusters of Cinema, Music, TV and Radio are in line with (Cook and Pandit, 2012) who found that strong clusters in Film and Television sectors promote entrepreneurship. Similarly, results for the fashion cluster encouraging the fashion manufacturer's entry, are in line with (Randelli and Lombardi, 2014)on the Florence fashion leather cluster which continue to have a positive rate of new firms.

On a final note, the CBD variable has a positive and significant effect on the graphic arts and printing and publishing firms only. Obviously, those firms are art-related and this finding supports literature emphasizing the capability of cultural districts in attracting art activities, among which is the study of (Murzyn-Kupisz and Działek, 2017) who argue that while some CCI firms favor locating in inner city areas (historic quarters) to benefit from social contacts, large flows of customers (mainly tourists) and prestigious image of the city and cultural heritages, while others prefer less prestigious periphery parts of the city, targeting local clients and benefiting from other advantages.

5. Conclusions

This paper has some light on location patterns of CCIs using data for the Functional Urban Area (FUA) of Barcelona between 2010 and 2013. We have analysed whether the existence of CCIs clusters does attract new firms from the same industries. We conclude that clusters of CCIs encourages the entry of a firm (both CCIs and Non-CCIs) to a specific municipality/district. This finding highlights the need to incorporate cluster policies in agendas of local governments based on a well-informed analysis of clusters at local level.

This paper adds some key insights to location literature, as entry patterns of CCIs have been previously analysed using rough measures of clustering of stock of CCIs firms, whilst we address these limitations by using the Scan methodology, which identifies the localization of clusters and assign a statistically significance.

Main limitation of this paper refers to the dataset. In this sense, this paper relies on Mercantile Register data), which is the most usual source for studies of the location of economic activity in Spain. Although this dataset provides a clear picture of the overall distribution of economic activity, it is about firms, not about establishments. Nevertheless, although this issue could be a problem in case of multi-plant firms (i.e., for which data refers only to main plant), this is not the case for most of CCIs firms, as most of them have only a single plant.

Our results have important policy implications in terms of firm entry promoting policies, as public administrations must know in a detailed way the type of economic, social and cultural environment firms do require in order to settle down in a given area.

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Figures

Figure 3: Firm entries in FUAB (2010-2013)

Figure 3a Total Firms Entries in FUAB (2010-2013)

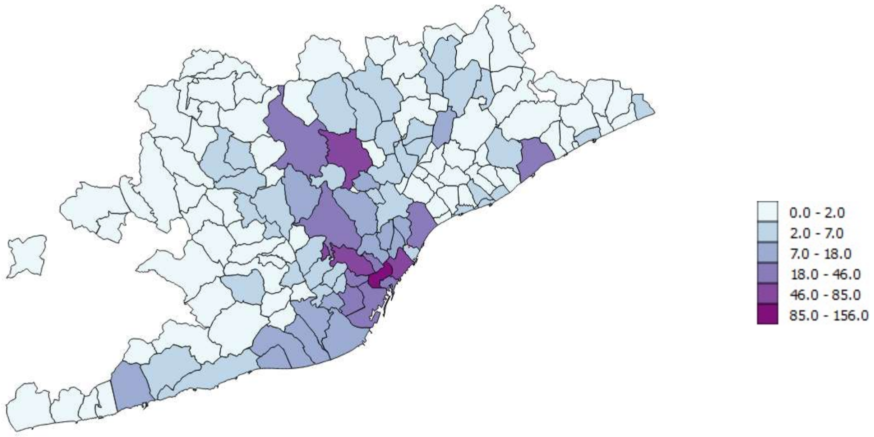


Figure 3b Entries of CCIs to FUAB (2010-2013)

