UNIVERSITAT ROVIRA i VIRGILI
Departament d'Economia

UNIVERSITAT ROVIRA i VIRGILI

ECO SOS
CENTRE DE RECERCA EN ECONOMIA I SOSTENIBILITAT

WORKING PAPERS ECO & ECO-SOS

Cultural and Creative Industries: Empirical Evidence on Employment Growth

Lina S. Maddah
Josep-Maria Arauzo-Carod

Document de treball n. **03 - 2021**

Edita:

Departament d'Economia
Universitat Rovira i Virgili
Facultat d'Economia i Empresa
Av. de la Universitat, 1
43204 Reus
Tel.: +34 977 759 811
Tel.: +34 977 759 812
Email: sde@urv.cat

ECO-SOS
www.eco-sos.urv.cat
Universitat Rovira i Virgili
Departament d'Economia
Av. de la Universitat, 1
43204 Reus
Tel.: +34 977 758 936
Email: eco-sos@urv.cat

Adreçar comentaris al Departament d'Economia / ECO-SOS

ISSN: 2696-5097

Cultural and Creative Industries: Empirical Evidence on Employment Growth

Lina S. Maddah (♣): lina.maddah@urv.cat
Josep-Maria Arauzo-Carod (♣): josepmaria.arauzo@urv.cat

Abstract

This paper analyses the role played by cultural and creative industries (CCIs) in employment growth at local level in Catalonia between 2001 and 2011. This is a novel approach as, differently to most of previous contributions, several profiles of municipalities (i.e., small, medium and large) and CCIs subsectors are considered. Our results indicate that specialization in some CCIs boost employment but only for high-growth municipalities (in terms of employment). In view of these heterogeneous effects, policy measures regarding CCIs should be more selective and focus on these industries / areas where there is a potential effect over employment.

Keywords: creative industries, employment growth, cities, Catalonia.
JEL codes: C11, R11, R58

(♣) Universitat Rovira i Virgili, Departament d'Economia (QURE & ECO-SOS); Av. Universitat 1; 43204 - Reus (Catalonia, Spain); phone +34 977 758 902.

Acknowledgements

This research was partly funded by the Martí i Franquès COFUND (European Commission, Horizon 2020), FEDER/Ministerio de Ciencia, Innovación y Universidades (Grant ECO2017-88888-P), the "Xarxa de Referència d'R+D+I en Economia i Polítiques Públiques" and the SGR Program (2017-SGR-159) of the Catalan Government.

1. Introduction

Do cultural and creative industries (CCIs) fulfil a role as engines for economic growth? This issue has attracted considerable attention among economists and policymakers over the last two decades as governments have started to look for “hard” evidence explaining the dynamics of these industries and their ability to boost economic activity. In the current literature there is a general argument that supports the idea that, by and large, CCIs are vital for encouraging economic growth in urban areas and regions. Theoretically speaking, there is also a debate on whether local growth is boosted by specialization or diversity between and within sectors (i.e. for all sectors) taking into account possible positive externalities and spatial spillovers. Thus, in recent years, the position of CCIs in the development agendas of the European Union has gradually shifted from marginal to more central, with an increasing number of discussions of the economic potential of these industries in terms of local development, economic growth, innovation and resilience capabilities in a post-crisis situation (OECD, 2018; UNCTAD, 2010).

Increasing funding for and investment in CCIs is also the subject of much discussion in Spain, Europe and worldwide. The main dialogue involves their social and economic contributions and ranges from seeking a clear definition of the sectors to be termed as CCIs to defining the role they play in social and economic cohesion (noting the tangible benefits and intangible values of artistic activities). How does the composition of these economic activities within regions influence the growth of other economic activities and ultimately that of cities and regions? How important are CCIs for regional and local economic development and employment growth? Does “space” in terms of the geographical location of companies, proximity and accessibility (infrastructures) influence the growth of industries and hide significant spatial spillovers? How can all of the above be quantified to provide a better understanding? These are just a few of the many questions raised by policymakers. As stressed by Higgs and Cunningham (2008) along with other researchers in the field, it is essential for us to accurately evaluate the contribution of CCIs to economic activity in order to help policymakers reflect on the key findings and then decide on the level and timing of investments, especially since, at the present time, CCIs are on the agendas of the main public administrations and economic organizations.

However, some of the above considerations about CCIs are based mainly on economic intuition and indirect rather than solid empirical evidence (Banks and O’Connor, 2009). The ability to “quantify” and empirically investigate this relationship is still limited, despite significant discussion among researchers in this field on the importance of CCIs and their respective positive impact on various dimensions of local and regional economies. Research on specialization in CCIs and total employment growth at a local level is limited as most of contributions focus on big urban areas, neglecting smaller and peripheral ones, and this is a serious shortcoming in view of the urgent need to disentangle the economic mechanisms operating in these industries. This is a key point since public investments favoring CCIs are very appealing nowadays (due to the positive spillover effects of these activities in terms of reputation, social cohesion and the educational level of the population, among other things), but it is not at all clear whether all these investments can be justified or whether they should be focused on more specific areas in which the expected returns could be much higher.

The contribution of this paper to the ongoing discussion is twofold. First, we investigate the impact of specialization in CCIs on total employment growth at the municipality level in Catalonia, using data from 2001 and 2011. This exploration specifically addresses the issues of agglomeration economies from an empirical point of view. Analyzing the Catalan case is of interest not only due to the lack of contributions similar to this one, but also because of its geographical and economic structure –small and compact enough to allow close interactions across different regions– and the sizeable share of CCIs in terms of employment and GDP. In addition, focusing on employment growth connects with a major concern for policymakers. Since we want to develop a more complete picture of the effects of CCIs, we focus on what is happening in small- and medium-sized peripheral Catalan municipalities in addition to the capital, Barcelona. Secondly, we investigate whether the effects of local specialization in CCIs are the same across territories and industries, in order to identify whether there are spatial/sectorial specificities that may intensify/decrease the positive effects of these industries. This is a novel approach, since the empirical literature analyses almost exclusively large cities without considering the mechanisms that may exist in small rural areas. Finally, the role played by CCI subsectors also receives attention in this paper, to explore the existence of heterogeneity is their economic impacts.

The structure of the paper is as follows. Section 2 reviews the literature, addresses the main points raised by scholars discusses agglomeration externalities and their effect on local growth, while section 3 details the characteristics of the dataset, defines CCIs, describes the variables and provides some descriptive statistics. Section 4 describes the econometric strategy and discusses the main results and Section 5 concludes and suggests directions for further research.

2. CCIs as Drivers of Economic Growth

CCIs are one of the main contributors to the economy in developed countries (Higgs and Cunningham, 2008) and are considered as part of Smart Specialization Strategies (S3)**.** Their impact on economic growth has attracted considerable attention among economists and especially policymakers, indicating a desire among governments to exploit cultural and creative production in order to foster both employment and economic growth (Kourtit and Nijkamp, 2019). According to the European Commission (2016), CCIs employ, directly and indirectly, 15 million people, which accounts for 7.5% of the EU's employment workforce, subsequently making those sectors the 3rd largest employer in the EU. These figures place CCIs ahead of other industries in the EU, as it employs 2.5 times more people than automotive manufacturers and 5 times more than the chemical industry, in addition to enhancing quality of life (European Parliament, 2016). More recently, a study conducted by the European Union Intellectual Property Office Observatory (2019) revealed that CCIs generated around EUR 509 billion in 2018, which accumulates for 5.3% of the EU's total GDP. These potentialities of CCIs arise especially from their creative side and their role in economic development (Gouvea and Vora, 2018), from the higher spending on intangibles in CCIs (Scheffel and Thomas, 2011) and from their stronger growth capacity compared to other industries, as demonstrated, for instance, by Scheffel and Thomas (2011) for the case of the UK. But how to measure that? Evans (2005) suggested different measurements as increased property values/rents (residential and business), corporate involvement in the local cultural sector (leading to support in cash and in kind), higher resident and visitor spending arising from cultural activity (arts and cultural tourism), job creation (direct, indirect, induced), enterprise creation (new firms/start-ups, turnover/value added), retention of graduates in the area (including artists/creatives), creative clusters and quarters, enhanced production chains, joint R&D activities, public–private–voluntary sector partnerships ('mixed economy'), and investment growth (public–private sector leverage). Along similar lines, Potts *et al*. (2008) proposed and tested four models of the relationship between CCIs and the aggregate economy, mainly using data on relative growth rates, employment, entrepreneurship, income and profit for many countries over the period of a decade. The prevailing arguments among researchers on the potential impacts of CCIs on economic growth are inter-related and can be grouped into *i)* the role of CCIs as integral parts of local development, *ii)* the creative class, *iii)* the contribution of CCIs to innovation activities, *iv)* their clustering pattern, and *v)* their contribution to employment growth:

i) CCIs are integral parts of local development: This argument has made the headlines due to numerous policymaking reports and discussions, including most recently OECD (2018). Creative industries play a significant role in both the social and economic development of nations (UNESCO, 2013; UNCTAD, 2010) and the regeneration of cities and stimulation of fading urban economies (Lee, 2014).

ii) The creative class: One way of approaching the creative economy is to consider the creative class, a term coined by Florida (2004) who argues that the creative class is a major driver of urban and regional growth, but this claim is subject to much criticism, mainly concerning the lack of clear empirical evidence (e.g., see Vossen *et al*., 2019, for the German case), in addition to causality concerns.

iii) The contribution of CCIs to innovation activities: CCIs generate innovation in different ways. The general argument is that these industries are innovative in themselves and contribute to innovation in other sectors. Florida (2004) was among the first to argue that the presence of a creative class leads to the creation of new ideas and technological advances. One NESTA report by Bakhshi *et al*. (2013) reveals that CCIs can robustly influence development and innovation in the wider economy, in *all* sectors.

iv) Clustering, positive consumption and production externalities: The contribution of CCIs is evident from the positive externalities resulting from their clustering and agglomeration. This translates into the expansion and growth of cultural and creative neighborhoods and districts, the creation of networks of cooperation within the creative sector through creative milieus, the easy exchange of ideas and spillovers to other sectors, and the boosting of entrepreneurial activities. Researchers also argue that workers in CCIs contribute to the growth of the "new" economy involving information technologies and digital developments, the generation of "agglomeration benefits" (Murzyn-Kupisz and Dzialek, 2017) and the promotion of the relevant areas as tourist attractions and creating a positive image and recognition (Landry, 2008)

v) Employment growth: CCIs have a relevant role in generating employment and enhancing well-being (Kemeny *et al.*, 2020), although typically causality is not addressed when discussing this point. In this sense, because studies over the last decade have had mixed findings, the economic implications of these industries need to be properly measured and it should be established whether they are shaped by local/regional economic, social and institutional characteristics. Considering both innovation and employment spillovers in the Netherlands, Stam *et al*. (2008) find that firms in creative industries located in urban areas are more innovative than their rural counterparts and that (with the exception of the metropolitan city of Amsterdam) there is no spillover effect of any great size from creative industries. Lee (2014), on the other hand, argues that CCIs are indeed capable of boosting employment growth in the wider economy in the UK. These findings are consistent with the idea that the creative industries help other sectors to grow, but with reservations concerning urban areas. However, when only urban areas are considered, creative industries do drive wage growth but do not increase employment. Other findings regarding the contribution of CCIs reveal that an increase in the number of firms active in the creative industries has a positive effect on regional employment growth (Piergiovanni *et al*., 2012). From a regional employment growth perspective, Mossig (2011) investigate CCIs in the German context and finds that they have a more significant effect on employment growth in urban areas and that rural areas cannot benefit from the growth in CCIs. On the contrary, Lazzeretti *et al.* (2017), for Italy, find that creative industries *cannot* have an impact on employment growth in the wider economy.