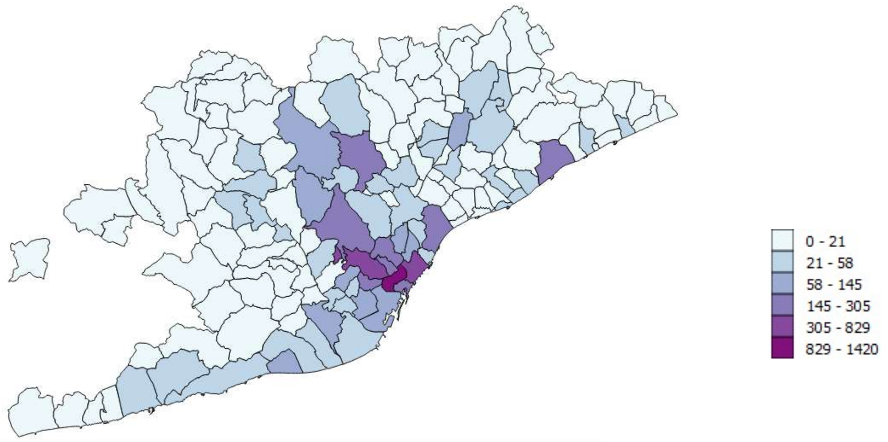
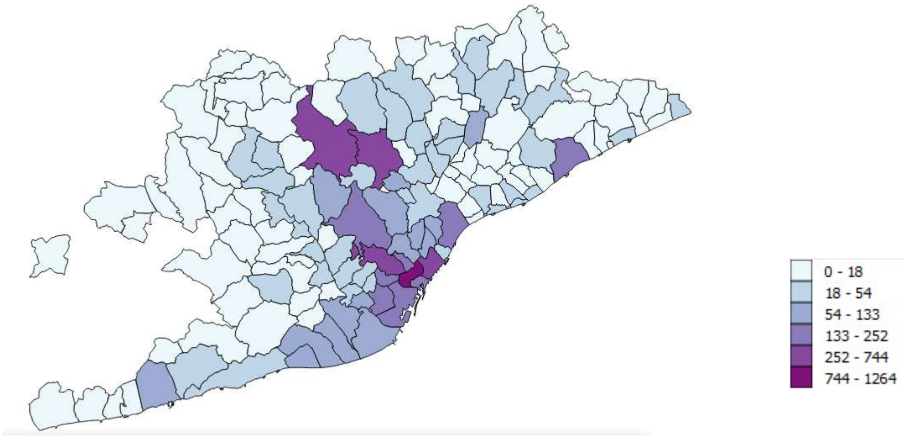
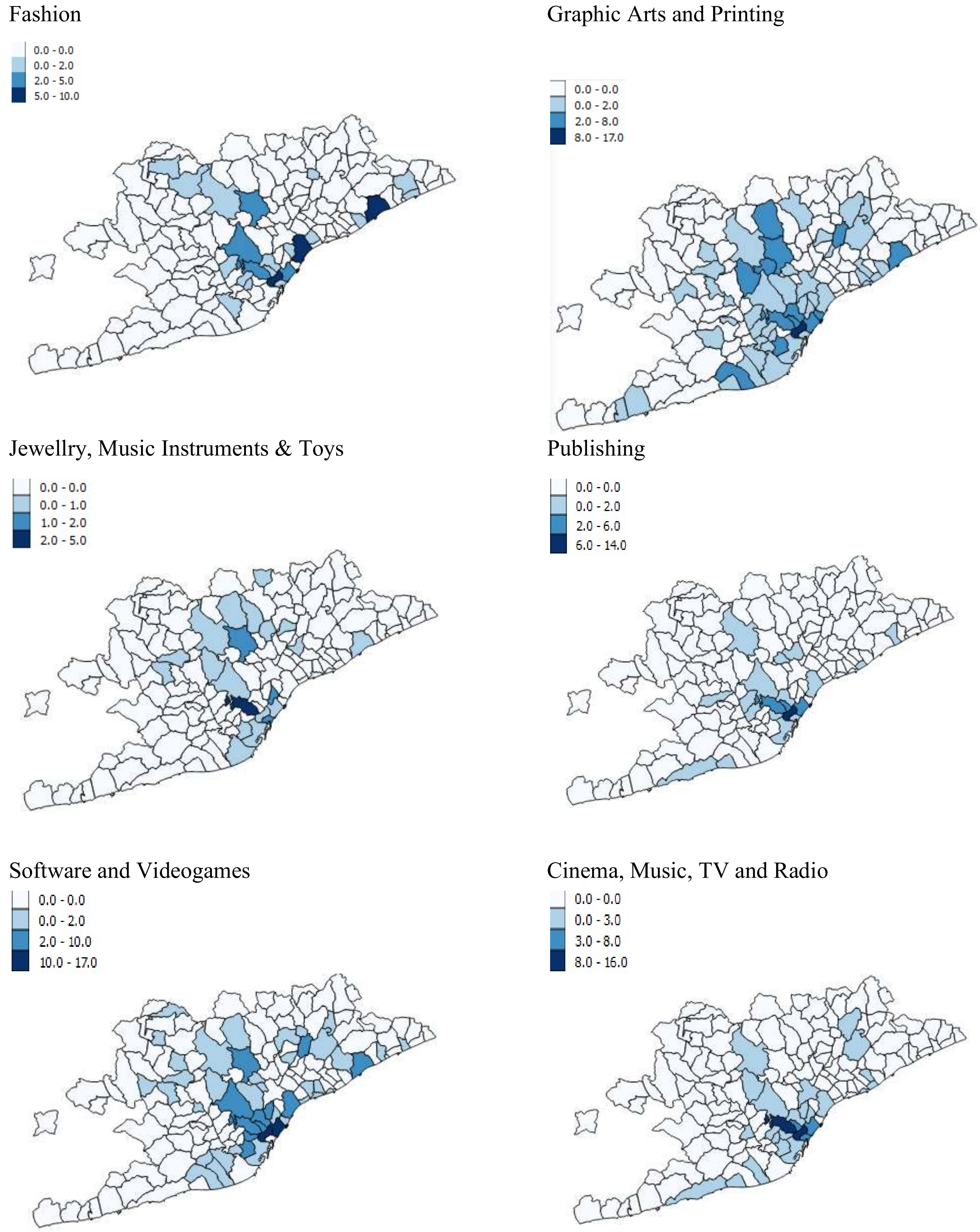


Figure 3c Non-CCIs Entries in FUAB (2010-2013)

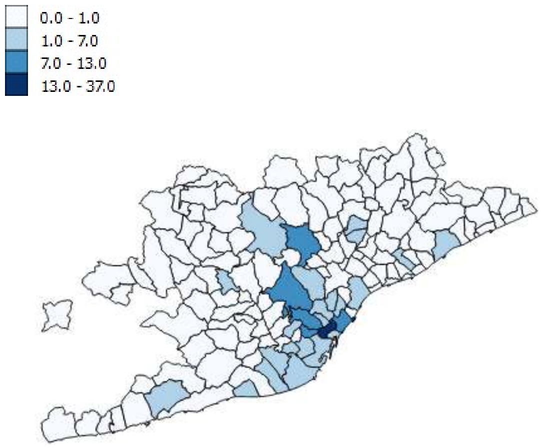


Source: Authors' own elaboration

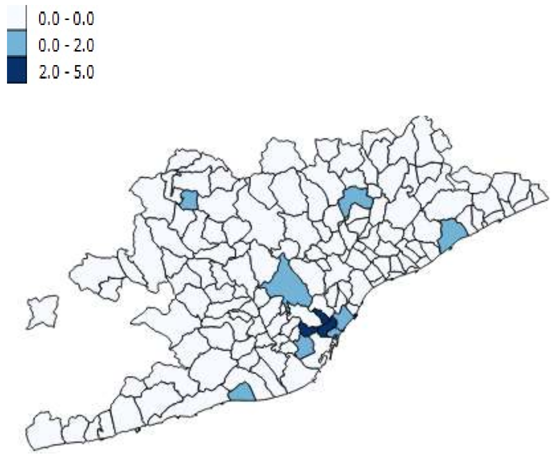
Figure 4. Entries of CCIs-Subsectors Firms in FUAB (2010-2013)