In conclusion, the relative modest set of research findings is both mixed and somewhat inconclusive in examining causal relationships between CCIs and the economy as a whole. As only a small number of empirical works evaluates the impact of specialization in CCIs on employment growth at a local level, this area remains relatively unexplored. Unfortunately, research on the effects of CCIs suffers from extreme heterogeneity of the data sets (i.e., there is not yet a clear agreement about the industries and activities to be included, as highlighted by Kemeny *et al*., 2020) and geographical areas, the variables used, the specific focus, and demand v. supply effects. As far as data sets and geographical areas are concerned, empirical evidence is provided for many areas in (mainly) capitalist economies, ranging from countries to regions and cities (Lazzeretti, *et al*, 2017; Piergiovanni *et al*., 2012; Mossig, 2011; Potts *et al*., 2008 and Stam *et al*., 2008), and also for a wide typology of economic areas ranging from developed countries such as the US (Americans for the Arts, 2017) and the UK (Lee, 2014; Department of Culture, Media and Sport (DCMS), 2013) to developing countries (Ginsbourgh and Throsby, 2006).

Certainly, since the share of CCIs is stronger for developed countries (and also, therefore, its economic relevance), there are some concerns about causality between the weight of these industries and growth. Another consideration regarding this aspect is that urbanization is conducive to CCI growth (Florida, 2004). However, taking into account the general arguments on the potential of CCI concentration on local development, innovation and the creation of positive externalities and knowledge spillovers, employment growth may be one of the resulting spillovers that enhance a region's competitiveness. It can be taken as an indicator of competitiveness and economic growth, following studies such as Stam *et al*. (2008).

Bearing in mind that the analysis in this study lies at the heart of agglomeration economies, the relevant theories and empirics on urbanization, specialization, diversity and related variety are briefly reviewed in the following section alongside the economic contribution of CCIs so as to help understand their "input" to employment generation. The theoretical framework for our empirical analysis is an adaptation of the approach of Glaeser *et al*. (1992) that has been commonly used by many similar studies such as Proost and Thisse (2019), O'Connor *et al*. (2018), Eriksson *et al*. (2017), Bishop and Gripaios (2009) and De Vor and De Groot (2008).

Agglomeration economies can be approached through urbanization economies, localization economies and Jacobs' externalities. Urbanization economies involve the external factors that have an effect on a firm located is a specific region regardless of the nature of the sector in which it operates. They are mainly reflected in population density, universities and infrastructures including transport, which facilitate knowledge creation and thus boost innovation (Frenken *et al.*, 2007). Localization economies (also known as MAR externalities) are generated through sectoral specialization, are only available to firms operating in the same sectors and are associated with high local levels of concentration (De Vor and De Groot, 2008). As for Jacobs' externalities, these mainly stem from variety and diversity in the local industrial structure within a region (diversification into a bulky mix of sectors) that fosters the creation of new markets, radical innovation and regional economic growth. A further branched concept, building on Jacobs' hypothesis, is related variety (RV). This typology, introduced by Frenken *et al*. (2007), differs in the sense that it is not RV *per se* that influences regional and urban growth, but it is the RV between sectors that are technologically interconnected with one another that matters.

The main study that empirically assessed the effects of MAR v. Jacobs' externalities along with other local determinants of regional growth, as measured by employment growth at the city-industry level, was that by Glaeser *et al*. (1992), which was then followed by a wide range of studies that had mixed findings, as Henderson *et al*. (1995). Early findings were later thrown into doubt by Combes (2000) who concluded that Jacobs' externalities are favorable for employment growth in service sectors, while in manufacturing the industrial mix and variety reduce employment growth. De Vor and De Groot (2008) find that, at site level, specialization slows growth. Further investigations on the impact of spatial externalities in the UK are conducted by Bishop and Gripaios (2009), who find that *i)* specialization has a negative impact on growth, *ii)* the impact of diversity is heterogeneous across sectors, and *iii)* strong local competition has a generally positive impact. Similarly, focusing on the UK's services sector, Johnston and Huggins (2017) argue that diversity and related variety have significant positive implications for regional development.

In short, although it appears complicated to come to any clear-cut conclusions on the nature of the relationship between different externalities and employment growth at a local level, this framework is considered very useful when it comes to investigating the performance of sectors/cities and their trends and economies, which will form the basis of the methodology in this study. Even if some of previous results might be considered contradictory, this is not true if it is assumed that knowledge generation and transmission varies across industries and, therefore, the effects of spatial agglomeration (i.e., specialization vs. diversification) may also depending on industries and spatial areas considered.[1]

Accordingly, based on preceding literature and the aim of our analysis we put forward the following hypotheses:

> **Hypothesis 1** Specialization in CCIs has a positive impact on total employment growth in Catalan municipalities between 2001 and 2011, and its effect varies at their sectoral level.
>
> **Hypothesis 2** The impact of specialization in CCIs on employment growth is different between urban and rural areas of Catalonia.

3. Methodology

3.1 Definition of CCIs

Despite growing efforts to fix a widely-accepted classification of CCIs, heterogeneities are still important. Creative industries were initially defined as "those industries which have their origin in individual creativity, skill and talent and which have the potential for wealth and job creation

[1] Chung and Hewings (2019) show differences reported when analysis is conducted using US state level data or when using US county level data.

through the generation and exploitation of intellectual property" (DCMS, 2001, p.4). Generally speaking, most definitions follow the structure provided by the UK DCMS model (2001) and then those from the OECD (2007), UNCTAD (2008) and the European Commission (2012), but there are still controversies. Bakhshi *et al*. (2013), for example, criticized the DCMS model and called for the inclusion of a major creative sector in the shape of software design, while Lazzeretti *et al*. (2008) and Coll-Martínez and Arauzo-Carod (2017) further developed the definition, with Lazzeretti *et al*. (2017) using a narrower definition by focusing on "core creative industries." In this paper, we try to accommodate previous studies and policy-oriented reports with the nature of the Catalan context and the intensity of creative occupations in certain industries. Consequently, we consider the following cultural and creative activities[2]: fashion, publishing, graphic arts, printing, jewelry, musical instruments, toys, software, videogames, research and development, architecture and engineering, advertising, photography, design, cinema, video, music, TV, radio, writers, performing arts, visual arts, crafts and heritage-related activities.

3.2 Geographical scope of the data

In the literature on employment growth, most studies take a regional or national-level approach (e.g. O'Connor *et al*., 2018, for Ireland; Eriksson *et al*., 2017, for Denmark and Sweden), or consider county levels, looking at both metropolitan and non-metropolitan counties (e.g., Fallah *et al*., 2013, for the US), or city levels focusing on urban areas alone (e.g. Illy *et al*., 2011, for Germany). In addition to these papers, there is a branch of the literature that assumes that employment growth processes are strongly driven by agglomeration economies, which operate at shorter distances such as in counties, metropolitan areas or municipalities.

The data in this paper refer to municipalities[3] in Catalonia[4], an autonomous region in north-eastern Spain whose capital is Barcelona. Catalan municipalities are quite heterogeneous in terms of population, employment and urbanization, especially when compared to Barcelona. Local spatial scale has been selected due to that heterogeneity (e.g., the size municipalities range from 27 inhabitants to 1.5 millions) in order to capture different trends regarding the effects of CCIs over employment growth. The dependent variable measures local employment growth (in logs) between

[2] See Table A.1 in the Appendix.
[3]The current number of Catalan municipalities is 948, but we omitted 5 of them due to lack of data.
[4]Catalonia has about 7.5 million inhabitants (15 per cent of Spain's population) and covers an area of 31,895 km2. It accounts for 19 per cent of Spanish GDP.

2001 and 2011, while the independent variables refer to a number of local characteristics (measured in 2001) hypothesized to explain that process. In order to select these variables, numerous factors have been taken into account, such as the variables used in previous studies (see Table 1), the scope of this paper, data availability and data characteristics (e.g., correlations between variables, goodness-of-fit tests, etc.).

[INSERT TABLE 1 ABOUT HERE]

The data (see Table 2 for a description) were collected from different sources: the general employment data were obtained from the IDESCAT (Catalan Statistical Institute) and the Census of Population and Housing for 2001 and 2011 from the INE (Spanish Institute of Statistics).

[INSERT TABLE 2 ABOUT HERE]

As we aim to estimate the local employment change as a function of local specific characteristics described below (as well as spatially weighted factors):

$$y = \beta X + \varepsilon$$

where y is the dependent variable (employment growth in general terms), X is a matrix containing all independent variables plus an intercept, and ε is the error term. The fact that the main covariate has some degree of spatial dependence renders the inclusion of spatial lagged variables, since the assumption of non-dependence between cross-sectional observations is presumably not satisfied. Therefore, although most articles dealing with job creation have neglected such spatial issues, we consider that they have to be tackled.