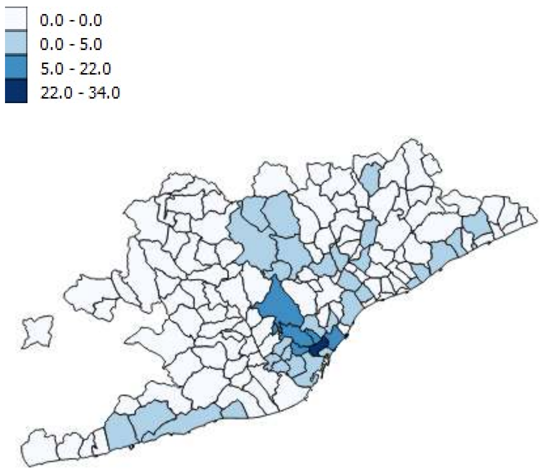
Architecture and Engineering



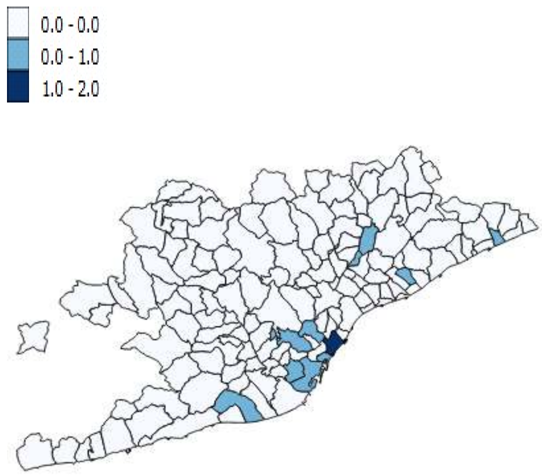
Research and Development



Advertising



Photography



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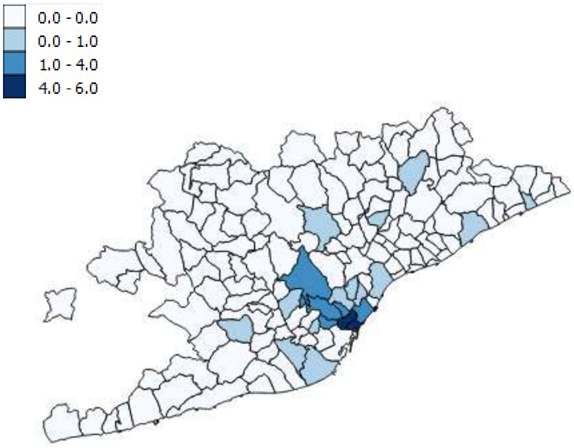

Source: Authors' Own Elaboration

Tables

Table 1. Descriptive Statistics-Explanatory Variables

Variable	Description	Source	Obs	Mean	Std. Dev.	Min	Max	Variance
Clucci	Total CCIs Clusters (Dummy Variable x=1 if municipality has a cluster; x=0 otherwise)	Maddah et al., (2020)	147	0.027	0.163	0	1	0.027
Cluanycci	Any CCIs Clusters	Maddah et al., (2020)	147	0.293	0.456	0	1	0.208
Cluadv	Advertising Clusters	Maddah et al., (2020)	147	0.041	0.199	0	1	0.039
Cluarc	Architecture and Engineering Clusters	Maddah et al., (2020)	147	0.027	0.163	0	1	0.027
Clucin	Cinema, Music, TV and Radio Clusters	Maddah et al., (2020)	147	0.034	0.182	0	1	0.033
Clufas	Fashion Clusters	Maddah et al., (2020)	147	0.048	0.214	0	1	0.046
Clugra	Graphic Arts and Printing Clusters	Maddah et al., (2020)	147	0.204	0.404	0	1	0.164
Clujew	Jewellry, Music Instruments and Toys Clusters	Maddah et al., (2020)	147	0.034	0.182	0	1	0.033
Clupub	Publishing Clusters	Maddah et al., (2020)	147	0.041	0.199	0	1	0.039
Clusof	Software and Videogames Clusters	Maddah et al., (2020)	147	0.034	0.182	0	1	0.033
Cluwri	Writing, Performing Arts, Visual Arts and Crafts firms	Maddah et al., (2020)	147	0.027	0.163	0	1	0.042
pop_09	Population per municipality/district (2009)	Idescat, from the INE's Continuous Register	147	33567.780	55071.220	308	269188	3030000000
stock_09	Total Number of Companies(2009)	SABI (2010)	147	383.456	854.930	0	5946	730905.2

irpf_09	General tax base per taxpayer (EUROS)	Own calculation based on Idescat	147	22600.640	5149.928	15597	45964	26500000
migr_09	Total migratory balance	Idescat, based on the INE's Continuous Register	147	290.837	901.704	-1476	6060	813070.7
Seaside	Dummy Variable; x=1 if municipality is on the seashores, x=0 otherwise	Own Observation	147	0.190	0.394	0	1	0.155
CBD	Dummy Variable Central Barcelona District (Eixample=1; 0 otherwise)	Own Observation	147	0.007	0.082	0	1	0.007

Table 2. Correlation Matrix of Independent Variables

	Cluanycci	pop_09	CBD	seaside	stock_09	irpf_09
Cluanycci	1					
pop_09	0.5536*	1				
CBD	0.1287	0.3553*	1			
Seaside	0.0689	0.2420*	-0.0401	1		
stock_09	-0.0334	-0.0734	-0.0131	0.1326	1	
irpf_09	0.0402	-0.0668	0.0909	0.0434	0.1132	1

Legend: * Significance at 5%

Tables 3. Descriptive Statistics-Dependent Variables

Variable	Description	Obs	Mean	Std. Dev.	Min	Max	Variance	Count
Enttotal	Total Firms' Entries	147	59.388	149.857	0	1420	22457.14	8730
Entccis	Total CCIs' Entries	147	6.020	16.870	0	156	284.6	885
Entnonccis	Total Non-CCIs' Entries	147	53.367	133.439	0	1264	17805.9	7845
Entadv	Entries of Advertising Firms	147	0.966	3.667	0	34	13.444	142
Entarch	Entries of Architecture & Engineering Firms	147	1.367	3.785	0	37	14.330	201
Entcin	Entries of Cinema, Music, TV and Radio Firms	147	0.524	1.967	0	16	3.868	77
Entfas	Entries of Fashion Firms	147	0.401	1.441	0	10	2.078	59
Entgraph	Entries of Graphic Arts and Printing Firms	147	0.878	1.930	0	17	3.725	129
Entjew	Entries of Jewellry, Music Instruments and Toys Firms	147	0.190	0.577	0	5	0.333	28
Entphoto	Entries of Photography Firms	147	0.082	0.299	0	2	0.089	12
Entpub	Entries of Publishing Firms	147	0.340	1.421	0	14	2.021	50
Entrd	Entries of Research and Development Firms	147	0.150	0.666	0	5	0.443	22
Entsoft	Entries of Software and Videogames Firms	147	0.857	2.344	0	17	5.493	126
Entwri	Entries of Writing, Performing Arts, Visual Arts and Crafts firms	147	0.265	0.855	0	6	0.731	39

Source: Author's own calculation with data from SABI.