In order to account for the spatial dependence of specialization in CCIs we need to define the spatial range of the existing interactions among municipalities. In this regard we use a row-standardised spatial-neighbour matrix (W).[5] Among the various approaches that can be used – distance-based neighbours or k-nearest neighbours among others (Getis and Aldstat, 2004) – we assume a contiguity criterion (i.e., two municipalities are neighbours if they share a common border), but it is important to note that our results were quite robust to alternative formulations of W matrices. Once W is identified, we calculate the spatial lagged LQCCIs, and then the spatial lagged variable for each of the LQ at subsector level (i.e., WLQ-Fashion, WLQ-Advertising, etc.).

[5] Using both highly disaggregate spatial units and spatial lagged variables help to tackle potential endogeneity problems.

Formally, for observation *i*, the spatial lag of x_i, referred to as $[Wx]_i$ (variable Wx observed for location *i* is:

$$[Wx]_i = w_{i1}x_1 + w_{i2}x_2 + \cdots + w_{in}x_n$$

$$[Wx]_i = \sum_{j=1}^{n} W_{ij}x_j$$

Where the W_{ij} consist of the elements of the *i*-th row of the matrix *W*, matched up with the corresponding elements of the vector *x*.

Given that we assume that specialization in creative industries is a key driver of employment growth, we will first focus our analysis on several indicators of that specialization. In addition, and in line with the previous literature, the econometric specifications include different vectors of variables referring to a combination of social, economic, geographical and infrastructural factors that are hypothesized to influence employment growth. Consequently, these variables include several vectors related to *i)* agglomeration economies, *ii)* transport infrastructures, *iii)* human capital, and *iv)* market structures.

For agglomeration economies and sector specialization, we use the *Location Quotient* of CCIs (*LQCCIs*) as well as its spatial lagged version (*WLQCCIs*)[6]. We hence try to capture the spatial spillover effects, knowing that the latter are likely to be more significant as we move to smaller geographical scales as municipalities, the ones used in this paper (Chung and Hewings, 2019). The approach by Glaeser *et al*. (1992) and Henderson *et al*. (1995) was recently revisited by Francasso and Vittucci Marzetti (2018), who examine the confusion surrounding the definition and estimation of localization economies in empirical work. Therefore, we follow their suggestion that applied researchers can "select between the size of the local industry, the specialization index and the location quotient to proxy for these externalities as far as they also encompass a correct proxy for the size of the local economy." Population density provides a proxy for the degree of urbanization and may be relevant for some activities requiring a high degree of potential interactions between firms and clients.

Transport infrastructures are proxied using the mean travelling time to the four Catalan provincial capitals (*Infracap*). Proximity to administrative and economic cores is needed in order to access

[6] Queen contiguity weight matrix (alternatives *W* matrices were also tested).

the higher-level services mainly provided there rather than elsewhere (Guimarães *et al*., 2000) and also because the main markets tend to be there. Human capital is proxied through the percentage of workers holding university degrees (*University*); this is a key location factor regardless of the industry to which a firm belongs, since firms need a skilled workforce. Finally, market structures are proxied by using the entropy index (*Entropy*) and the percentage of workforce in firms with up to 50 employees (*Smallfirms*). The entropy index makes it possible to identify whether a municipality is homogeneous or diverse in terms of its sectoral structure (the higher the value of the index, the greater the diversity). In this regard, although there is lively debate as to whether specialization (MAR externalities) or diversification (Jacobs' externalities) is more important in terms of fostering employment growth; it seems that diversified economies may benefit from knowledge spillovers boosting economic activity, with these spillovers being quite important for skilled activities like CCIs. Company structure in terms of size also matters because areas in which SMEs predominate are more likely to see the creation of new firms and then increased employment levels (Arauzo-Carod, 2008). The correlation matrix (see table A.3.) shows that there are no major problems among variables, as the stronger significant correlations are only 0.37.[7]

In terms of the spatial distribution of these variables, figures 1 and 2 provide a clear insight into the aforementioned heterogeneities among Catalan municipalities. Figure 1 shows the spatial distribution of employment both in CCIs and in all activities; they are clearly agglomerated around the metropolitan area of Barcelona and in some other major urban areas, as is all economic activity.

[INSERT FIGURES 1 AND 2 ABOUT HERE]

In view of this huge agglomeration in the Barcelona area, it would be better to focus on relative measures of employment distribution. Figure 2 shows the weight of CCIs at local level in terms of employment and also the CCIs location quotients (LQ) calculated related to employment in Catalonia. This provides a broad overview of the location patterns of employment in CCIs, although it covers all the CCIs analyzed in this paper together, including very different industries.

[7] Independent variables with high significant correlation among them have been removed from the model

4. Econometric Strategy and Main Results

The econometric strategy consists of three stages: first, a baseline OLS model is estimated separately for i) all municipalities, ii) all municipalities except outliers, and iii) outliers; secondly, an OLS model focusing on sectoral LQ (instead of overall LQ) is estimated; and thirdly, a quantile regression (QR) model and an interquantile (IQR) model are estimated.[8]

The use of QR is justified when trying to analyze the determinants of employment growth rates at a local level when there are enormous heterogeneities among the local units (i.e., the Catalan municipalities). QR overcomes some of the disadvantages of OLS estimations (Koenker and Bassett, 1978), since it allows for different conditional distributions to be analyzed instead of only the mean, as in the case of OLS. This strategy provides much more comprehensive results since the heterogeneity among municipalities is not captured by explanatory variables. The QR procedure divides the population into *n* parts (quantiles) with equal proportions in each of them, and this enables the relationship between independent and dependent variables inside each quantile to be analyzed rather than just the mean. In order to do this, we have estimated the results for quantiles $\theta = 0.25, 0.50, 0.75$, and 0.90, obtaining the complete distribution of y conditional on x.

The analysis of employment growth shows very different patterns (see table 3), with small municipalities (especially those below 1,000 inhabitants) showing immense employment dynamism in relative terms while changes, albeit positive, are much smaller for larger municipalities, such as those with between 20,000 and 50,000 inhabitants, those with between 100,000 and 1,000,000 inhabitants, and the city of Barcelona. Nevertheless, the pattern is not strictly linear in terms of lower growth rates when the population increases, so there are obviously additional factors at work that help to explain this asymmetric behavior.

[INSERT TABLE 3 ABOUT HERE]

An initial strategy used to control for these heterogeneities is to separately regress all municipalities, all municipalities except outliers (filtered) and outliers. At this point, it is important to correctly identify the profile of those municipalities considered as outliers (see table A.3.) – they are smaller in size, covering an area ranging from 5.2 km^2 to a maximum of 145.6 km^2, with a population of 35 inhabitants being the minimum and 1,066 the maximum, with a mean of 227.

[8] The variance inflation factor (VIF) was measured to check for multicollinearity and all scores for the models and variables were below 1.25.

Size is quite relevant in terms of explaining employment growth in relative terms because it is easier to achieve high growth rates when starting from very low levels.

[INSERT FIGURE 3 ABOUT HERE]

In terms of geographical distribution, Figure 3 shows that the outliers are inland municipalities spread all over Catalonia, but all of them far in distance from metropolitan Barcelona and other major urban areas. This geographical remoteness restricts the potential growth of these areas, making it more difficult to benefit from the agglomeration economies generated in the main urban areas, but at the same time this makes production costs lower, enhancing the potential for growth. The results of the baseline OLS model (see Table 4) show that local specialization in CCIs (*LQCCIs*) plays a different role depending on the relative local employment growth. Specifically, when considering all municipalities the *LQCCI* has a (small) positive and significant effect on employment growth. In contrast, the spatial lagged version of *LQCCI* has a negative effect, suggesting that there is not a clustering of municipalities where specialization in CCIs boosts total employment. The estimation for outliers corroborates this finding, as *LQCCI* retains this positive and significant effect, but now *WLQCCI* becomes insignificant. Overall, these results suggest a spatially discontinuous pattern of municipalities whose employment growth is fostered by CCIs. In addition, this effect completely disappears when regressing without outliers,[9] as the *LQCCI* (and also its spatial lagged version) becomes insignificant. An interpretation of these differences highlights the existence of different growth mechanisms, suggesting that specialization in CCIs is positive for employment growth, but only in certain circumstances. In this regard we might advance the idea of there being certain thresholds above which CCIs lead to job creation. Our results corroborate those of Lee (2014) in the UK, as the author finds that creative industries drive employment growth in other sectors; however, when only urban areas are considered, CCIs do not increase employment. Lee (2014) argues that CCIs help other sectors to grow, but may force out declining industries from urban areas. However, it is essential to recognize difference in spatial scales, as in Lee (2014) travel-to-work-areas are used, which are quite larger than the ones used in this paper, although both cover urban and rural areas.

[INSERT TABLE 4 ABOUT HERE]

[9] Outlier municipalities are defined as those where percentage employment growth between 2001 and 2011 was greater than 145%.

In general terms, the literature shows two types of results regarding the effect of CCIs on employment growth. The first argue that these industries act positively on the economy as a whole, while the second identify certain heterogeneous effects depending on urban/rural profiles. Regarding the first type of results, Piergiovanni *et al*. (2012) found an overall positive effect on regional employment growth in the case of Italy. The results of this paper fit with the second group of contributions, such as those from Lazzeretti *et al*. (2017), again for Italy, that limit the positive effects of CCIs to certain industries; from Sörvik *et al*. (2019) about CCIs as part of S3 priorities of less populated and remote areas; and from Lee (2014), for the UK. Concretely, Lee (2014) finds that creative industries drive employment growth and help other sectors grow, especially in rural areas, but with reservations concerning urban areas. Further insights are provided by Mossig (2011), for Germany, who argues that CCIs have a more significant effect on employment growth in urban areas and that rural areas cannot benefit as much. Specific geographic effects are also found by Stam *et al*. (2008) for the Netherlands, but in the opposite direction to Lee (2014), since they identify the spillover effects from creative industries occur only in the metropolitan area of Amsterdam.

[INSERT TABLE 5 ABOUT HERE]

The results from the OLS model focusing on sectoral LQ (see table 5) show that the role played by local specialization in CCIs is asymmetric and relies heavily on certain industries and typologies of municipalities; most of these municipalities do not really have the capacity to promote employment growth. In this regard, when considering only the effects for outliers (i.e., municipalities with great dynamism in terms of employment growth), the positive effects point solely to interior design sector while the effects for other industries are not significant at all or negative (i.e., cinema, video, music, TV and radio). Local specialization in these specific CCIs has no effect on employment growth for all municipalities; thus, the specialization positive effects appear to be driven solely by outliers.

Regarding the rest of industries, when considering all municipalities and excluding outliers, surprisingly there is a negative effect for all subsectors, except publishing, activities related to heritage, writers, performing arts, visual arts and crafts, although only significant for fashion, jewelry, musical instruments and toys. Nevertheless, judging by the previous results shown in table 4 we can suggest that there is a similar mechanism to explain these differences, such as the role played by local specialization in certain CCIs possibly varying depending on local patterns of employment growth. This is consistent with the arguments made by Combes (2000) and Johnston and Huggins (2017) on the need to distinguish between industries in order to better decode the effect of specialization. This will be addressed next investigating CCIs and noting their significant sectoral and spatial heterogeneity. Hence, aiming at more comprehensive findings given the heterogeneity in the municipalities, we have estimated as well a quantile regression model.

[INSERT TABLE 6 ABOUT HERE]

The results of the quantile regression model (see table 6)[10] corroborate previous economic intuition, such as the effect of *LQCCI* being significant and positive only for upper quantiles (i.e. from 0.75). This finding also suggests that although local specialization in CCIs is positive for local employment growth, the relationship is restricted to more dynamic areas in terms of job creation, which are predominantly small municipalities. As the dependent variable is measured in relative terms, the upper levels of employment growth (tend to) correspond with areas that have initially low levels of employment thereby resulting in relatively high growth spurts. From these results, therefore, it seems that specialization in CCIs has effects only for small municipalities, but not for large municipalities or urban areas. Nevertheless, these results refer to CCIs as a whole, since table 5 reports specificities at an industry level.

[INSERT FIGURE 4 ABOUT HERE]

The asymmetric roles of municipalities are easier to observe in the following figures (see figure 4), in which both quantile and OLS coefficients are reported.[11] The interpretation of these figures (where the horizontal axis portrays quantiles and the vertical axis portrays regression coefficients) is as follows: the solid black line with dots shows estimates of the regression coefficients for each quantile while the grey areas are the confidence intervals at 95%, and the solid red line (parallel to the horizontal axis) shows estimates of the OLS coefficient, while the red dotted lines are the confidence intervals at 95%.

The solid black line is the zero line, the reference whereby the significance of the coefficients can be appreciated as follows: given that *none* of the confidence intervals overlap with the solid black line, then this reflects a significant effect and vice versa. If we focus on the LQ variable, it is easy to see that the OLS coefficients and quantile coefficients differ greatly, especially for the lower

[10] Interquantile regressions are shown at table A.4 at the appendix.

[11] Figure 4 portrays the results of both estimation (1) in Table 4 and the estimation in Table 6.

quantiles. These findings support the use of a quantile regression strategy rather than focusing only on a specific part of the distribution. Specifically, the first graph shows that the effect of local specialization in CCIs – the *LQCCI*– increases with employment growth and that the effect is only significant for the upper quantiles (0.75) and (0.90),while for the other quantiles (0.25 and 0.50) the confidence intervals overlap with the zero line, depicting a non-significant effect. The significant positive effects in the upper quantiles may be due to the characteristics of the municipalities. As for the entropy variable, the effect is significantly negative across all four quantiles. For the rest of the variables, there is a similar effect in terms of the dissimilarity of the effect of covariates on the dependent variable depending on its distribution. The quantile regression model justifiably outperforms the linear regression in these findings, since the latter fails to capture variations in the impact of specialization and other variables relative to the characteristics of the municipalities.

Glaeser *et al*. (1992) argue that "at the city-industry level, specialization hurts and diversity boosts employment growth." On the basis of our findings, we cannot completely agree with this as it applies to CCIs in Catalan municipalities for 2001-2011. As we have already mentioned, specialization in CCIs does have a positive yet heterogeneous effect among sectors and municipalities, while diversity has a negative effect. Clear examples of this include the decreasing (negative) effect of entropy, which indicates that industrial diversity (typically correlated with urban size) has a negative (and increasing) effect on employment growth that is significant for all quantiles. While a wide range of the literature finds diversity to be important for employment growth (Glaeser *et al*., 1992; Frenken *et al*., 2007; Bishop and Gripaios, 2009; Johnston and Huggins, 2017; O'Connor *et al*., 2018), our findings are in contrast to this argument, but the profile of local units (i.e., smaller) is different to previous one. Given the Catalan context and our data timeframe,[12] Jacobs' externalities (diversification among all sectors) are not found to be capable of generating employment growth at a local level. Similarly, for urbanization economies, population density is only significant for the first quantile and *infracap* is only significant for the upper quantile. According to the above results, we can conclude that Hypothesis 1 is partly supported by the empirical evidence, while there is total support for Hypothesis 2. Firstly, the

[12] It is important to take into account that the time period includes an important economic crisis (i.e., from 2008) that may have affected employment creation and destruction in an heterogeneous way depending on each municipality.

econometric results indicate that specialization in CCIs does not boost employment growth in all circumstances, but only for high-growth employment areas. In addition, when looking at industry-specific location quotients, the results show asymmetric effects among different CCIs. Secondly, the econometric and (especially) the descriptive results show an unequal spatial distribution of the effect of specialization on employment growth, since significant effects were identified mainly for high-growth areas located away from the main urban cores, suggesting that CCIs may play also a role at rural and peripheral areas, which is a novelty in view of lack of analyses about that profile of municipalities.

5. Conclusions

This paper has provided some insights on the role played by CCIs in local employment growth using data for Catalan municipalities between 2001 and 2011. We have analyzed whether local specialization in CCIs might boost total employment growth. Our interest in CCIs comes from their increasing importance in developed countries, the existence of positive externalities that may arise from them and reach other economic activities, the large number of contributions that highlight the enormous potential of these industries for advanced economies, and the increasing efforts devoted by public administrations to stimulate these industries, both in urban and rural areas (Sörvik *et al*., 2019). All these analyses must be presented with the caveat that there is still some skepticism regarding the measurement of CCI effects. For all these reasons, additional research is needed in order to corroborate previous (potential) positive effects.

The main conclusion of this paper suggests that the role of CCIs is still unclear and merits additional analysis since, on the one hand, there is widespread empirical evidence pointing to its positive effects on economic growth, job creation and knowledge generation, but on the other hand, there is also evidence indicating that their weight and influence is still small. It might be suggested that a potential explanation of this apparent contradiction depends on industry and municipality profiles, and we have tried to disentangle earlier ambiguous results by considering both detailed CCIs as well as different typologies of municipalities. In this regard, our results corroborate the initial hypothesis that the effects of CCIs vary considerably across heterogeneous areas, implying that public administrations should take care when choosing where and how to promote these activities.

While there are some demonstrable conclusions, it is clear that more work needs to be done. This paper has used data on small and medium-sized municipalities, whilst most of literature focuses on what happens in big urban areas (e.g., London or New York) not considering the rest of territories. Nevertheless, as it is also true that municipalities are quite small and that spatial range of labor markets may be larger than municipality boundaries, alternative spatial aggregation levels such as counties or local labor markets should therefore also be tested in order to corroborate previous findings.

In general terms, our results have important implications for policy measures, since the potentialities of CCIs should be carefully analyzed by taking into account specific industries and spatial units, given that the expected effects are quite heterogeneous in the combined industry/space dimension. It is important to clarify that we are not diminishing the potential effects of CCIs, but trying to precisely specify the conditions under which these positive effects can be demonstrated. Smart specialization in CCIs, and relative subsectors, shall be more emphasized in policy-making, since it is clear that *place* matters. In this sense, as highlighted by McCann and Ortega-Argilés (2019), smart specialization is aimed at transforming policy-thinking from traditional top-down and predominantly sectoral-led approaches to a more local, bottom-up innovation led approach.

Finally, regarding future research directions, additionally to consider alternative spatial settings, in order to disentangle the potentially restrictive effects caused by the economic crisis starting in 2008, we intend to explore whether the results hold for alternative periods.

References

Americans for the Arts (2017) "The Creative Industries in the United States." Available at https://www.americansforthearts.org/by-program/reports-and-data/research-studies-publications/creative-industries.

Apparicio, P., Martori, J.C., Pearson, A.L., Fournier, E. and Apparicio, D. (2014) "An open-source software for calculating indices of urban residential segregation," *Social Science and Computer Review* **32(1)**: 117-128.

Arauzo-Carod, J.M. (2008) "Industrial location at a local level: comments on the territorial level of the analysis," *Tijdschrift voor Economie een Sociale Geografie* **99 (2)**: 193-208.

Bakhshi, H. Freeman, A. and Higgs, P. (2013) "*A Dynamic Mapping Of The UK's Creative Industries*". Available at:
https://media.nesta.org.uk/documents/a_dynamic_mapping_of_the_creative_industries.pdf
[Accessed 3 February 2019].

Banks, M. and O'Connor, J. (2009) "After the Creative Industries," *International Journal of Cultural Policy* **15(4)**: 365-373.

Bishop, P. and Gripaios, P. (2009) "Spatial Externalities, Relatedness and Sector Employment Growth in Great Britain," *Regional Studies* **44(4):** 443-454.

Chung, S. and J.D. Hewings, G. (2019) "A Short Exercise to Assess the Effects of Temporal and Spatial Aggregation on the Amounts of Spatial Spillovers". In Franklin R. (eds) *Population, Place, and Spatial Interaction*, 1st ed. Springer, pp.35-56.

Coll-Martínez, E. and Arauzo-Carod, J.M. (2017) "Creative milieu and firm location: An empirical appraisal," *Environment and Planning A* **49(7)**: 1613-1641.

Combes, P. (2000) "Economic Structure and Local Growth: France, 1984–1993," *Journal of Urban Economics* **47(3):** 329-355.

DCMS (2001) "Creative Industries Mapping Document 2001" Department for Culture Media and Sport, London

DCMS (2013). *Department for Culture Media and Sport*. Available at: http://old.culture.gov.uk/what_we_do/creative_industries/default.asp[Accessed 6 Feb. 2018].