Table 4. Dependent Variables-Percentiles Summary (For Count Model Selection)

	1%	**5%**	**10%**	**25%**	**50%**	**75%**	**90%**	**95%**	**99%**
enttotal	0	0	1	6	18	44	130	269	829
entccis	0	0	0	0	2	4	12	26	85
entnonccis	0	0	1	5	17	41	119	233	744
entadv	0	0	0	0	0	1	2	3	22
entarch	0	0	0	0	0	1	4	6	13
entcin	0	0	0	0	0	0	1	2	13
entfas	0	0	0	0	0	0	1	2	10
entgraph	0	0	0	0	0	1	2	4	8
entjew	0	0	0	0	0	0	1	1	2
entphoto	0	0	0	0	0	0	0	1	1
entpub	0	0	0	0	0	0	1	2	6
entr&d	0	0	0	0	0	0	0	1	4
entsoft	0	0	0	0	0	1	2	4	17
entwri	0	0	0	0	0	0	1	1	5

Source: Authors' own calculation

Table 5. Location Determinants of Firms' Entries in FUAB (2010-2013)

Entries	**All Firms**		**CCIs**		**Non-CCIs**	
	(Poisson)	Robust Std. Error	(ZINBM)	Std. Error	(NBREGM)	Std. Error
Cluanycci	0.873***	(0.181)	0.488**	(0.181)	0.717***	(0.181)
pop_09	0.000***	(0.000)	0.000***	(0.000)	0.000***	(0.000)
CBD	0.414**	(0.179)	0.017	(0.632)	-0.612	(0.944)
Seaside	0.198	(0.172)	0.313*	(0.171)	0.503**	(0.188)
stock_09	-0.000**	(0.000)	0.000	(0.000)	-0.000	(0.000)
irpf_09	0.000***	(0.000)	0.000***	(0.000)	0.000**	(0.000)
Constant	1.231***	(0.146)	-0.976**	(0.315)	1.209***	(0.334)
Inflate Variables						
pop_09			-0.001**	(0.000)		
Constant			3.307**	(1.104)		
N	147		147		147	
Non-zero observations			99			
Pseudo R2	0.8476				0.16	
Log pseudolikelihood	-1653.72					
LogLikelihood			-277.19		-600	
AIC	3319.44		574.38		1216	
Lnalpha			-1.233***	(0.25)	-0.408	(0.135)
Alpha			0.292	(0.073)	0.665	(0.09)

legend: * p<0.1; ** p<0.05; ***p<0.001

Source: Author's Own Calculation

Table 6. Location Determinants of Firms' Entries in FUA (2010-2013): Spatial Dependence

Entries	**All Firms_W**		**CCIs_W**		**NonCCIs _W**	
	(Poisson)	Robust Std. Error	(ZINBM)	Std. Error	(NBREGM)	Std. Error
Cluanycci	0.478***	(0.164)	0.099	(0.238)	0.326	(0.250)
pop_09	0.000***	(0.000)	0.000***	(0.000)	0.000***	(0.000)
CBD	0.345**	(0.169)	0.098	(0.591)	-0.522	(0.920)
Seaside	0.201	(0.166)	0.363**	(0.166)	0.538**	(0.185)
stock_09	-0.000*	(0.000)	0.000	(0.000)	0.000	(0.000)
irpf_09	0.000***	(0.000)	0.000***	(0.000)	0.000**	(0.000)
WCluanycci	0.702**	(0.243)	0.773**	(0.305)	0.726**	(0.329)
Constant	1.246***	(0.144)	-0.982**	(0.304)	1.216***	(0.330)
Inflate Variables						
pop_09			-0.001**	(0.000)		
Constant			3.302**	(1.125)		
N	147		147		147	
Non-zero observations			99			
Pseudo R2	0.8560				0.16	
Log pseudolikelihood	-1562.5					
LogLikelihood			-274.09		-597.84	
AIC			570.18		1213.68	
Lnalpha			-1.364***	0.266	-0.448	0.136
Alpha			0.256	0.679	0.639	0.09