De Vor, F. and de Groot, H. (2008) "Agglomeration externalities and localized employment growth: the performance of industrial sites in Amsterdam," *The Annals of Regional Science* **44(3):** 409-431.

Eriksson, R., Hansen, H. and Winther, L. (2017) “Employment growth and regional development: industrial change and contextual differences between Denmark and Sweden,” *European Planning Studies* **25(10):** 1756-1778.

European Commission. (2016). *Boosting The Competitiveness Of Cultural And Creative Industries For Growth And Jobs*. [online] Available at: <https://ec.europa.eu/growth/content/boosting-competitiveness-cultural-and-creative-industries-growth-and-jobs-0_en> [Accessed 10 September 2020].

European Parliament. (2016). *Report On A Coherent EU Policy For Cultural And Creative Industries*. [online] Available at: <https://www.europarl.europa.eu/doceo/document/A-8-2016-0357_EN.html> [Accessed 3 October 2020].

European Union Intellectual Property Office Observatory (2019). [online] Available at: <https://www.euipo.europa.eu/ohimportal/en/web/observatory/ip-contribution#ip-contribution_1> [Accessed 19 September 2020].

Evans, G. (2005) “Measure for Measure: Evaluating the Evidence of Culture's Contribution to Regeneration,” *Urban Studies* **42(5-6)**: 959-983.

Fallah, B., Partridge, M. and Rickman, D. (2013) “Geography and High-Tech Employment Growth in US Counties,” *Journal of Economic Geography* **14(4):**683-720.

Florida, R. (2004) *The Rise of the Creative Class*, New York: Basic Books.

Fracasso, A. and Vittucci Marzetti, G., 2018. Estimating dynamic localization economies: the inadvertent success of the specialization index and the location quotient. *Regional Studies*, 52(1), pp.119-132.

Frenken, K.; Van Oort, F. and Verburg, T.(2007) “Related Variety, Unrelated Variety and Regional Economic Growth,” *Regional Studies* **41(5):** 685-697.

Getis, A., and Aldstadt, J. (2004) “Constructing the spatial weights matrix using a local statistic,” *Geographical Analysis* ***36*** **(2):** 90-104.

Glaeser, E.L., Kallal, H.D., Scheinkman, J.A. and Shleifer, A. (1992) “Growth in Cities,” *Journal of Political Economy* **100 (6)**: 1126-152.

Gouvea, R. and Vora, G.(2018) “Creative industries and economic growth: stability of creative products exports earnings,” *Creative Industries Journal* **23:**1-32.

Guimarães P., Figueiredo, O. and Woodward, D. (2000) “Agglomeration and the location of foreign direct investment in Portugal,” *Journal of Urban Economics* **47**: 115–135.

Henderson, J.V., Kuncoro, A. and Turner, M. (1995) “Industrial Development in Cities,” *Journal of Political Economy* **103(5)**: 1067-1090.

Higgs, P. and Cunningham, S. (2008) “Creative Industries Mapping: Where have we come from and where are we going?” *Creative Industries Journal* **1(1) :**7-30.

Illy, A.; Schwartz, M.; Hornych, C. and Rosenfeld, M. (2011) “Local Economic Structure and Sectoral Employment Growth in German Cities, *”Tijdschrift voor Economie een Social e Geografie* **102(5)**:582-593.

Johnston, A. and Huggins, R. (2017) “Regional Growth Dynamics in the Service Sector: The Determinants of Employment Change in UK Regions, 1971-2005,” *Growth and Change* **49(1):** 71-96.

Kemeny, T.; Nathan, M. and O’Brien, D. (2020) “Creative differences? Measuring creative economy employment in the United States and the UK”, *Regional Studies* **54 (3)**: 377-387.

Kourtit, K. and Nijkamp, P. (2019) “Creative actors and historical–cultural assets in urban regions”, *Regional Studies* **53 (7)**: 977-99.

Koenker, R. and Bassett, G. (1978) “Regression quantiles,” *Econometrica* **46(1)**: 33-50.

Landry, C. (2008) *The Creative City: A Toolkit for Urban Innovators*. 2nd ed., London,. Earth Scan.

Lazzeretti, L., Boix, R. and Capone, F. (2008) “Do Creative Industries Cluster? Mapping Creative Local Production Systems in Italy and Spain,” *Industry & Innovation* **15(5):** 549-567.

Lazzeretti, L., Innocenti, N. and Capone, F. (2017) “The impact of related variety on the creative employment growth,” *The Annals of Regional Science* **58(3**): 491-512.

Lee, N. (2014) “The creative industries and urban economic growth in the UK,” *Environment and Planning A* **46:**455–470.

McCann, P. and Ortega-Argilés, R. (2019) “Perspectives on Smart Specialisation Policies in Lagging Regions,” *Regional Studies Policy Impact Books* **1(2):** pp.17-27

Mossig, I. (2011) “Regional Employment Growth in the Cultural and Creative Industries in Germany 2003–2008,” *European Planning Studies* **19(6)**: 967-990.

Murzyn-Kupisz,M. and Działek, J. (2017) *The impact of artists on contemporary urban development in Europe*, Heidelberg, Springer.

O'Connor, S., Doyle, E. and Doran, J. (2018) “Diversity, employment growth and spatial spillovers amongst Irish regions,” *Regional Science and Urban Economics* **68**: 260-267.

OECD (2018): *The Value Of Culture And The Creative Industries In Local Development* 1st ed. Available at: http://www.oecd.org/cfe/leed/2018-SACCI-Handbook.pdf[Accessed 3 August 2019].

Piergiovanni, R. Carree, M. and Santarelli, E. (2012) "Creative industries, new business formation, and regional economic growth," *Small Business Economics* **39(3)**: 539-560.

Potts, J. Cunningham, S. Hartley, J. and Ormerod, P. (2008) "Social network markets: a new definition of the creative industries," *Journal of Cultural Economics* **32(2):**166-185.

Ribeiro, L., Lopes, T., Montenegro, R. and Andrade, J., 2017. Employment dynamics in the Brazilian tourism sector (2006–2015). *Tourism Economics*, 24(4), pp.418-433.

Sánchez-Serra, D. (2016) "Determinants of the Concentration Of Creative Industries In Europe: A Comparison Between Spain, Italy, France, United Kingdom And Portugal," unpublished Ph.D. dissertation, Universitat Autònoma de Barcelona.

Scheffel, E. and Thomas, A. (2011) "Employment and intangible spending in the UK's creative industries - A view from the micro data," *Economic & Labour Market Review* **5(1)**:79-104.

Sörvik, J.; Teräs, J.; Dubois, A. and Pertoldi, M. (2019): "Smart Specialisation in sparsely populated areas: challenges, opportunities and new openings", *Regional Studies* **53(7)**: 1070-1080.

Stam, E., de Jong, J. and Marlet, G. (2008) "Creative industries in the Netherlands: structure, development, innovativeness and effects on urban growth," *Geografiska Annaler: Series B, Human Geography* **90(2)**: 119-132.

UNCTAD (2010) "*Creative Economy Report*", 1st ed. [ebook] Geneva: UNCTAD, 1-19. Available at: https://unctad.org/en/Docs/ditctab20103_en.pdf [Accessed 19 February 2019].

UNCTAD (2008) *Creative Economy Report 2008*, Geneva, United Nations Conference on Trade and Development.

UNESCO (2013) *Creative Economy Report 2013*. Available at: https://en.unesco.org/creativity/publication/creative-economy-report-2013 [Accessed 16 March 2019].

Vossen, D.; Sternberg, R. and Alfken, C. (2019) "Internal migration of the 'creative class' in Germany", *Regional Studies* **53 (10)**: 1359-1370.

Wang, C., Madsen, J. and Steiner, B. (2016) "Industry diversity, competition and firm relatedness: the impact on employment before and after the 2008 global financial crisis," *Regional Studies* **51(12):** 1801-1814.

Tables

Table 1. Variables used in the Previous Literature on Agglomeration Economies

Variables	Dep. Var	Sector Specialization		Emp. Concen.	Diversity		UnRV	Compe-tition	Urbanization Economies		Spatial Hetero.	Level of Human Capital		Income Distr.
Authors	Emp-Growth	LQ	Speciali-zation Index	LQ	Other sectors' emp	Inverse HHI	Entropy	% firms/worker	Pop-Density	Reg/Pop Dummies	Regional Dummies	Residence/ Work Ratio	High Edu	Gini Coefficient
Glaeser *et al*. (1992)	✓		✓		✓			✓			✓			
Henderson *et al*. (1995)	✓		✓			✓							✓	
Combes (2000)	✓		✓			✓			✓		✓			
Bishop and Griupaios (2009)		✓					✓	✓	✓		✓			
Eriksson et al. (2017)	✓			✓	✓			✓		✓		✓	✓	✓
Ribeiro et al. (2017)	✓	✓	✓		✓				✓					
Wang et al. (2016)	✓			✓	✓		✓	✓						

Notes: "EmpGrowth" indicates the change in the log of employment in a sector in a particular area over a period of time; "LQ" indicates the proportion of local employment accounted for by a sector in a specific locality divided by the proportion of employment accounted for by the sector nationally; "Other sectors' emp" measures the logarithmic value of total employment minus the industry class in question; "Inverse HHI" indicates the inverse of a Herfindahl index of sectoral concentration based on the share of all sectors, except the one considered; "PopDensity" measures population per square kilometer; "Residence/Work Ratio" controls for the differences in qualitative functionality of municipalities (residential municipalities v. employment municipalities); and "HighEdu" measures the share of workers with at least a Bachelor's degree.
Source: Authors' own elaboration

Table 2. Variables: Data Sources and Descriptive Statistics

Variable	Definition	Year	Source	Mean	SD	Min	Max
Code	Municipality Code		IDESCAT				
Name	Municipality Name		IDESCAT				
Emp Growth	Employment Growth	2001 - 2011	Own calculation (based on employment data for 2001 and 2011 from the Census of Population and Housing by INE)	43.33	100.02	-78.06	1800
LQCCIs2001	Location quotient in CCIs	2001	Own calculation	0.67	0.75	0	8.08
Entropy	Diversity index	2001	Own calculation using the Geo-Segregation Analyzer (Apparicio et al., 2014)	0.57	0.14	0.05	0.81
InfraCap	Mean distance to four provincial capitals (minutes)	2001	Own calculation	86.92	23.9	0	190
University	Intermediate and advanced university degree (% of workers)	2001	Own calculation from IDESCAT	16.34	6.17	2.32	50
Smallfirms	Jobs in firms with 0 to 50 employees (%)	2001	Own calculation	83.72	23.66	0	100
Popdensity	Population density	2001	IDESCAT	380.39	1522.4	0	21020

Table 3. Employment Growth and Municipality Size

	Employment growth 2001-2011 (%)	
Population	Mean	StdDev
< 1,000	65.30	127.35
≥ 1,000 &< 20,000	18.41	34.32
≥ 20,000 &< 50,000	.42	11.72
≥ 50,000 &< 100,000	6.81	19.34
≥ 100,000 &< 1,000,000	.15	13.34
≥ 1,000,000	2.08	-
Total	43.35	100.07

Source: Authors’ elaboration

Table 4. Baseline OLS Model						
	(1)		**(2)**		**(3)**	
	All Municipalities		**Filtered**		**Outliers**	
Dependent Variable	**Employment Growth 2001-2011**					
	Coeff	**Robust Std Err**	**Coeff**	**Robust Std Err**	**Coeff**	**Robust Std Err**
Constant	**1.04*** **	(0.118)	**0.44*** **	(0.089)	**1.64*** **	(0.247)
LQCCIs	**0.06***	(0.031)	0.002	(0.018)	**0.125***	(0.048)
WLQCCIs	**-0.09***	(0.035)	-0.04	(0.027)	0.01	(0.162)
Entropy	**-1.34*** **	(0.126)	**-0.62*** **	(0.097)	**-0.99***	(0.468)
University	**0.01** **	(0.002)	**0.007*** **	(0.002)	0.01	(0.009)
Popdensity	0.00	(0.000)	-0.00	(0.000)	0.00	(0.000)
Infracap	**-0.002** **	(0.001)	-0.000	(0.001)	**-0.004*** **	(0.001)
Smallfirms	0.001	(0.001)	0.000	(0.000)	0.00	(0.001)
R-Squared	0.1990		0.0822		0.3602	
R2-A	0.1930		0.0764		0.2816	
Number of Observations	943		878		65	
Significance codes: * p<0.05; ** p<0.01; *** p<0.001						
Source: Authors' elaboration						

Table 5. Baseline Model at Subsector Level

Models		(1) All Municipalities		(2) Filtered		(3) Outliers	
	Dependent Variable	**Employment Growth 2001-2011**					
		Coeff	**Robust Std Err**	**Coeff**	**Robust Std Err**	**Coeff**	**Robust Std Err**
(A)	Constant	**1.08*** **	(0.122)	**0.47*** **	(0.09)	**1.60*** **	(0.261)
	LQ Fashion	-0.02	(0.012)	**-0.002***	(0.01)	0.12	(0.06)
	WLQFashion	-0.01	(0.015)	-0.00	(0.013)	-0.04	(0.046)
(B)	Constant	**1.02*** **	(0.117)	**0.42*** **	(0.088)	**1.51*** **	(0.234)
	LQ Publishing	-0.00	(0.01)	0.00	(0.009)	-0.02	(0.027)
	WLQPublishing	-0.03	(0.025)	-0.03	(0.024)	0.22	(0.141)
(C)	Constant	**1.03*** **	(0.119)	**0.42*** **	(0.09)	**1.60*** **	(0.230)
	LQ Graphic Arts and Printing	-0.16	(0.018)	-0.00	(0.015)	0.11	(0.085)
	WLQGraphic Arts	-0.00	(0.028)	-0.02	(0.025)	0.05	(0.133)
(D)	Constant	**1.04*** **	(0.117)	**0.43*** **	(0.088)	**1.54*** **	(0.26)
	LQ Jewelry, Musical Instruments and Toys	-0.01	(0.012)	**-0.02** **	(0.007)	-0.00	(0.003)
	WLQ Jewelry	-0.007	(0.011)	0.001	(0.009)	0.37	(0.085)
(E)	Constant	**1.00*** **	(0.118)	**0.41*** **	(0.088)	**1.58*** **	(0.205)
	LQ Software and Videogames	0.03	(0.036)	-0.01	(0.021)	0.04	(0.091)
	WLQ Software	0.06	(0.048)	0.03	(0.040)	0.07	(0.126)
(F)	Constant	**1.04*** **	(0.117)	**0.42*** **	(0.089)	**1.59*** **	(0.238)
	LQ Research and Development	0.00	(0.005)	-0.00	(0.003)	-0.00	(0.012)
	WLQ R&D	-0.1	(0.009)	-0.00	(0.008)	-0.00	(0.026)
(G)	Constant	**1.01*** **	(0.114)	**0.42*** **	(0.089)	**1.41*** **	(0.245)
	LQ Architecture and Engineering	0.03	(0.022)	-0.00	(0.019)	0.04	(0.019)
	WLQ Arch&Eng	0.00	(0.032)	-0.03	(0.026)	0.12	(0.149)
(H)	Constant	**1.028*** **	(0.117)	**0.42*** **	(0.088)	**1.63*** **	(0.261)
	LQ Advertising	-0.01	(0.013)	-0.00	(0.011)	0.01	(0.042)
	WLQ Advertising	-0.03	(0.023)	-0.02	(0.021)	-0.11	(0.152)
(I)	Constant	**1.02*** **	(0.117)	**0.41*** **	(0.088)	**1.57*** **	(0.229)
	LQ Interior Design	0.01	(0.022)	-0.01	(0.018)	**0.03***	(0.012)
	WLQ Int Design	-0.00	(0.032)	-0.02	(0.023)	0.00	(0.085)
(J)	Constant	**1.02*** **	(0.117)	**0.41*** **	(0.088)	**1.63*** **	(0.249)
	LQ Cinema, Video, Music, TV and Radio	-0.01	(0.025)	-0.01	(0.02)	**-0.09***	(0.041)
	WLQ Cinema	0.01	(0.043)	-0.01	(0.036)	-0.11	(0.212)
(K)	Constant	**1.02*** **	(0.117)	**0.41*** **	(0.088)	**1.553*** **	(0.232)

	LQ Writers and Crafts	0.00	(0.01)	0.00	(0.001)	0.01	(0.232)
	WLQ Writers	0.01	(0.015)	-0.00	(0.013)	-0.03	(0.044)
(L)	Constant	**1.02*** **	(0.117)	**0.42*** **	(0.089)	**1.54*** **	(0.257)
	LQ Heritage	0.01	(0.004)	0.00	(0.004)	0.01	(0.009)
	WLQ Heritage	0.00	(0.012)	0.00	(0.009)	0.02	(0.032)
Number of Observations			943		878		65

Significance codes: * p<0.05; ** p<0.01; *** p<0.001

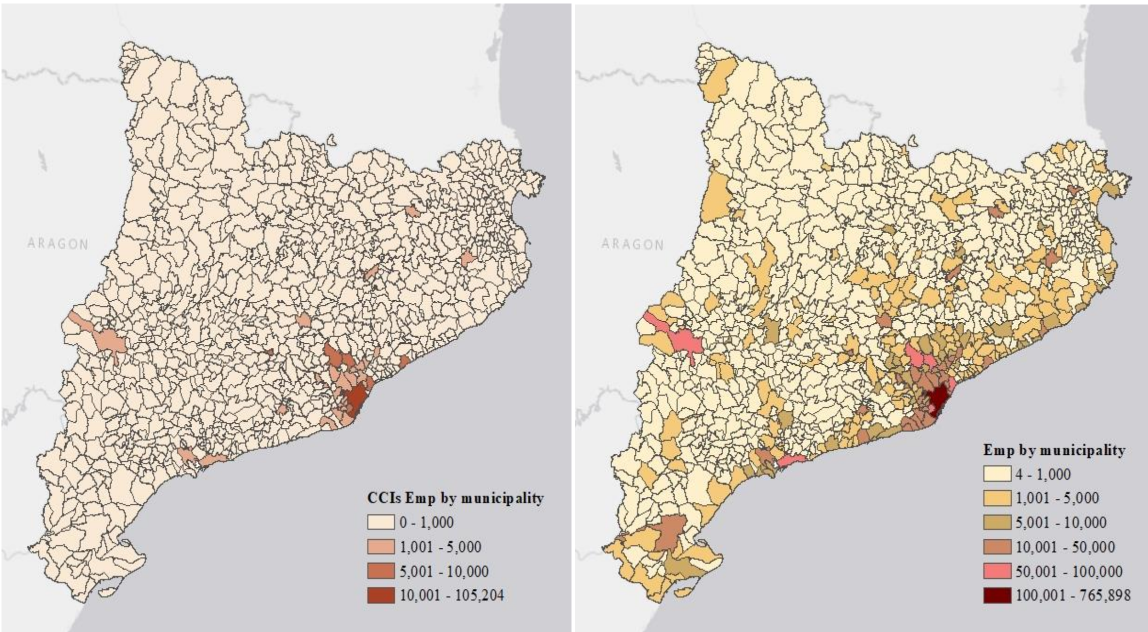
Note: there is only one independent variable for each of these regressions

Source: Authors' elaboration

Table 6. Quantile Regression Model				
Θ	**0.25**	**0.50**	**0.75**	**0.90**
Constant	**0.43*** **	**0.91*** **	**1.32*** **	**2.15*** **
	(0.108)	(0.098)	(0.128)	(0.174)
LQCCIs	-0.01	-0.00	**0.06** **	**0.12*** **
	(0.019)	(0.017)	(0.022)	(0.031)
Entropy	**-0.76*** **	**-1.32*** **	**-1.70*** **	**-2.47*** **
	(0.11)	(0.097)	(0.126)	(0.173)
University	**0.01*** **	**0.01** **	**0.01* **	0.00
	(0.002)	(0.002)	(0.002)	(0.004)
Popdensity	**-0.00** **	0.00	-0.00	0.00
	(0.000)	(0.00)	(0.000)	(0.000)
Infracap	-0.00	-0.00	-0000	**-0.003** **
	(0.000)	(0.000)	(0.000)	(0.001)
Smallfirms	-0.00	0.00	0.00	0.00
	(0.000)	(0.000)	(0.000)	(0.000)
Number of Observations	943	943	943	943
Pseudo R2	0.0554	0.1348	0.1978	0.2667
Significance codes: * p<0.05; ** p<0.01; *** p<0.001				
Source: Authors' elaboration				