legend: * p<0.1; ** p<0.05; ***p<0.001

Source: Author's Own Calculation

Table 7. Location Determinants of Firms' Entries in FUA (2010-2013): Subsectors

Variable	ADV	ARCH	CIN	FAS	GRAPH	JEW	PUB	SOFT	Wri
Cluadv	**0.829****								
Cluarc		0.294							
Clucin			**1.531*****						
Clufas				**1.816****					
Clugra					0.123				
Clujew						0.797			
Clupub							0.588		
Clusof								**0.856****	
Cluwri									**1.773****
pop_09	0.000***	0.000***	0.000**	0.000**	0.000***	0.000**	0.000**	0.00***	0.000
CBD	-0.256	0.476	0.353	0.388	0.96**	-1.221	0.895*	-0.209	-0.294
Seaside	-0.071	0.027	0.436	-0.091	0.253	0.044	0.565	0.287	-0.374
stock_09	-0.000	0.000	0.000	0.000	-0.000*	0.000	0.000	0.000	0.000
irpf_09	0.000***	0.000**	0.000***	0.000**	0.000**	0.00**	0.00***	0.00***	0.000**
constant	-4.022**	-1.630**	-2.686***	-4.049***	-1.008**	-3.337**	-3.968***	-2.042***	-1.944**
Inflate									
pop_09	-0.000*	-0.00**	-0.00*	-0.000	-0.000**	-0.00	-0.000	-0.000	-0.000**
stock_09									
constant	2.402**	1.651**	4.13**	0.003	2.659**	0.887	5.915	2.643*	3.300***
Lnalpha									
constant	-1.292**	-2.008**	-16.01	-0.661	-14.347	-118.82	-125.76	-15.04	-15.799

legend: * p<.1; ** p<.05; *** p<.001; Source: Authors' own elaboration

Table 8. Location Determinants of Firms' Entries in FUA (2010-2013): Subsectors-Spatial Dependence

Variable	ADV_W	ARCH_W	CIN_W	FAS_W	GRAPH_W	JEW_W	PUB_W	SOFT_W	Wri_W	PHO_W	Rnd_W
cluadv	0.004										
cluarc		0.294									
clucin			**1.033****								
clufas				**1.816****							
clugra					-0.089						
clujew						0.797					
clupub							0.672				
clusof								**0.843****			
cluwri									0.506		
cluanycci										-1.075	2.696
wcluadv	**1.891*****										
wcluarc		(omitted)									
wclucin			**1.18****								
wclufas				(omitted)							
wclugra					0.451						
wclujew						(omitted)					
wclupub							-0.144				
wclusof								0.068			
wcluswri									**2.902*****		
wcluanycci										0.929	0.059
pop_09	0.000***	0.00***	0.00**	0.00**	0.000***	0.000**	0.000***	0.000***	0.000***	0.000**	0.000
CBD	0.677**	0.476	0.504	0.388	0.771	-1.221	0.604	-0.202	-0.701	-21.809	0.751
seaside	0.108	0.027	0.621*	-0.091	0.278	0.044	.73799874*	0.291	-0.526	1.284*	0.974
stock_09	0.00	0.00	0.00	0.00	-0.000*	0.000	0.000	0.000	0.000	0.001	-0.005**
irpf_09	0.00***	0.00**	0.000***	0.00**	0.000**	0.000**	0.000***	0.000***	0.000***	0.000	0.000**

constant	-3.762***	-1.630**	-3.421***	-4.049***	-1.232**	-3.337**	-4.955***	-2.056***	-4.501***	-5.657***	-8.9**
inflate											
pop_09	-0.000*	-0.000**	-0.00	-0.00	-0.000**	0.000		0.000			-0.000*
stock_09							0.077		0.072	0.057	
constant	2.383**	1.651**	4.192**	0.003	2.678**	0.887	-230.151	2.646*	-212.976	-104.624	2.205**
lnalpha											
_cons	-28.005	-2.008**	-16.488	-0.661	-12.848	-118.828	-15.866	-16.608	-17.920	-18.497	-16.238

legend: * p<.1; ** p<.05; *** p<.001
Source: Authors' own elaboration

Appendix

This appendix shows the CCIs definition for this study along with their 4 and 5-digits NACE Rev. 2. For 2009 and equivalence for NACE 93 Rev. 1