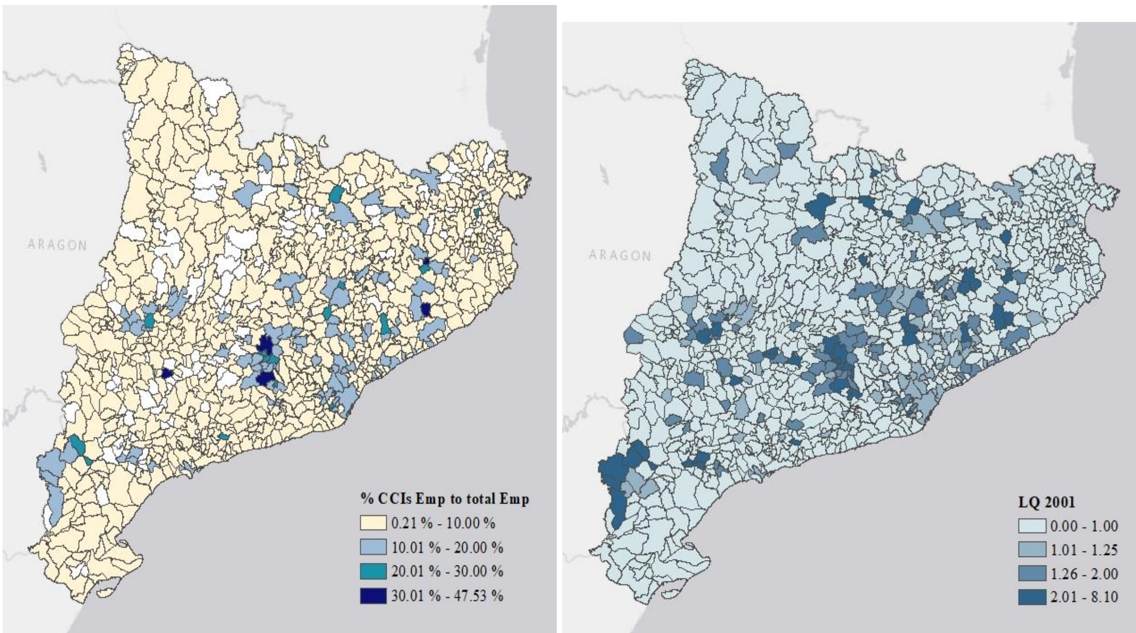
Figures

Figure 1. CCI Employment by Municipality in 2001



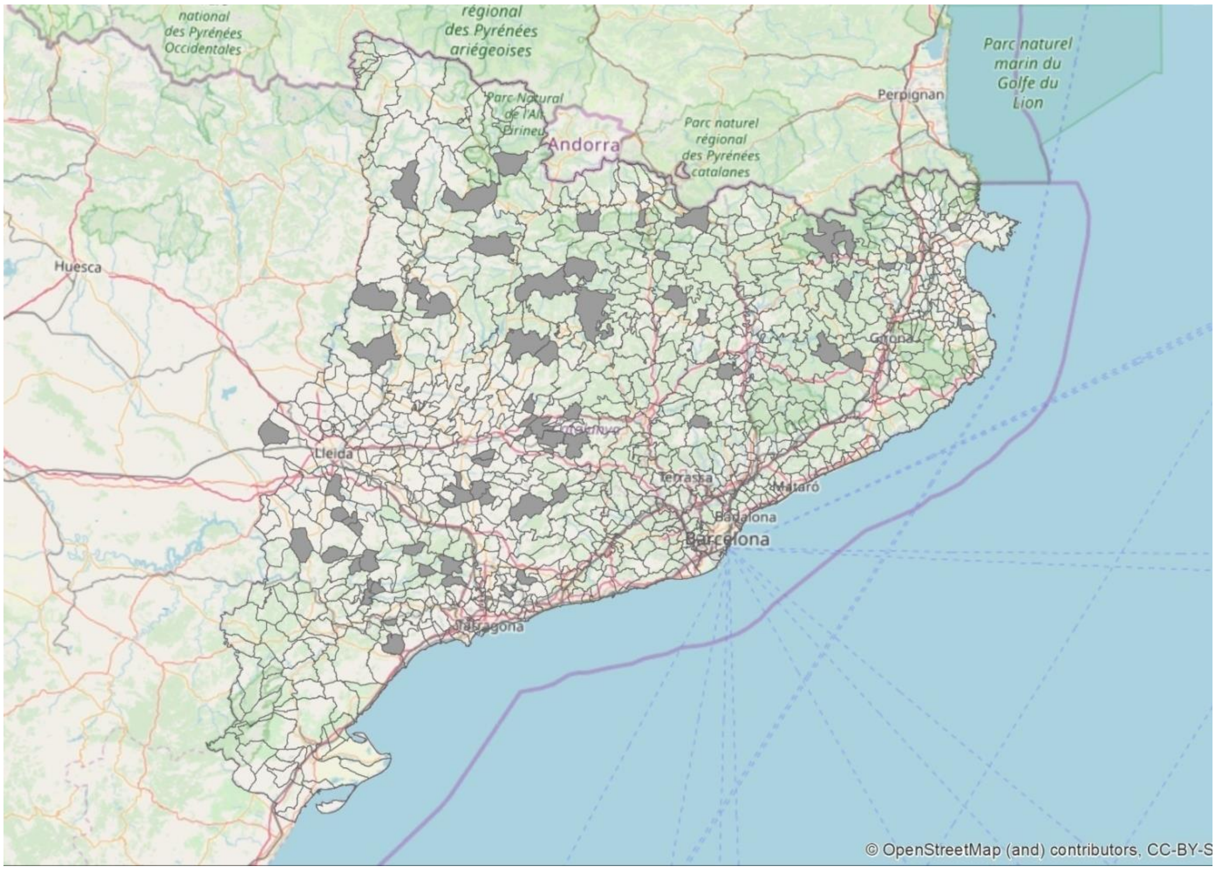
Source: Authors' elaboration.

Figure 2. Degree of Specialization in CCIs in 2001



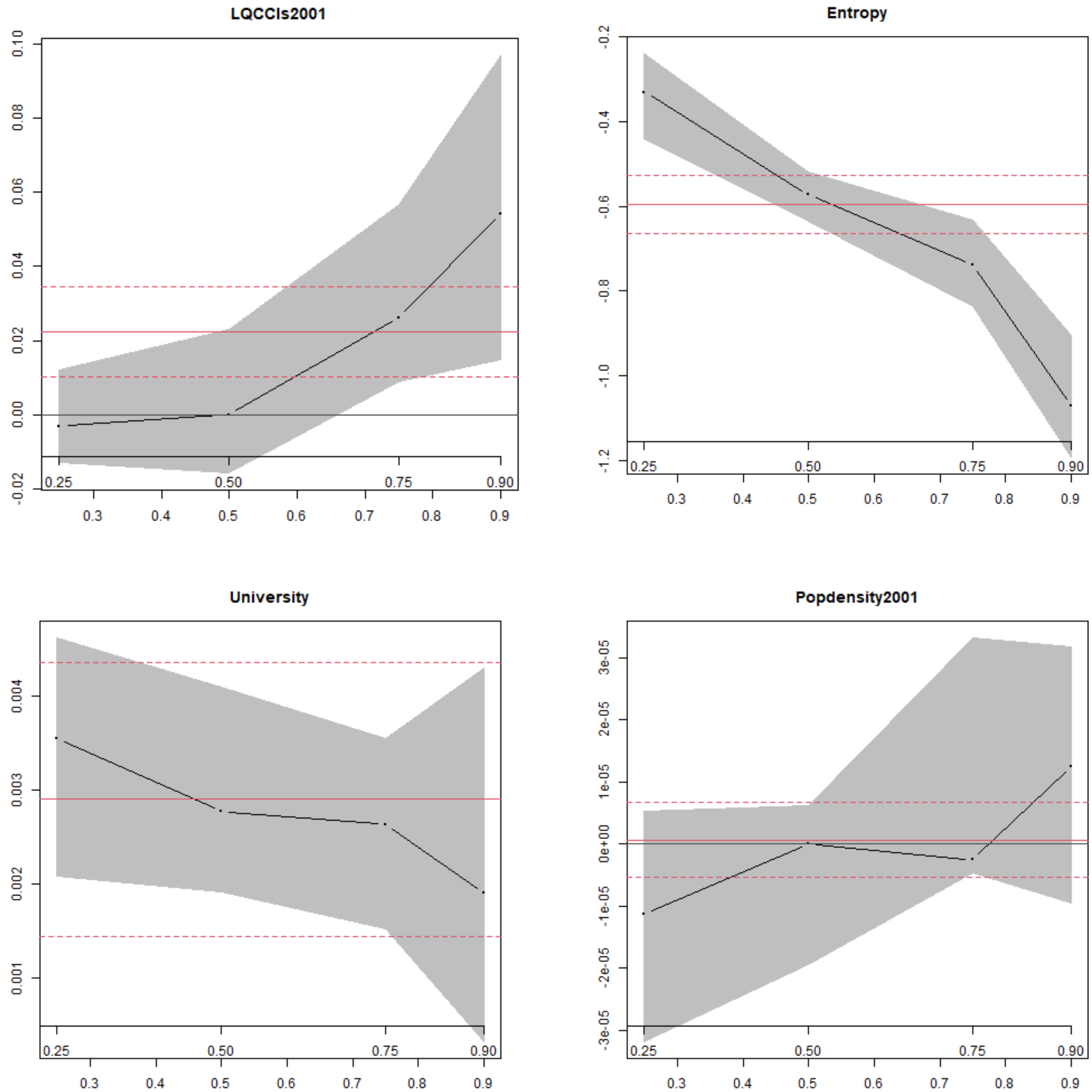
Source: Authors' elaboration.