	NACE 2009	Equivalence NACE 93 Rev. 1
Fashion		
Manufacture of leather garments	1411	18100
Preparation of work clothes.	1412	18210/25241
Preparation of other outer garments.	1413	18221/18222/25241
Making of underwear.	1414	18231/18232
Manufacture of other garments and accessories.	1419	17710/18241/18242/18243
Hosiery manufacturing	1431	17710
Manufacture of other knitwear.	1439	17720
Dressing, tanning and finishing of leather; Preparation and dyeing of skins.	1511	18301/19100
Footwear manufacturing	1520	19300
Graphic Arts and Printing		
Graphic arts and related services.	1811	22210
Other printing and graphic arts activities.	1812	22220
Prepress and media preparation services.	1813	22240/22250
Binding and related services.	1814	22230
Specialized design activities.	7410	74841
Jewelry, Music Instruments and Toys		
Manufacture of jewelry and similar items.	3212	33500/36221/36222
Manufacture of jewelry and similar items.	3213	33500/36610
Manufacture of musical instruments.	3220	36300
Manufacture of games and toys.	3240	36500
Other manufacturing industries n.c.o.p.	3299	

		18243/19202/20510/20521/22110/25130/25241/26820/28753/33100/36630
Publishing		
Book edition	5811	22110
Editing directories and postal address guides.	5812	22110/72400
Newspaper edition	5813	22120
Editorial of magazines	5814	22130/72400
Other editorial activities	5819	22150/22220/72400
Software and Videogames		
Videogame edition	5821	72210/72400
Editing other computer programs	5829	72210/72400
Computer programming activities	6201	72220/72400
Computer consulting activities	6202	72100/72220
Cinema, Music , TV and Radio		
Postproduction activities of film, video and television programs.	5912	92112
Film exhibition activities.	5914	92130
Film and video production activities.	5915	92111
Activities of television program productions.	5916	92202
Activities of distribution of films and videos.	5917	92121/92122
Distribution activities of television programs.	5918	92202
Activities of sound recording and music editing.	5920	22140/72400/74843/92112/92201
Broadcasting activities	6010	64200/72400/92201
Programming activities and television broadcasting.	6020	64200/72400/92203
Reproduction of recorded media.	1820	22310/22320/22330
Architecture and Engineering		
Architectural technical services	7111	74201
Technical engineering services and other activities related to technical advice.	7112	74202/74203/74204
Research and Development		
Research and experimental development in biotechnology.	7211	73100

Other research and experimental development in natural sciences and techniques.	7219	73100
Research and experimental development in social sciences and humanities.	7220	73100/73200
Advertising		
Advertising agencies	7311	74401/74402
Photography		
Photography activities	7420	74811/74812/92400
Writers, Performing Arts, Visual Arts and Crafts		
Performing Arts	9001	92311/92312/92343
Auxiliary activities to the performing arts.	9002	92313/92342/92343
Artistic and literary creation.	9003	92311/92400
Management of exhibition rooms.	9004	92320
Heritage Activities		
Activities of the museums	9102	92521
Management of historical places and buildings.	9103	92522
Activities of botanical gardens, zoos and nature reserves.	9104	92530
Activities of the library	9105	92510
File activities.	9106	75140/92510

Source: Developed by the authors; CCIs selection adapted from the literature, and codes equivalence adapted from INE (National Statistics Institute, 2010) and based on author's own judgment.