Figure 3. Geographical Distribution of Outliers



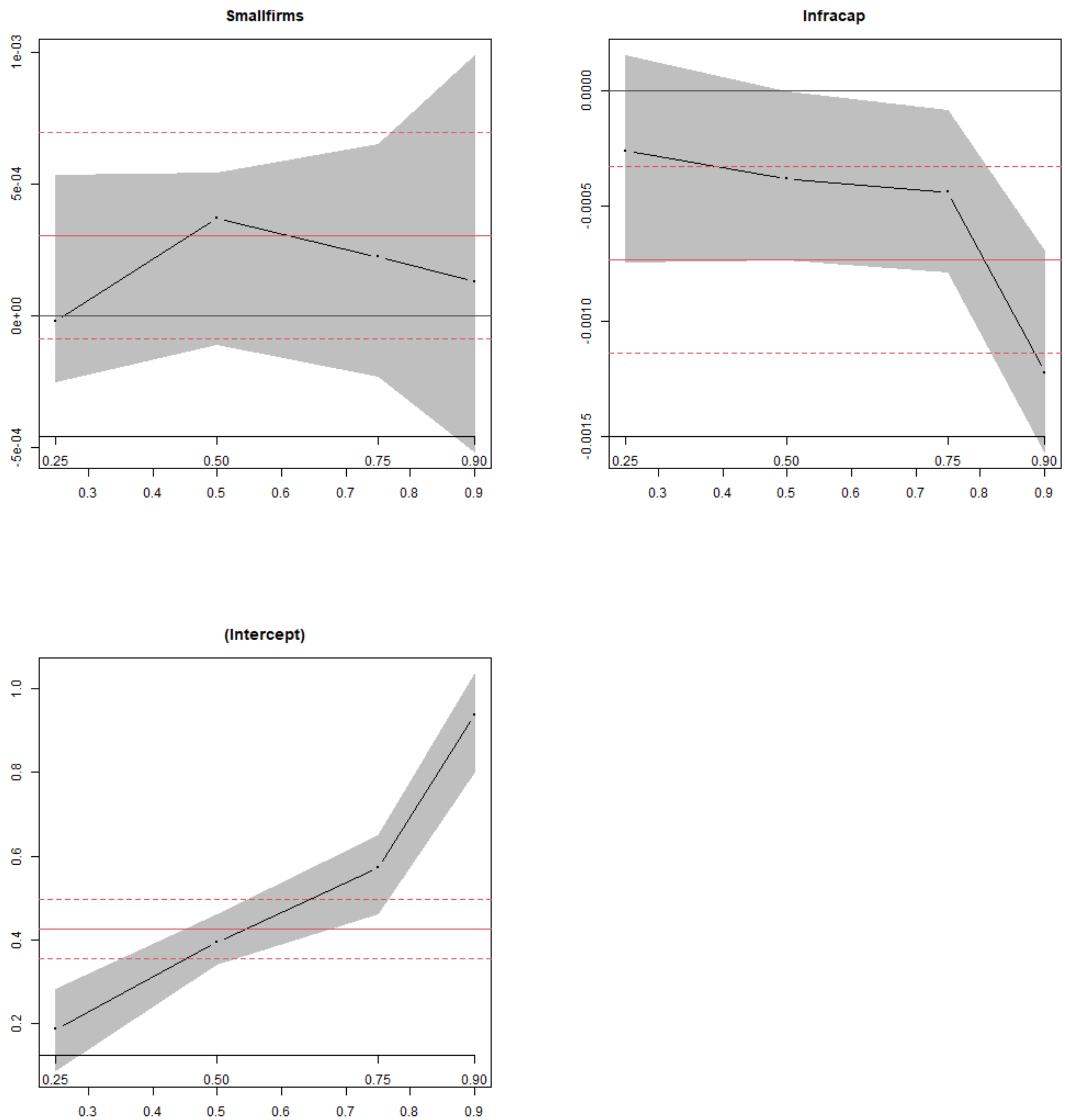
Source: Authors' elaboration using an OpenStreetMap layer.

Figure 4. OLS and Quantile Regression Coefficients



Source: Authors' elaboration.

Figure 4.OLS and Quantile Regression Coefficients (cont.)



Source: Authors' elaboration.

Appendix

Table A.1. Cultural and Creative Industries Definition

Code	Fashion	Code	Research and Development
17710	Manufacture of knitted and crocheted hosiery	73100	Research and experimental development in natural sciences and engineering
17720	Manufacture of other articles with knitted fabrics	73200	Research and experimental development in social sciences and humanities
18100	Manufacture of leather garments		**Architecture and Engineering**
18210	Manufacture of workwear	74201	Architectural technical services
18221	Manufacture of industrial clothing	74202	Engineering technical services
18222	Tailor-made clothing	74203	Mapping and surveying technical services (Cartography and Topography)
18231	Manufacture of men's underwear		**Advertising**
18232	Manufacture of female lingerie	74401	Advertising agencies and consultants
18241	Manufacture of babies' garments	74402	Advertising media management
18242	Manufacture of sportswear		**Photography**
18243	Manufacture of other types of clothing and accessories	74811	Development laboratories, printing and photographic enlargement
18301	Preparation, tanning and dyeing of fur	74812	Photographic studies and other photography activities
18302	Manufacture of articles of fur		**Design**
19100	Preparation, tanning and finishing of leather	74841	Non-industrial design and interior decoration
19201	Manufacture of leather goods and luggage		**Cinema, video, music, TV and Radio**
19202	Manufacture of other articles of leather	22310	Reproduction of sound-recorded media
19300	Manufacture of footwear	22320	Reproduction of video-recorded media
	Publishing	22330	Reproduction of data-recording
22110	Publishing of books	92111	Production of films
22120	Publishing of newspapers	92112	Assistance activities to cinematographic and video production
22130	Magazine publishing	92121	Distribution of cinematographic films and videotapes
22140	Publishing of sound recordings	92122	Distribution of films on videotape
22150	Other publishing activities	92130	Film showings
	Graphic Arts and Printing	92201	Radio activities
22210	Printing of newspapers	92202	Production and distribution of television
22220	Other printing activities	92203	Broadcasting of TV programs
22230	Binding and finishing	64200	Telecommunications
22240	Composition and photoengraving		**Writers, performing arts, visual arts and crafts**
22250	Other graphic activities	92311	Artistic and literary creation, interpretation of dramatic art, music and similar activities
	Jewelry, Musical Instruments and Toys	92312	Production of entertainment shows
36221	Manufacture of jewelry items	92313	Other activities related to entertainment shows
36222	Manufacture of articles of gold and silverware	92320	Management of entertainment venues
36300	Manufacture of musical instruments	92330	Activities of amusement and theme parks
36500	Manufacture of games and toys	92341	Dance halls, discotheques and similar activities
36610	Manufacture of customized jewelry	92342	Bullfighting shows and activities
	Software and Videogames	92343	Other entertainment activities
72100	Activities of computer consultancy		**Activities related to Heritage**
72200	Software consultancy and supply of computer applications and programs	92510	Library and archive activities
		92521	Museum activities
		92522	Conservation of historical sites and buildings
		92530	Activities of botanical and zoological gardens, nature reserves and national parks

Source: Own elaboration based on Sánchez-Serra (2016), DCMS (2013), Lazzeretti *et al*. (2011), UNCTAD (2010)

Table A.2. Correlation Matrix

	EmpGrowth	LQCCIs2001	Entropy	University	Popdensity2001	InfraCap	Smallfirms
EmpGrowth	1	0.11	-0.37*	0.08*	0.12*	-0.02	-0.03
LQCCIs	0.11	1	0.19*	0	-0.07	-0.21	0.03
Entropy	-0.37	0.19	1	0	-0.21	-0.33	0.18
University	0.08	0	0	1	0	0.04	0.02
Popdensity2001	0.12	-0.07*	-0.21*	0	1	0.01	-0.19
InfraCap	-0.02	-0.21*	-0.33*	0.04	0.01	1	-0.01
Smallfirms	-0.03	0.03	0.18*	0.02	-0.19*	-0.01	1

Significance level (p<0.05)

Table A.3. Profile of Outlier Municipalities: Filtered (878) v. Outliers (65)

	Mean		Median		SD		Min		Max		Sum	
	Filtered	**Outliers**	**F**	**O**	**F**	**O**	**F**	**O**	**F**	**O**	**F**	**O**
Employment 2001	3,137.94	26.91	262.50	17	32,589.61	35.57	3	0	946,119	221	2,755,110	1,749
Employment 2011	3,275.44	84.40	311	54	33,301.23	104.86	4	5	965,810	662	2,875,834	5,486
%Emp. Growth	25.29	284.10	18.93	204	38.25	251.87	78.36	12.12	143.42	1,800	22,202	18,466.67
Emp. in CCIs 2001	293.01	1.63	12	1	3,601.37	2.75	0	0	105,204	13	257,266	106
LQ-CCIs 2001	0.66	0.78	0.48	0.30	0.70	1.25	0	0	8.09	6.55	577.76	50.71
Infracap	86.83	88.32	82	85	23.57	28.32	0	0	190	152	76,234	5,741
Pop 2001	7,203.16	226.83	919	165	53,646.28	191.75	26	35	1,503,884	1,066	6,324,373	14,744

Source: Authors' elaboration

Table A.4. Interquantile Regression Models			
Θ	**0.25-0.50**	**0.50-0.75**	**0.75-0.90**
Constant	**0.48***** (0.102)	**0.41***** (0.135)	**0.84***** (0.197)
LQCCIs	0.01 (0.22)	**0.06*** (0.039)	0.06 (0.041)
Entropy	**-0.56***** (0.109)	**-0.38**** (0.167)	**-0.77***** (0.246)
University	-0.00 (0.002)	-0.00 (0.002)	-0.00 (0.002)
Popdensity	0.00 (0.000)	-0.00 (0.000)	0.00 (0.000)
Infracap	-0.00 (0.000)	-0.00 (0.001)	**-0.00**** (0.000)
Smallfirms	0.00 (0.000)	-0.00 (0.135)	-0.00 (0.000)
Number of Observations	943	943	943
Pseudo R2	“0.50”: 0.1348 “0.25”: 0.0554	“0.75”: 0.1978 “0.50”: 0.1348	“0.90”: 0.2667 “0.75”: 0.1978
Significance codes: * p<0.05; ** p<0.01; *** p<0.001 Bootstrap (20) Standard Errors			
Source: Authors’ elaboration			